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OPTIMAL DISPATCH OF POWER GENERATION USING ARTIFICIAL NEURAL NETWORK

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Abstract— In the practical power system, power plants are not at the same distance from the centre of load and their fuel costs are also different. Generally the power generation capacity is more than the total load demand and losses under normal operating conditions. Thus there is a need to find an effective real and reactive power scheduling to power plants to meet load demand as well as to minimize the operating cost. There are many Optimal Power Flow methods used to determine Optimal Dispatch of Power Generation and one such method is Newton method. This method is well-known in the area of Power Systems and provides a very powerful method because of its rapid convergence near the solution. This method will lead to an economic operation of the power plant and yields an economic dispatch of real power generation. As this is too slow, we proposed a soft computing based approach i.e. Back Propagation Neural Network (BPNN) for determining Optimal Dispatch of Power Generation. This method provides fast and accurate results compared with the above conventional method.

Keywords: Optimal Dispatch of Power Generation, Optimal Power Flow, Artificial Neural Network, Back Propagation Algorithm (BPNN).

I. Introduction

When generators are interconnected with various loads the generation capacity is much larger than the loads. Hence the allocation of the loads[1] on the generators can be varied. It is important to reduce the cost of electricity as much as possible, hence the "Optimal" division of load (meaning the least expensive) is desired. The most expensive cost of generation is the fuel cost and other expenses are labour, repairs and maintenance. These are all "Economical" factors[8][9].

In the practical power system, power plants are not at the same distance from the centre of load and their fuel costs are different. More over under normal operating conditions the generation capacity is more than the total load demand and losses. Thus there is one main option for scheduling generation is to find an effective real and reactive power scheduling to power plants to meet load demand as well as to minimize the operating cost.

This optimal division of load[2] can be shared by the generators using different methods. In those methods we are using Newton method [1] because of its rapid convergence near the solution. But this is too slow , so we proposed a soft computing based approach i.e. Back Propagation Neural Network (BPNN)[5] for determining Optimal Dispatch of Power Generation. This method provides fast and accurate results when compared with the above proposed conventional method.

Back Propagation is a systematic method for training multilayer artificial networks. It is a multilayer forward network learning rule, commonly known as back propagation rule. Back propagation provides a computationally efficient method for changing the weights in a feed forward network, with differential activation function units, to learn a training set of input-output examples. Being a gradient descent method it minimizes the total squared error of the output computed by net. The network is trained by supervised learning method.

In this paper, the optimal dispatch [4] of power generation is determined using both newton as well as BPNN and results are compared.

II. Optimal Power Flow methods

The optimal power flow is a power flow problem in which certain controllable variables are adjusted to minimize an objective function such as the cost of active power generation or the losses,while satisfying physical and operating limits on various controls, dependent variables. The types of controls that an optimal power flow must be able to accommodate are active and reactive power injections, generator voltages and phase-shift angles transformer tap ratios and phase-shift angles. There are many optimal power flow methods available, but we have considered the following methods.

II.I Newton Method

Newton's[1] method is well-known in the area of power systems. It has been the standard solution algorithm for the power flow problem for decades. Newton's method is a very powerful solution algorithm because of its rapid convergence near the solution. This property is especially useful for power

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system applications because an initial guess near the solution is easily attained. System voltages will be near rated system values, generator outputs can be estimated from historical data, and transformer tap ratios will be near 1.0 p.u.

II.II Algorithm for Newton OPF method:

1 .Read cost function coefficients a_i, bi, ci, number of nodes n and number of control variables n_1.

