Application of Artificial Neural Network in Economic Generation Scheduling of Thermal Power Plants

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Abstract- *The artificial neural network has been applied to the economic* generation scheduling *of six thermal power plants with very promising results. In this problem equality constraints of power balance and inequality plant generation capacity constraints are considered. The transmission losses occurring are also considered. The inputs to the neural network contain the total load supplied. The electric power generation of six thermal power plants and the total system transmission losses are taken as the output of the neural network. A program in C language is developed to generate training and test pattern for the network developed. At the end performance and time taken in execution of the neural network is compared with the Classical Kirchmayer Method and it is observed that the neural network being very fast and accurate. Therefore, it may replace effectively the conventional practices presently performed in different central load dispatch centers.*

1. Introduction

The size of electric power system is increasing rapidly to meet the energy requirements. A number of power plants are connected in parallel to supply the system load by interconnection of power stations. With the development of grid system it becomes necessary to operate the plant unit most economically. The economic generation scheduling problem involves two separate steps namely the unit commitment and the online economic dispatch. The unit commitment is the selection of unit that will supply the anticipated load of the system over a required period of time at minimum cost as well as provide a specified margin of the operating reserve. The function of the online economic dispatch is to distribute the load among the generating units actually paralleled with the system in such a manner as to minimize the total cost of supplying the minute to minute requirements of the system [1, 4]. Thus, economic load dispatch problem is the solution of a large number of load flow problems and choosing the one which is optimal in the sense that it needs minimum cost of electric power generation. Accounting for transmission losses results in considerable operating economy. Further more this consideration is equally important in future system planning and in particular, with regard to the location of plants and building of new transmission lines. To calculate electric power generation of various units with different load demands (Training data), the usual Classical Kirchmayer Method is used.

In this paper an Artificial Neural Network [ANN] based method is proposed. ANN can be defined as a class of mathematical algorithms designed to solve a specific problem. Basically ANNs are parallel computational models comprised of densely interconnected adaptive processing units. An extremely important and human characteristic of ANNs is their adaptive nature, where learning by experience replaces programming in solving problems [2, 3]. ANNs learn the pattern on which they are trained. In this work ANN is trained with different load demands. Once it has been trained, it acquires the ability to give load scheduling pattern for any value for load demand.

2. Problem Formulation

A number of thermal power plants are connected to a common grid which supplies power to different load centers. The load demand is totally at the discretion of the consumers and it varies over a wide range. The cost of power generation is not the same for every unit. So, to have the minimum cost of generation for a particular load demand, we have to distribute the load among the units which minimize the overall generation cost with the constraint that no unit is overloaded. The majority of generating units have a non linear cost function C_i. The variation of fuel cost of each generator with active power output P_{Gi} is given by a quadratic polynomial.

$$C_i = a_i P_{Gi}^2 + b_i P_{Gi} + d_i \qquad \ldots(1)$$

Where a_i is a measure of losses in the system, b_i is the fuel cost and d_i is the salary and wages, interest and depreciation.

The optimal dispatches for the thermal power plants should be such that the total electric power generation equal to the load demand plus line losses, which can be written as:

$$\sum_{i=1}^{K} P_{Gi} - P_D - P_L = 0 \qquad \ldots(2)$$

where,

K = total number of generating plants,

P_{Gi} = generation of i'th plant,

P_L = total system transmission loss,

P_D = system load demand

The transmission losses which occur in the line when power is transferred from the generating station to the load centers increases with increase in distance between the two [2, 4, 6]. The transmission losses may vary from 5 to 15 % of the total load. If the power factor of load at each bus is assumed to remain constant the system loss P_L can be shown to be a function of active power generation at each plants i.e.

$P_L = P_L(P_{G1}, P_{G2}\ldots\ldots\ldots P_{GK})$ …(3)

One of the most important, simple but approximate method of expressing transmission loss as a function of generator powers is through B-Coefficients and is given by Kron's loss formula [1] as:

$$P_L = \sum_{i=1}^{k}\sum_{j=1}^{k} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{k} B_{0i} P_{Gi} + B_{00} \quad \ldots (4)$$

Where,

P_{Gi}, P_{Gj} = real power generation at i'th and j'th power unit

B_{ij}, B_{0i} = loss coefficients, constant for certain conditions

B_{00} = loss constant

The inequality constraints is given by

$P_{Gmin} \leq P_{Gi} \leq P_{Gmax}$ …(5)

The maximum active power generation P_{Gmax} of source is limited by thermal consideration and minimum active power generation P_{Gmin} is limited by the flame instability of a boiler [1, 4, 6].

