A Neural Network-Based Approach for Control of Capacitors Installed on Distribution Systems for Power Loss Reduction

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ABSTRACT

A neural network for capacitor switching in electric distribution systems for the purpose of power loss reduction is presented in this paper. An optimization technique (sensitive node method) for allocating the compensating capacitors is used to generate the training set patterns of the neural network. The required input data of the neural network at varying loading conditions are directly obtained from a load flow study of the distribution system. Load variations are assumed to follow a random matrix that generates a randomized function which is employed for implementing the different load levels. The developed neural network is based on a feed-forward model and a backpropagation algorithm. It has been applied to a 30-bus radial distribution test system and the obtained results show that the proposed approach can perform quite satisfactorily under slight and extreme variations of loading conditions.

KEYWORDS: Distribution Systems, Loss Reduction, Compensating Capacitors, Neural Networks, Sensitive Node.

1. Introduction

Challenges facing electric power utilities, including increasing competition and financial and environmental constraints, are adding significant complexities to the operation of electric power distribution systems. More sophisticated real time control techniques are needed for existing distribution systems to provide electric power with higher efficiency, quality and security without building new facilities. Computation methods based on conventional mathematical models are not adequate for real time automation of present and future distribution systems because of their complexity, non-linear nature, and long computation time. On the other hand, artificial neural networks (ANN) which simulate the structure of biological nervous systems have many properties that make them suitable for real time power system control. Most reactive power compensation methods for distribution systems are based on a load forecasting approach in which all system loads are assumed to change in the same proportion [1-3]. In practice, however, several load groups do not vary over the daily load cycle in the same manner as the rest of the system. Thus, to prevent load profile from being limited, it is necessary to control the capacitance value according to different load patterns. Otherwise, they may not meet their design objective and can instead cause voltage problems and increase losses.

Conventional optimization approaches such as dynamic programming, for determining capacitor switching operation are time consuming and difficult for large systems. The main problem with this approach is the long computation time required as well as the impracticality to monitor all loads continuously. A time consuming optimization procedure has to be performed for each load profile. Similar load profiles will still require separate optimization processes. Therefore, it is desirable to develop a computationally efficient control strategy for the optimal capacitor settings which should be based on a limited number of on-line measurements. With the ability of better generalization and simpler calculations, the advantages of neural networks are considerable in many applications in power systems. Therefore, many papers have been published on ANN applications in power systems [4]. Some of these papers are devoted to ANN-based control of
capacitors in distribution systems with and without considering voltage regulators [5-7].
In this paper, it is proposed to solve the optimal capacitor control problem by designing a special artificial neural network configuration and learning it by using the results obtained from the sensitive node technique to solve the loss reduction problem for the distribution system under consideration. This control strategy has been developed for a 30-bus radial distribution system. Results show that the proposed neural network can perform quite satisfactorily under slight and extreme variations of loading conditions.

2. Problem Description
In this study, it is assumed that the locations and maximum sizes of the used compensating capacitors are pre-determined and only their switching states have to be found. It is assumed also that the distribution system has no other form of voltage control.
Given the loading range of the distribution system, the problem is to define the sizes of compensating capacitors (i.e., the on/off states of capacitors) at each load level so that the \( P/R \) loss of the whole distribution system is minimized without violating standard or special voltage limits. In this work, the optimization problem is solved using the sensitive node technique mentioned in [8] for allocating the compensating capacitors. It has been found that this technique cannot solve the problem on real-time basis due to the non-linearity of the problem specially if the number of capacitors and their states are large. Therefore, a trained neural network will provide a computationally efficient way to solve the problem in real time, although the training process may take a long time and is generally conducted offline.

3. The Design of the Neural Network Controller
There are numerous ANN approaches with different structures, transfer functions, and training algorithms [9]. In this paper, an ANN approach with a threelayer feed-forward structure and the backpropagation algorithm is adopted because of its relative simplicity, maturity in regards to applications in different fields, and common use. The inputs to the neural network controller are the line current flow at some selected points of the distribution system. The input and associated outputs for the selected points and states of operation of the distribution system should contain enough information to solve the optimization problem. However, how many measurement points are needed, where should the locations of these points be, and which circuit parameters should be used as inputs to the ANN still remain open questions. The answers to these questions have practical significance because the fewer the number of measuring points the lower the cost of the control system. Intuitively, the locations of these measurement points should be close to the locations of controllable devices.

The number of outputs is determined by the number of controlled devices (capacitors) and their states. In order to reduce the number of ANN outputs, one ANN output is assigned to each device instead of each state.
With regards to the ANN architecture, it is important to determine the number of hidden layers and the number of neurons in each hidden layer. In practice, if there is a little or no prior knowledge about the problem, the best structure can only be determined by experience or trial and error. A set of known input and output data are needed to train the ANN, where the input data is the measured active and reactive currents \( I_{active} \) and \( I_{reactive} \) at some measurement points, and the output is the optimal switching states of capacitor banks for some given load patterns of the distribution system. The performance of the trained neural network is dependent, to a large degree, on the selection of the training data. Thus, the training data should reasonably cover the whole input space under possible operating conditions, and it is important to carefully select or design the training data.
After building the neural network and training it, a test process must be carried out. The test process should use those input/output pairs that are not used in the training process.