2. Form Y_{bus} by using Y_{bus} Algorithm.

3. Calculate the initial values of P_{gi} (i=1, 2,…..,Ng) and λ by assuming PL=0

$$\lambda pi = \frac{\sum_{i=1}^{Nl} Pdi + \sum_{i=1}^{Ng} \frac{b_i}{2a_i}}{\sum_{i=1}^{Ng} \frac{b_i}{2a_i}} \quad (i = 1,2\ldots NG)\ldots\ldots(1)$$

$$Pgi = \frac{\lambda - b_i}{2 * a_i}$$

(i=1,2……………….NG) ....(2)

$$Qgi = Pgi * \frac{\sum_{i=1}^{MB+1} Qdi}{\sum_{i=1}^{NB} Pdi}$$

(i=1,2……………….NG) ....(3)

Initialize

λpi =λ (i =1,2………………...NG)

λqi=0 (i=NV+1…………..….NB)

Vi=1 (i=2,3………………...NB)

δ=0 (i=2,3,………………...NB)

4. By using initial values calculate the Jacobean and Hessian matrix element

$$[H]\begin{bmatrix}\Delta Pg\\ \Delta\delta\\ \Delta\lambda p\\ \Delta V\\ \Delta\lambda q\end{bmatrix} = -\begin{bmatrix}\frac{\partial L}{\partial Pg}\\ \frac{\partial L}{\partial \delta}\\ \frac{\partial L}{\partial \lambda p}\\ \frac{\partial L}{\partial V}\\ \frac{\partial L}{\partial \lambda q}\end{bmatrix} \qquad \ldots\ldots\ldots\ldots(4)$$

By using Gauss elimination determine ΔPgi, Δδi, Δλpi, ΔVi, Δλqi

5. Check convergence

$$\left[\sum_{i=1}^{NG}(\Delta Pgi)^2 + \sum_{i=2}^{NB}(\Delta\delta i)^2 + \sum_{i=1}^{NB}(\Delta\lambda pi)^2 + \sum_{i=NV+1}^{NB}(\Delta vi)^2 + \sum_{i=NV+1}^{NB}(\Delta\lambda qi)^2\right]^{\frac{1}{2}} \le \epsilon \qquad \ldots\ldots\ldots\ldots(5)$$

If condition is not satisfied then go to step6 else go to step8

6. Modify the variables as below

$$p_{gi} = P_{gi} + \Delta P_{gi} \qquad (i = 1,2\ldots\ldots\ldots NG)$$
$$\delta_i = \delta_i + \Delta\delta_i \qquad (i = 2,3\ldots\ldots\ldots NB)$$
$$\lambda_{pi} = \lambda_{pi} + \Delta\lambda_{pi} \qquad (i = 1,2\ldots\ldots\ldots NB)$$
$$V_i = V_i + \Delta V_i \qquad (i = NV+1\ldots\ldots\ldots NB)$$
$$\lambda_{qi} = \lambda_{qi} + \Delta\lambda_{qi} \qquad (i = NV+1\ldots\ldots\ldots NB)$$

7. Check the limits, if any limit of a variable is violated, then impose or remove power flow equation and go to step4 to update the solution.

8. Stop**.**

III .Artiftial Neural Network

Numerous advances have been made in developing intelligent systems, some inspired by biological neural networks. Researchers from many scientific disciplines are designing artificial neural networks to solve a variety of problems in pattern recognition, prediction, optimization, associative memory, and control.

Conventional approaches have been proposed for solving these problems. Although successful applications can be found in certain well-constrained environments, none is flexible enough to perform well outside its domain. ANNs provide exciting alternatives, and many applications could benefit from using them. One of the important training technique of artificial neural network is Back Propagation Algorithm.

III.I Back Propagation Algorithm

Back Propagation is a systematic method for training multilayer artificial networks. It is a multilayer forward network using extend gradient-descent based delta-learning rule, commonly known as back propagation rule. Back propagation provides a computationally efficient method for changing the weights in a feed forward network, with differential activation function units, to learn a training set of input-output examples. Being a gradient descent method it minimizes the total squared error of the output computed by net. The network is trained by supervised learning method. The aim of this network is to train the net to achieve a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good responses to the input that are similar.

The nueral network is designed in such a way that it is having 6 numbers of input neurons, 6 numbers of output neurons, 3 numbers of output neurons and one bias neuron. It is trained with 150 number of training patterns and tested with 12 patterns. The architecture of the proposed Back Propagation Neural Network [5]has been shown in fig.1.