3. Software Description

A program in C language is developed for generating training patterns by Classical Kirchmayer Method and Error Back-propagation Method.

3.1 Classical Kirchmayer Method: This method [1, 4, 6] is used to generate the output data for six thermal power plants considering transmission losses. The Algorithm is as follows:

1. Start
2. Read the constants a_i, b_i, loss coefficient matrices B_{ij}, and B_{0i}, constant B_{00}, power demands P_D, maximum *PGMX*, minimum *PGMN* generators real power limits
3. Assume a suitable value of $\lambda = \lambda_0$. This value should be greater than the largest intercept of the incremental cost of the various units. Calculate P_{G1}, P_{G2}, ---------- ,P_{Gi} based on equal incremental cost.
4. Calculate the generation at all buses using

$$P_{Gi} = \frac{1 - B_{0i} - \dfrac{b_i}{\lambda} - \sum_{\substack{j=1 \\ j\neq 1}}^{k} 2B_{ij}P_{Gj}}{\dfrac{2a_i}{\lambda} + 2B_{ii}} \quad i = 1,2,------,k$$

…(6)

keeping in mind that the values of powers to be substituted on the RHS of Eq.(6) during zeroth iteration correspond to the values calculated in step 3. For subsequent iterations the values of powers to be substituted corresponds to the powers in the previous iteration. However if any generator violates the limit of generation that generator is fixed at the limit violated.

5. Check if the difference in power at all generator buses between two consecutive iterations is less than the specified value, otherwise go back to step 2
6. Calculate the losses using the relation

$$P_L = \sum_{i=1}^{k}\sum_{j=1}^{k} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{k} B_{0i} P_{Gi} + B_{00} \quad \ldots(7)$$

7. Calculate,

$$\Delta P = \sum_{i=1}^{k} P_{Gi} - P_D - P_L \quad \ldots(8)$$

8. If ΔP is less than a specified value ε, stop calculation and calculate cost of generation with values of powers. If $\Delta P < \varepsilon$ is not satisfied go to step7.
9. Update λ as $\lambda^{(k+1)} = \lambda^{(k)} - \Delta\lambda^{(k)}$ where $\Delta\lambda$ is the step size [7, 8, 9].
10. Stop

3.2 Back Propagation Algorithm:

1. Start
2. Read the input values, *(X)*, target values, *(T)*, learning rate coefficient, *(ή)*, tolerance limit of error, *(ε)*, momentum constant, *(α)*, maximum number of iterations, *(itrmax)*, neurons in hidden layer, *(n)*, input nodes, *(m)*, output nodes,*(z)*, total number of input pairs, *(p)*, maximum value of input, *(x_max)*, maximum value of target, *(t_max)*, and constant, *(SEED)* to generate weight matrices.
3. Normalize the input and target vector.
4. Activate the first node of the input by *1.0* and the rest by the normalized inputs.
5. Generate the random weights.
6. Set all the elements of error weight matrices *dW1* and *dW2* equal to zero.
7. Set *i = 0.0*
8. Set *serr = 0.0*
9. Calculate output *Y1* using

   *Y1 (i, j) = X (i, k) * W1(k, j)* where *j=0, 1, …n-1; k=0, 1,…m-1;*
10. Process output of hidden layer through a non linear activation function (positive sigmoid function) to produce output of hidden layers.

    Y1 (i, j) =1/(1+exp(-Y1 (i, j)))
11. Calculate the final output using

    *Y1 (i, 1) = Y1 (i, j) * W2 (j, 1)*

12. Process again through sigmoid function to find output of network.

    Y (i, 1) =1/(1+exp(-Y (i, 1)))

13. Calculate square error as

    $e(i, 1) = T(i, 1) – Y (i,1)$

    $serr + = e(i, 1) * e(i, 1)^T$

14. Adjust the weights of output layer

    $d12 (i, 1) = Y (i,1) *(1- Y (i,1)) * e (i,1)^T$

    *dW2(j, 1) = ή*d12 (i,1) * (Y (i,j)) +α * dW2 (j,1)*

    W2 (j,1) +=dW2(j,1)

15. Adjust the weight of hidden layer.

    sum = 0.0;

    *sum + = d12(i,1) * W2 (j,1)*

    *d11 (i, j) = sum * Y1 (i,j) *(1- Y1 (i,j))*

    *dW1(k, j) = ή *d11 (i,j) * X (i, k) + α * dW1 (k, j)*

    W1 (k, j) + =dW1(k, j)