4. Simulation Test Studies
The solution algorithm developed for this study is implemented on the 30-bus distribution test system shown in Fig. (1). The data of the system, including loads, are listed in [5]. The capacitor rating applied in this paper is 300 kVAR.

![Fig. (1) - One-Line Diagram of the 30-bus Distribution Test System](image)

4.1 Generation of Training Patterns
The available data in this system are only the peak (max.) values of loads at each bus (node) system. A set of training patterns is generated by applying the
operational optimization process for each load profile. Load profile is the combination of each load levels at each bus system. In [5], the training load patterns were obtained by forming all possible combinations of load levels (50%, 70%, 85% and 100% of peak values) at each bus. In [7], each bus load was uniformly divided from zero to maximum into 12 segments. Thus, 13 load levels were used to obtain the training patterns.

In this paper, a new method for generation of training patterns is developed. A randomized matrix is applied to the loads of the system to cover a wider range of input space. The training load patterns are obtained by forming all possible combinations of the system load levels ranging from 50% to 100% of peak values. A dynamic programming module in MATLAB is used. This module searches for the sensitive nodes in the distribution system and inserts the available capacitor banks at each sensitive node. In this study, the training set consists of 50 patterns.

It is found that the number of sensitive nodes for all loading conditions ranges between 10 and 14, while the maximum number of sensitive nodes obtained for all studied cases is 19. These nodes are (2, 3, 5, 6, 7, 8, 9, 11, 14, 17, 18, 20, 21, 22, 23, 25, 27, 28, 29, 30).

Statistics of the obtained results showed that nodes 7, 9, 11, 28, 29, 30 are more sensitive than all other nodes. Consequently, these nodes are selected as measuring nodes for the ANN inputs.

4.2 Construction of the Neural Network Used

The ANN model used in this study has 12 input neurons (real and reactive current at the 6 measuring points i.e. at the sections before the 6 sensitive nodes) and 19 output neurons representing the states of the capacitors installed on the 19 sensitive nodes obtained. The number of neurons in the hidden layer is varied from 10 to 100 and it is found that 65 neurons in the hidden layer give the best performance according to this construction.

The neural network model used for the capacitor control problem presented in this paper finds the state of the capacitors installed on the sensitive nodes. This capacitor switching state secures the optimum loss reduction in the distribution system for the given real and reactive currents at the load buses. It is supposed to have output values from the neural network between 0 and 1. The number of outputs of the neural network represents the capacitors placed at the sensitive nodes and their states. However, output values more and less than 0.5 are classified as on and off capacitor switching states in this study.

The neural network is trained for a minimum average error of $1 \times 10^{-6}$ and 10000 iterations using MATLAB with a back propagation learning algorithm. The learning rate ($\beta$) and the momentum constant ($\alpha$) are taken as 0.01 and 0.98 respectively.

4.3 Testing

40 test samples are generated to examine the performance of the neural network. Table (1) represents the optimal capacitor locations obtained from the sensitive node technique (actual locations) and the locations found by the ANN-based approach for the 40 test samples. Table (2) represents the total loss reduction in (kW), its percentage to the total losses, the loss reduction due to the reactive component of the current in (kW), its percentage to the total losses and the percentage error in loss reduction for the 40 test samples. This error is taken as the difference between the loss reduction achieved by the ANN approach and that achieved by the original optimization technique. Fig. (2) and Fig. (3) show a plot for the results obtained.

![Fig. (2) – Total Loss Reduction (kW)](image1)

![Fig. (3) – Loss Reduction due to Reactive Component (kW)](image2)

Fig. (2) and Fig. (3) show a plot for the results obtained.

5. Conclusion

An artificial neural network-based approach has been developed for the control of capacitors installed on distribution networks for the purpose of reducing the TR losses in feeders. From the measurements at certain buses, the control network provides the capacitor settings such that the system losses are minimized for a non-conformable varying load profile. The neural network has been developed for a 30-bus distribution system and the obtained results are quite satisfactory. This method requires much less computation time as compared with that necessary.
for an optimization process. Therefore, it is suitable for on-line implementation of the capacitor control even for large distribution systems.

The application of the proposed capacitor control will be mainly limited by the computation time required for the learning process which in turn depends on conforming load groups and capacitors installed rather than the number of system buses. Considering the practically realistic number of conforming load groups and capacitors in the given example and the fact that the relatively time consuming parameter computation is performed only in the learning stage, the applicability of the control technique to distribution systems with many more buses than in the example seems to be promising.

6. References


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