ARTIFICIAL NEURAL NET APPROACH FOR CAPACITOR PLACEMENT IN POWER SYSTEM

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Abstract: This paper proposes a new methodology for controlling multitap capacitors in a power system using a three layer feedforward neural network. The neural network, in the proposed scheme is separately trained with two algorithms namely backpropagation and combined backpropagation-Cauchy's learning algorithm. Studies on 30 bus IEEE test system are carried out and quite satisfactory results are obtained. The inputs to the net are the real power, reactive power and voltage magnitude at a few selected buses and the network's outputs are the values of capacitive var injection. Performance comparison is made between two algorithms and the combined backpropagation-Cauchy's algorithm is found to be better than the other.

INTRODUCTION

Conventionally var planning problems in a transmission or distribution system is handled by trial and error approaches utilizing a power flow program to keep the voltage profile within the acceptable limits and to reduce losses at different load profiles. Early works on var planning focussed on introducing a optimization technique with suitable objective function. Linear programming, nonlinear programming and quadratic programming have been used to optimize the objective function. An accurate optimal capacitor in real-time can be obtained by modifying the algorithm of an optimal capacitor design keeping in mind that the control part of the capacitors are already available up to their maximum ratings.The main problems associated with the conventional approaches are the heavy computational burden as well as the impracticability to monitor all the loads continuously. The time consuming optimization process has to be performed for various load profiles including the similar load profiles. These difficulties motivated the researchers to develop a computationally efficient control strategy for optimal capacitor settings which should be based on limited number of on-line measurements.

Artificial neural network(ANN), a kind of artificial intelligence, has attracted a widespread interest in the recent times. This approach can be adapted to recognizing learned patterns of behaviour in electrical networks where exact functional relationship are not easily defined. The application of ANN to Power Systems is still in infant stage. Recently a few of its applications in Power Systems have been reported in the literatures[1,2,3,4,5]. A neural net was used to associate patterns of prefault voltage angles and immediate postfault accelerating power with critical clearing time for a faulted line[2]. In another paper[5], a neural network strategy was used to recognize current waveforms associated with incipient (high impedance) faults on distribution feeders. Recently, a two- stage neural network approach is proposed [1] for real time control of multitap capacitors installed on a distribution system with a non-conforming load profile. Neural networks make initial estimates of harmonic sources in a power system with nonlinear loads[3]. In this paper, capacitor control is performed using a three layer feedforward neural network which can learn from patterns encountered previously. The inputs to the network are the P, Q and |V| at preselected buses [6] where capacitors are placed and the outputs are the corresponding capacitor values at those buses. Besides these buses, a few more sensitive buses are identified by carrying out sensitivity analysis and P, Q an |V| values of those buses are also fed to the net along with the previous inputs. The results obtained are compared with the previous one to show the effect of the additional buses on capacitive vars required. The network is trained with two different algorithms and convergence characteristics are compared. The capability of producing output even with inadequate inputs is verified. A simulation of the proposed scheme is carried out in Micro-VAX II and validated on a modified IEEE 30 bus test system[7]. The load profile is varied from 80% to 110% of their maximum values.

NEURAL NETWORK & TRAINING

Neurocomputing is a new approach to information processing that does not require algorithm or rule development and that often significantly reduces the quantity of software. Primary information processing structure of interest in neurocomputing is neural network. A neural network is composed of non-linear computational elements operating in parallel[8]. The processing elements are connected by links with weights that are selected to produce desired associations. Several types of neural net models are available for different applications. Updating the weights in the net is an important attribute, known as learning or training[9]. Various adaptive algorithms are available for adjusting the weights. The net may be single layer or multiple layer.

A typical three layer feedforward network consisting of multiple non-linear neurons associated with suitable activation function is shown in fig.1. Each neuron forms the weighted sum of the inputs and pass it through the non-linear activation function to produce a output which serves as the input to the next

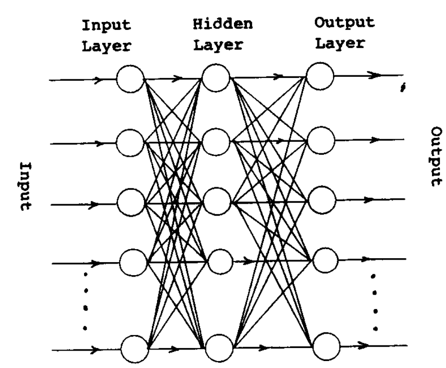

Fig. 1
Typical Three Layer Feedforward Neural Net

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layer. The net is trained to minimize the objective function which is defined as the half of the sum of squares of the differences between the predicted one and the corresponding desired output component.

Training Algorithms:

Training of the network is an important feature in the neurocomputing discipline. The net should learn properly with the requisite training algorithm to achieve efficient generalization[10,11]. Here the algorithms employed are backpropagation, and combined algorithm.