16. Increase by one and if $i<p$ go to step 8.
17. Check for tolerance, if $serr > \varepsilon$ then go to step 7.
18. Stop

4. Application Example

The cost functions for six thermal power plants [5] are shown in table 1.1

Table 1.1

Cost of i'th unit C_i	a_i	b_i	d_i
1	0.0070	7.0	240
2	0.0095	10.0	200
3	0.0090	8.5	220
4	0.0090	11.0	200
5	0.0080	10.5	220
6	0.0075	12.0	190

The inequality plant capacity constraints i.e. the generator's real power limits are given in table 1.2

Table 1.2

Generator Real Power Limits		
Generator	**Min. MW**	**Max. MW**
1	100	500
2	50	200
3	80	300
4	50	150
5	50	200
6	50	120

The loss coefficient matrix used is

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_{0i} = [\ -0.3908 \quad -0.1297 \quad 0.7047 \quad 0.0591 \quad 0.2161 \quad -0.6635\ ]$$

and constants $B_{00} = 0.0056$

4. Results

The results are shown in Table 1.3 and 1.4 (Appendix). It is to be noted that the results obtained by ANN are very close to the results obtained by conventional classical method.

5. Conclusion

This work aim to carry out development for ANN based method to determine economic generation scheduling considering transmission losses of thermal power plants very efficiently and accurately. In a power system there is a large variation in load from time to time and it is not possible to have the load scheduling pattern for every possible load demand. As there is no general procedure for finding out the economical load scheduling pattern. This is where ANN plays an important role as we need small number of training data sets for the training of ANN. A trained ANN can then be applied to find out the economical load scheduling pattern for a particular load demand in a fraction of second. There is no need of having loss matrices, B_{ij} , B_{i0}, and loss constant B_{00} in an ANN based method.

Results obtained are very much closed to the results obtained by Kirchmayer Method's. A remarkable saving in the computation time has been observed.

Due to flexibility in ANN several other practical constraints can also be easily incorporated as input-output information of the training sets. For future work it is suggested to design a general ANN for such problems. Also, methods can be thought of which reduced the training time. The effect of complexity of the neural network on the performance of system may also be studied.

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LOAD PD MW	KIR PK1 MW	ANN PA1 MW	ERR %E1	KIR PK2 MW	ANN PA2 MW	ERR %E2	KIR PK3 MW	ANN PA3 MW	ERR %E3	KIR PK4 MW	ANN PA4 MW	ERR %E4	KIR PK5 MW	ANN PA5 MW	ERR %E5	KIR PK6 MW	ANN PA6 MW	ERR %E6	LOSSES (MW)		ERR %EL
																			PLK	PLA	
840	307.03	307.42	-0.046	110.5	111	-0.064	213.6	214.15	-0.064	87.15	87.16	-0.002	104.4	105.1	-0.083	50	49.3	0.084	33.94	34.03	-0.011
850	309.35	309.36	-0.001	112.3	112.4	-0.01	216.1	216.08	-0.002	89.49	88.99	0.059	106.5	106.6	-0.016	50.06	50.93	-0.103	34.69	34.68	0.002
875	314.51	314.22	0.034	116.2	116	0.031	221.3	220.93	0.038	94.2	93.62	0.067	111	110.6	0.037	55.17	55.18	0	36.46	36.35	0.013
900	318.96	319.06	-0.01	119.6	119.5	0.007	225.8	225.8	-0.004	98.27	98.31	-0.004	114.8	114.7	0.013	59.58	59.61	-0.004	38.04	38.07	-0.004
950	328.83	328.72	0.012	127	126.8	0.027	235.8	235.59	0.018	107.3	107.8	-0.048	123.3	123	0.039	69.33	68.97	0.038	41.69	41.68	0
1000	338.61	338.37	0.023	134.4	134.1	0.029	245.7	245.45	0.027	116.3	117.1	-0.084	131.7	131.3	0.038	78.98	78.78	0.021	45.52	45.5	0.002
1050	348.29	348.1	0.018	141.7	141.5	0.015	255.6	255.42	0.02	125.2	126.1	-0.09	140	139.8	0.019	88.53	88.75	-0.021	49.54	49.53	0.001
1100	357.89	358	-0.01	148.9	149	-0.013	265.5	265.61	-0.01	134	134.5	-0.051	148.3	148.5	-0.017	97.98	98.61	-0.057	53.73	53.8	-0.006
1150	368.06	368.21	-0.013	156.5	156.7	-0.017	276	276.15	-0.013	143.4	142.3	0.095	157	157.2	-0.024	108	108.1	-0.009	58.4	58.36	0.004
1175	372.94	373.46	-0.045	160.2	160.6	-0.039	281.1	281.6	-0.046	147.9	145.8	0.175	161.1	161.7	-0.05	112.8	112.6	0.015	60.73	60.77	-0.004
1200	378.48	378.84	-0.03	164.3	164.6	-0.03	286.8	287.21	-0.039	150	149.1	0.075	165.5	166.3	-0.036	118.4	116.9	0.122	63.26	63.29	-0.002
1225	385.06	384.34	0.059	169.4	168.8	0.053	293.8	293	-0.062	150	152.2	-0.177	171.8	170.9	0.068	120	121	-0.085	65.98	65.93	0.004