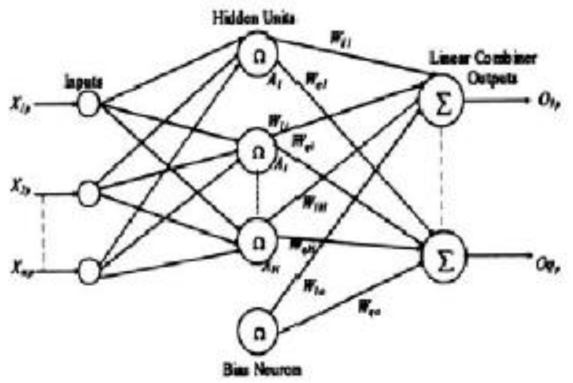

Fig.1 BPNN Achitecture

Back Propagation Algorithm

Initialization of the weights

Step1: Initialize weights to small random values

Step2: While stopping condition is false do Steps 3-10

Step3: For each training pair do steps 4-9

Feed Forward

Step4: Each hidden unit receives the input signal xi and transmits the signals to all units in the layer above i.e. hidden units

Step5: Each hidden unit sums its weihted input signals

$$Z_{\_inj} = V_{oj} + \sum_{i=1}^{n}(X_i * V_{ij}) \quad \text{..........................(6)}$$

applying activation function for to get output

$$Z_j = f(Z_{\_inj}) \quad \text{…………………(7)}$$

Step6: Each output unit sums its weighted input signals

$$Y_{\text{-}ink} = W_{ok} + \sum_{j=1}^{p}(Z_j * W_{jk}) \quad \text{..........................(8)}$$

and apply activation function to calculate output

$$Y_k = f(Y_{\_ink})$$

Back Propagation of errors

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

$$\delta_k = (t_k - y_k) * f(Y_{\_ink}) \quad \text{...............................(9)}$$

Step8: Each hidden unit sums its delta from units in the layer above

$$\delta_{\_inj} = \sum_{k=1}^{m}(\delta_j * W_{ik}) \quad \text{................................(10)}$$

The error information term is calculated as

$$\delta_j = \delta_{\_inj} * f(Z_{\_inj}) \quad \text{..........................(11)}$$

Updation of the weights

Step9: Each unit updates its bias and weights

The weight correction term is given by

$$\Delta W_{jk} = \alpha * \delta_k * Z_i \quad \text{...............................(12)}$$

And the bias correction term is given by

$$\Delta W_{ok} = \alpha * \delta_k$$

Therefore

$$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk}$$
$$W_{ok}(new) = W_{ok}(old) + \Delta W_{ok} \quad \text{...................(13)}$$

Each hidden unit updates its bias and weights

The weight correction term is given by

$$\Delta V_{ij} = \alpha * \delta_j * X_i \quad \text{..........................(14)}$$

And the bias correction term is given by

$$\Delta V_{ok} = \alpha * \delta_j \quad \text{..........................(15)}$$

There fore

$$V_{jk}(new) = V_{jk}(old) + \Delta V_{jk}$$
$$V_{ok}(new) = V_{ok}(old) + \Delta V_{ok} \quad \text{.....................(16)}$$

Step10: Test stopping condition

IV. Test System

Cost Functions are given as

F1 (Pg1) =120* $Pg1^2$ +175* Pg1+75

F2 (Pg2) =110* $Pg2^2$ +180* Pg2+50

F3 (Pg3) =160* $Pg3^2$ +110* Pg3+80

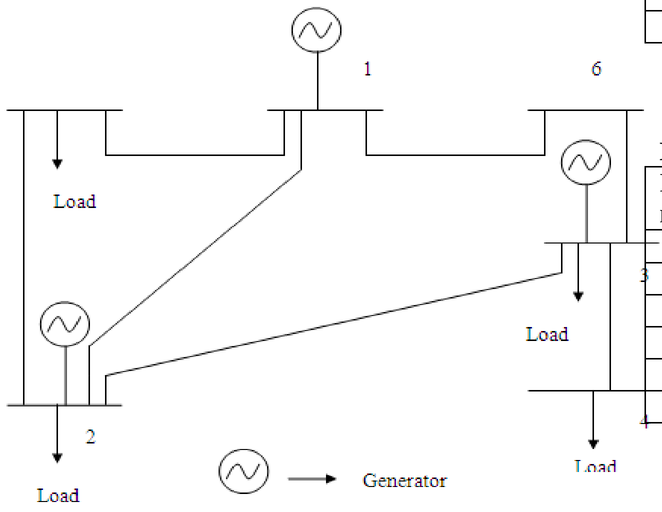

Fig.2.Six bus system

Line Data:

Line no	From bus	To bus	Line impedance (p.u)	B/2 (p.u)	Off-nominal tap ratioof transformer
1	1	2	0.01+j0.3	J0.01	0
2	2	3	0.03+j0.2	J0.01	0
3	2	5	0.03+j0.2	J0.01	0
4	3	4	0.01+j0.2	J0.01	0
6	1	5	0.0+j0.2	0	1.01
7	1	6	0.0+j0.2	0	1.02

Bus Data:

Bus no.	Bus type	V(p.u)	P_g	Q_g	P_d	Q_d
	Slack	$1.05\angle 0$	-	-	0.1	0
	PV	1	-	-	0.3	0.25
	PV	1.02	-	-	0.1	0.3
	PQ	-	0	0	0.15	0.2
	PQ	-	0	0	0.35	0.45
	PQ	-	0	0	0.3	0.5

V.Results

Comparison of Optimal Dispatch of Power Generation between Newton and ANN methods

	Input variables						Optimal Dispatch of Power generation using conventional (NEWTON) method			Optimal Dispatch of Power generation using ANN		
S.No	P_{d1}	P_{d2}	P_{d3}	P_{d4}	P_{d5}	P_{d6}	P_{g1}	P_{g2}	P_{g3}	P_{g1}	P_{g2}	P_{g3}
1	0.05	0.3	0.1	0.15	0.35	0.3	0.3804	0.3884	0.4841	0.3802	0.3880	0.4843
2	0.06	0.3	0.1	0.15	0.35	0.3	0.3840	0.3922	0.4486	0.3838	0.3919	0.4870
3	0.1	0.37	0.1	0.15	0.35	0.3	0.4229	0.4349	0.5151	0.4228	0.4347	0.5152
4	0.1	0.38	0.1	0.15	0.35	0.3	0.4264	0.4388	0.5177	0.4263	0.4386	0.5177
5	0.1	0.3	0.11	0.15	0.35	0.3	0.4018	0.4112	0.4999	0.4018	0.4112	0.5004
6	0.1	0.3	0.12	0.15	0.35	0.3	0.4053	0.4150	0.5026	0.4053	0.4150	0.5031
7	0.1	0.3	0.1	0.25	0.35	0.3	0.4333	0.4451	0.5248	0.4335	0.4455	0.5249

8	0.1	0.3	0.1	0.26	0.35	0.3	0.4368	0.4488	0.5276	0.4369	0.4493	0.5276
9	0.1	0.3	0.1	0.15	0.2	0.3	0.3440	0.3500	0.4582	0.3438	0.3502	0.4576
10	0.1	0.3	0.1	0.15	0.25	0.3	0.3621	0.3691	0.4712	0.3620	0.3693	0.4711
11	0.1	0.3	0.1	0.15	0.35	0.34	0.4126	0.4226	0.5078	0.4129	0.4229	0.5086
12	0.1	0.3	0.1	0.15	0.35	0.35	0.4162	0.4264	0.5105	0.4165	0.4267	0.5113

Time comparison between conventional (NEWTON) method and soft Computing method (ANN)

Time taken for the Conventional (Newton method) (in sec)	Time taken for ANN	
	Training time (in sec)	Execution time (in sec)
25.470878	1031.487415	0.009994

VI.Conclusions:-

Optimal Dispatch of Power Generation for the given load patterns by using conventional method i.e. NEWTON method are determined. As this is too slow, we proposed a soft computing based approach i.e. **Back Propagation Neural Network (BPNN)** for determining the load dispatching. This method provided fast and accurate results when compared with the conventional method. By using this soft computing method we can also reduce the execution time, which plays a vital role in load sharing.

In this paper load sharing for a given system requires 25.47 s by using Newton method and by using ANN it takes only 0.0099s.

In future this project can be extended by using **Radial Basis Function Neural Network (RBFNN).**

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