Demand Side Management by using Artificial Neural Network

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ABSTRACT

This paper presents the performance of maximum utilization of electrical energy by using demand side management. Load management in a feeder is very important term to understand to stable load shape. For the stability of load shape we have to manage the demand side. For managing the load (demand) we use demand response. The problem of surrounding occurred is that the continuously disturbances on load side within a day. Sometimes, in a day the load fluctuations is maximum and sometimes it becomes too low.Due to which generation or supply side cannot fulfill all these load demands of consumers within a day. Objective of this paper is the maximum utilization of electrical energy and by developing the load shift algorithm. The optimum utilization of electrical energy is need of time and for that in this paper we are using load shifting technique under demand side management by using Artificial Neural Networks (ANN) for minimizing the load at peak time and utilize the unutilized loading valley time. Methods by which we can manage the demand side are peak clipping, load shifting, load addition, valley clipping, demand response. In this system we are using the Artificial Neural Network (ANN) technique to manage the demand side. It is a self decision making system which also used for bidirectional communication.We present a simple accurate system to manage electricity load with ANN.

Key words: Demand side management (DSM), Load shift algorithm, Demand response, Artificial neural network (ANN).

I INTRODUCTION

Demand Side Management involves planning, analysis and implementation of utility activities to influence customer load shapes. Implementation of such a load shaping options as a load management, strategic conservation, and selective load growth can results in a efficient use of resources and reduced cost to both the customer and the utility. The Electric Power Research Institute (EPRI) has a recently sponsored several studies to document the lessons learned from the experienced of utilities DSM programs. [1]

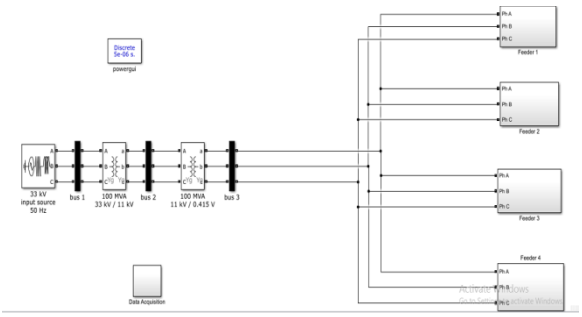
The most important problem with electric power today is energy efficiency and to manage the system with proper reliability it is very important to study and analyze the distribution system. Electric utililities have to deal with many such problems as high capital costs for installing new power plants and decrease in economical

performance. By convincing the consumer to shift their load in off peak periodswhen their will be the situation of over loading this help us to minimize the energy cost for utility sectors and consumers. With help of load shifting algorithm we can shift the load to its convenience and it also will improve the reliability and stability of the system. Here, we are using the Artificial Neural Network technique, it makes the system dynamic.

DEMAND SIDE MANAGEMENT (DSM)

The distribution system is the last stage to deliver the power to the consumer. It carries the power through the transmission line. Distribution power system try to distribute the same power to the last consumer without any interruption but it does not become possible because sometimes consumer demand increases that's why load increases that load feeders cannot carry, load shifting phenomenon is required.

So load is shifted when demand is increased. In some distribution power station load is shifted manually, in such case when load is shifted from one feeder to another feeder, first they shut down loaded feeder and load shifted another feeder having unloaded. This case consume time also use manual power. This method cannot provide and fulfill the consumer demand without interrupting also time consuming and so many losses are done also possibility of accident. In another case we can use SCADA system. In this system all work is automated but this is very costly to establish, that's why SCADA system is rarely use in distribution system. We shifted the load automatically using ANN. The system is not costly and also efficient.



In distribution system we consider the model having 33KV 50 Hz input source, two transformer of rating is 33/11KV and 11/0.415V, transformer used is step down transformer. It also consist of four feeders having 11KV capacity in this model we use the variable load for obtaining appropriate results. In a neural network techniques there is various types are available but we use feed forward back propagation neural network technique this technique gives us proper distribution of system.

The main cause to use the ANN network is to make a difference between two feeder system such as load and unloaded feeder. When we use this technique this gives the differential result on the basis of the specification.

ALGORITHAM

The back propagation algorithm (Rumelhart and McClelland, 1986) is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the *input layer*, and the output of the network is given by the neurons on an *output layer*. There may be one or more intermediate *hidden layers*. The back propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN *learns* the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

The activation function of the artificial neurons in ANNs implementing theback propagation algorithm is a weighted sum (the sum of the inputs x multiplied by their Xi respective weights W_{ji}):

$$A_j\left(\overline{x},\overline{w}\right) = \sum_{i=0}^{n} x_i w_{ji} \qquad (1)$$

We can see that the activation depends only on the inputs and the weights. If the output function would be the identity (output=activation), then the neuron would be called linear. But these have severe limitations. The most common output function is the sigmoid function:

$$O_j\left(\overline{x},\overline{w}\right) = \frac{1}{1+e^{A_j\left(\overline{x},\overline{w}\right)}} \qquad (2)$$

The sigmoidal function is very close to one for large positive numbers, 0.5 at zero, and very close to zero for large negative numbers. This allows a smooth transition between the low and high output of the neuron (close to zero or close to one). We can see that the output depends only in the activation, which in turn depends on the values of the inputs and their respective weights.