RESULT FOR MEAN SQUARE ERROR = 4.466038 E -06

TABLE 1.3 – RESULTS IN TRAINING MODE (COMPARISON OF TEST RESULTS OBTAINED BY KIRCHMAYER AND ANN METHOD ECONOMIC LOAD SHARING INCLUDING LOSSES OF SIX THERMAL POWER PLANTS)

LOAD PD MW	KIR PK1 MW	ANN PA1 MW	ERR %E1	KIR PK2 MW	ANN PA2 MW	ERR %E2	KIR PK3 MW	ANN PA3 MW	ERR %E3	KIR PK4 MW	ANN PA4 MW	ERR %E4	KIR PK5 MW	ANN PA5 MW	ERR %E5	KIR PK6 MW	ANN PA6 MW	ERR %E6	LOSSES (MW)		ERR %EL
																			PLK	PLA	
835	306.37	306.45	-0.009	109.97	110.34	-0.044	212.91	213.19	-0.033	86.48	86.26	0.027	103.75	104.28	-0.063	50	48.49	0.181	33.72	33.71	0.002
860	311.42	311.31	0.013	113.9	113.84	0.008	218.15	218.02	0.013	91.38	90.84	0.063	108.29	108.23	0.007	52.11	52.61	-0.058	35.39	35.24	0.006
890	317.25	317.12	0.015	118.3	118.09	0.023	224.04	223.85	0.02	96.71	96.43	0.031	113.33	113.06	0.03	57.89	57.82	0.008	37.42	37.38	0.006
925	323.74	323.89	-0.016	123.18	123.13	0.006	230.6	230.69	-0.01	102.64	103.03	-0.043	118.92	118.8	0.014	64.3	64.22	0.009	39.77	39.85	-0.008
975	333.56	333.54	0.002	130.57	130.41	0.017	240.58	240.51	0.007	111.63	112.46	-0.084	127.38	127.13	0.026	74	73.83	0.017	43.52	43.57	-0.005
1025	343.39	343.22	0.007	137.89	137.78	0.011	250.51	250.42	0.009	120.56	121.65	-0.106	135.75	135.58	0.017	83.6	83.76	-0.015	47.44	47.49	-0.005
1075	352.94	353.02	-0.008	145.14	145.23	-0.008	260.4	260.48	-0.008	129.43	130.4	-0.091	144.02	144.13	-0.01	93.11	93.71	-0.057	51.54	51.64	-0.009
1125	363.15	363.06	0.008	152.81	152.82	-0.001	270.93	270.83	0.009	138.83	138.5	0.029	152.76	152.82	-0.005	103.15	103.41	-0.023	56.12	56.04	0.007
1175	372.61	373.46	-0.072	159.92	160.62	-0.06	280.73	281.6	-0.075	147.56	145.8	0.15	160.85	161.71	-0.074	112.45	112.59	-0.012	60.57	60.77	-0.017
1210	380.73	381.02	-0.025	165.99	166.28	-0.024	289.08	289.51	-0.036	150	150.36	-0.03	167.8	168.13	-0.028	120	118.59	0.116	64.23	64.33	-0.008
1220	384.13	383.23	0.074	168.69	167.93	0.062	292.76	291.83	0.076	150	151.57	-0.129	170.93	170	0.076	120	120.23	-0.019	65.61	65.39	0.017
1230	386.92	385.45	0.119	170.88	169.61	0.104	295.78	294.19	0.129	150	152.75	-0.224	173.47	171.89	0.129	120	121.84	-0.15	66.74	66.48	0.022

TABLE 1.4 – RESULTS IN NON-TRAINING MODE (COMPARISON OF TEST RESULTS OBTAINED BY KIRCHMAYER AND ANN METHOD ECONOMIC LOAD SHARING INCLUDING LOSSES OF SIX THERMAL POWER PLANTS)