Backpropagation Algorithm:

Here the algorithm employs the iterative gradient algorithm to minimize the objective function. The activation function selected here is the sigmoid logistic function and is given by,

$$f(x) = A/(1+\exp(-(x-\theta)\lambda)) \qquad (1)$$

where A = maximum output

x = sum of the weighted inputs

θ = threshold

λ = scaling factor

The weights are adapted by a recursive algorithm starting at the output nodes and working back to the hidden layer. The weights are adjusted by

$$[W]_{ij}(t+1) = [W]_{ij}(t) + \eta\delta_j X_j \qquad (2)$$

where $[W]_{ij}(t)$ is the weight either from hidden node i to output node j or from input node i to output node j at any time t, X_j is either corresponding input to the net or the input to the hidden layer, η is the learning co-efficient, and j is an error term for node j. If node j is an output node then

$$\delta_j = y_j(1 - y_j/A)(d_j - y_j) \qquad (3)$$

where d_j is the desired output of the node j and y_j is the actual output.

If node j is an internal or hidden node then,

$$\delta_j = X_j(1 - X_j/A)\sum_k \delta_k [W]_{jk} \qquad (4)$$

where k is over all node to the right of node j.

Combined backpropagation-Cauchy's Algorithm

The combined algorithm[10] explores the potential features of two individual algorithms, namely backpropagation and Cauchy's. The other aspects like the activation function, the error signal and the objective function remain the same. In contrast to the other two, the weights are updated by the differential weights, partly contributed by the backpropagation and partly by Cauchy's algorithm. The weight at (t+1)th time step is

$$[W]_{ij}(t+1) = [W]_{ij}(t) + \eta[\alpha\Delta W_{ij}(t) + (1-\alpha)\delta_j X_j]\eta_1 + (1-\eta)X_c \qquad (5)$$

α = Momentum co-efficient, varies from 0. to 1.0.

$\Delta W_{ij}(t)$ = Previous weight change.

X_c = the weight change due to Cauchy's distribution.

η = convergence co-efficient, when is 1.0, the weight adjusments are due to pure backpropagation and 0.0 the weights are due to for pure Cauchy's algorithm.

η_1 = Weighting factor to control the convergence co-efficient when the change of weight is only due to backpropagation and its value varies from 0.0 to 1.

SIMULATION

A modified IEEE 30-bus system (fig. 2) is chosen to demonstrate the efficacy of the ANN based scheme for capacitor control problem. The weight matrix considered for the first case i.e. for input pattern with twelve data, is W_{12X10} and W_{10X4} for the hidden and output layers respectively. In an analogous manner the weight matrices are $[W]_{24X18}$ & $[W]_{18X4}$ for the second case with 24 inputs. The system parameters as reported in[7] are modified according to the following[6].

i) Tap-changing capacitor are available at buses 10,19,24 and 29.

ii) All the loads were represented by constant power sinks in power system simulation.

The load profile is varied from 80% to 110% of the maximum value. The loads of the system were assumed to change proportionally. The network is exposed to two types of inputs both for training and prediction. In the first stage P, Q and |V| are only measured at those buses where capacitors are connected. In the second case four more sensitive buses are selected and P, Q and |V| values of those buses are also fed to the net along with the previous inputs. These additional four buses are selected on the basis of the closeness to the buses where the capacitors are to be controlled. This is accomplished by a set of sensitivity factor $\partial V_i/\partial Q_i$ and $\partial V_i/\partial P_i$, where i is any bus sensitive to others. The

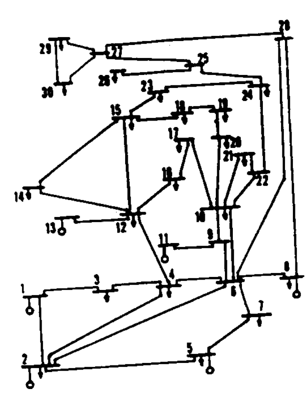

Fig. 2, Single Line Diagram of IEEE -30 Bus System.

former may be evaluated from the gradient matrix of the fast decoupled load flow

$$[\delta Q/V] = [B''][\delta V] \qquad (6)$$

By assuming that $|V| = 1$ for all busbars:

$$[\delta V/\delta Q] = [B'']^{-1} \qquad [7]$$

From the $[B'']^{-1}$ matrix the four more sensitive busbars are chosen. Busbars 18,21,23 & 30 are selected as additonal busbars to provide input to the network. The input patterns together with the target patterns are generated using an optimal power flow for a load profile 80%, 95% & 105% of the maximum value. The minimum voltage is always kept at 0.95 p.u.

RESULTS & DISCUSSION

Results are obtained for different cases and different algorithms. Fig. 3 shows the convergence characteristics of backpropagation and combined algorithm. The input pattern consists of 12 data and for this particular case the initial convergence is almost same for both the algorithms. The objective function for combined algorithm has settled down to -65dB where as backpropagation, it is arround -45dB, which clearly differentiates the learning with the two algorithms. Fig. 4 displays the learning of a particular weight $W_{3,1}$ of the output layer during the adaptation process with combined algorithm. The random fluctuations are marked due to the weight change contributed by Cauchy's algorithm. A particular weight, $W_{2,2}$ adapts smoothly with backpropagation algorithm. The net's outputs for both the nets are presented in Table-I. Due to better learning values determined by the combined algorithm is better than the backpropagation one. The difference between the results obtained with 12 inputs and 24 inputs is not appreciable, hence the additional inputs donot have predominant effect on the results. The results presented in Table - I also shows that the net produces consistant output even with 20% faults in the network and inadequate inputs.