Now, the goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and we need to adjust the weights in order to minimize the error. We can define the error function for the output of each neuron:

$$E_j\left(\overline{x},\overline{w},d\right) = \left(O_j\left(\overline{x},\overline{w}\right) - d_j\right)^2 \qquad (3)$$

We take the square of the difference between the output and the desired target because it will be always positive, and because it will be greater if the difference is big, and lesser if the difference is small. The error of the network will simply be the sum of the errors of all the neurons in the output layer:

$$E\left(\overline{x},\overline{w},\overline{d}\right)=\sum_{j}\left(O_j\left(\overline{x},\overline{w}\right)-d_j\right)^2 \quad (4)$$

The back propagation algorithm now calculates how the error depends on the output, inputs, and weights. After we find this, we can adjust the weights using the method of *gradient descendent*:

$$\Delta w_{ji}=-\eta\frac{\partial E}{\partial w_{ji}} \quad (5)$$

This formula can be interpreted in the following way: the adjustment of each weight (ΔW_{ij}) will be the negative of a constant eta (ή) multiplied by the dependence of the previous weight on the error of the network, which is the derivative of E in respect to w_i .The size of the adjustment will depend on ή , and on the contribution of the weight to the error of the function. This is, if the weight contributes a lot to the error, the adjustment will be greater than if it contributes in a smaller amount. (5) is used until we find appropriate weights (the error is minimal). If you do not know derivatives, don't worry, you can see

them now as functions that we will replace right away with algebraic expressions. If you understand derivatives, derive the expressions yourself and compare your results with the ones presented here. If you are searching for a mathematical proof of the back propagation algorithm, you are advised to check it in the suggested reading, since this is out of the scope of this material.

So, we "only" need to find the derivative of E in respect to w_{ij} . This is the goal of the Back propagation algorithm, since we need to achieve this backwards. First, we need to calculate how much the error depends on the output, which is the derivative of E in respect to O_j (from (3)).

$$\frac{\partial E}{\partial O_j}=2\left(O_j-d_j\right) \quad (6)$$

And then, how much the output depends on the activation, which in turn depends on the weights (from (1) and (2)):

$$\frac{\partial O_j}{\partial w_{ji}} = \frac{\partial O_j}{\partial A_j}\frac{\partial A_j}{\partial w_{ji}} = O_j(1-O_j)x_i \quad (7)$$

And we can see that (from (6) and (7)):

$$\frac{\partial E}{\partial w_{ji}} = \frac{\partial E}{\partial O_j}\frac{\partial O_j}{\partial w_{ji}} = 2\left(O_j - d_j\right)O_j(1-O_j)x_i \quad (8)$$

And so, the adjustment to each weight will be (from (5) and (8)):

$$\Delta w_{ji} = -2\eta\left(O_j - d_j\right)O_j(1-O_j)x_i \quad (9)$$

We can use (9) as it is for training an ANN with two layers. Now, for training the network with one more layer we need to make some considerations. If we want to adjust the weights (let's call them v_{ik}) of a previous layer, we need first to calculate how the errordepends not on the weight, but in the input from the previous layer. This is easy, we would just need to change x_i with w_{ij} in (7), (8), and (9). But we also need to see how the error ofthe network depends on the adjustment of v_{ik} . So:

$$\Delta v_{ik} = -\eta\frac{\partial E}{\partial v_{ik}} = -\eta\frac{\partial E}{\partial x_i}\frac{\partial x_i}{\partial v_{ik}} \quad (10)$$

Where:

$$\frac{\partial E}{\partial w_{ji}} = 2\left(O_j - d_j\right)O_j(1-O_j)w_{ji} \quad (11)$$

And, assuming that there are inputs u into the neuron with v (from (7)):

$$\frac{\partial x_i}{\partial v_{ik}} = x_i(1-x_i)v_{ik} \quad (12)$$

If we want to add yet another layer, we can do the same, calculating how the error depends on the inputs and weights of the first layer. We should just be careful with the indexes, since each layer can have a different number of neurons, and we should not confuse them.

IV CONCLUSION

It is concluded that this model is very efficient and important for the consumer and also for the utilities. Because day by day, load shedding problem occurred in many of the area, we cannot fulfillthe demand of last consumer and maximum losses present in area. That's why we discussed, analyzed and surveyed the distribution system and made this model. This model is beneficial for consumer and economical. this model very effective , useful and easy to handle .

It is seen that many accident happen in distribution system while shifting the load. In this model load shifting is automatic so there is no chance of accident. When load shifting is applied to the peak hours is utilized in the valley hour. The load shifting model is very effective used in peak time. If one feeder is having maximum load as compare to other feeder then that load is shifted to other feeder.

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