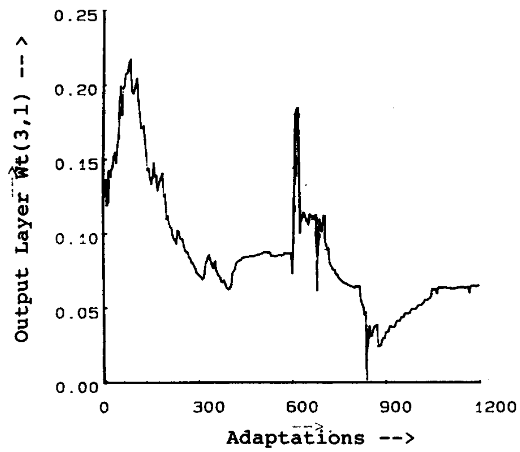

Fig. 4

Learning Curve for output layer's weight using the combined algorithm

CONCLUDING REMARKS

An alternative method is proposed for controlling the capacitors and hence injecting the vars at a few selected buses. The test system considered is IEEE 30 bus system. The buses are selected by carrying out the sensitivity analysis for the system. Besides, a few more sensitive buses are also considered to determine the effect on the computed values of the vars predicted earlier. A performance comparison is presented for the two learning algorithms and the combined al is found to outperform the other one. Also appreciable results are obtained with faulty net and incomplete information thereby exhibiting the robustness of the scheme. However, the concept of pattern recognition can be combined to make it more robust and to work under a wide variations of loads. The convergence time can be further improved to design a viable scheme for real time implementation.

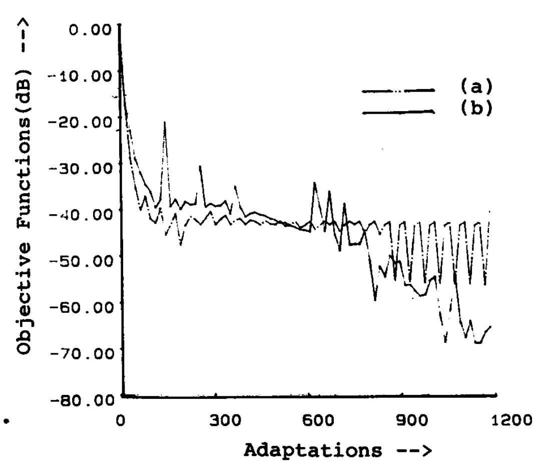

Fig. 3

Convergence Characteristics(12 inputs), (a) Backpropagation Algorithm, $A=1.3, \lambda=0.5, \eta=0.87$; (b) Combined Algoritm, $\eta=0.7$, $=0.5$, $A=1.6, \kappa=0.2$

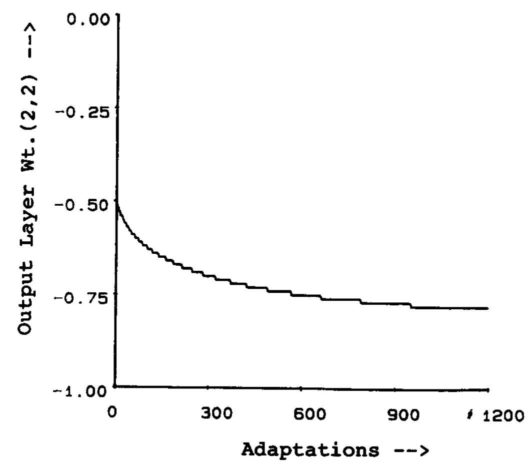

Fig. 5

Learning Curve for output layer's weight using backpropagation algorithm

ACKNOWLEDGEMENT

The authors express their gratitude to the Ministry

Human Resources Development, New Delhi for providing funds for carrying out this work.

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Table -I
Table showing the MVARs at busbars 10,19,24 & 29 resprectively.

Load Level	Actual Value MVAR	12 inputs Bp MVAR	12 inputs Combined MVAR	24 points Bp MVAR	12 points 20% Fault MVAR	12 points with 9 inputs MVAR
100% Load	20.136	19.89	20.01	19.95	19.121	19.23
	1.178	0.93	1.01	0.99	0.87	0.91
	5.254	6.12	6.02	6.23	5.41	5.29
	8.95	8.72	8.87	8.88	8.65	8.50
110% Load	20.926	20.01	20.27	20.31	19.56	19.45
	1.945	1.32	1.29	1.40	1.15	1.21
	6.711	6.32	6.01	6.29	5.97	5.85
	9.759	9.34	9.47	9.42	8.54	8.67