

APPLICATION OF ARTIFICIAL NEURAL NETWORKS (ANNs) IN REACTIVE POWER OPTIMIZATION

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Abstract-The reactive power optimization problem is one of the most important problems facing dispatching engineers when they are operating large scale power systems. Reactive power optimization is mathematical approach of the power system optimization problem which is to determine the least control movements to keep power system at a most desired state. It is very flexible and powerful tool which can address a wide range of planning and operation circumstances. However the complexity of reactive power optimization often discourages the user. This paper proposes a new artificial neural network-based approach (ANN) for reactive power optimization of interconnected power systems. Feed-forward ANN with Back Propagation (BP) training algorithm is used and the training data is obtained by solving several abnormal conditions using Linear Programming (LP). Considering generator voltages, reactive power sources and transformer taps as control variables, and load bus voltages and generator reactive powers as dependent variables. The relations are derived according to sensitivity relations based on Newton-Raphson load flow equations. The 220 kV network of the Unified Power System of Egypt (UPSE) was used in this paper to test the suggested approach.

Keywords: Reactive power optimization; hybrid intelligent system; linear Programming; Topology evaluation; knowledge base; neural networks.

1. INTRODUCTION

One of the main requirements in power system is to keep the load bus voltage within limits specified for the proper operation of equipment. Any changes to the system configuration or in power demands can result in higher or lower voltages in the system. The operator can improve this situation by reallocating reactive power generations in the system by control devices (transformer tap settings, generator voltage magnitudes and switching VAR sources). The main objective function of reactive power control is to:

- improve the voltage profiles, and
- minimize the system losses.

Earlier, several techniques have been employed using sensitivity relationships and gradient search approaches to overcome this complex problem [1, 2]. These techniques

give the approximate changes in bus voltages for a given control action. In these approaches, the bus voltage violations are alleviated one by one. So these methods can be used in small number of violations. In case of many violations, the method may run into an infinite number of iteration.

To avoid these difficulties linear programming (LP) approach [3-6] has been proposed to yield the control actions. In most of these studies, the LP problem has been formulated using real valued control variables in order to reduce the computational effort. However these methods

are complex and require significant computational effort to determine the required adjustments to control variables.

Artificial intelligence (AI) methods have also been applied to control the reactive power and voltage to be within acceptable limits. The expert system (ES) techniques [7] are applied to identify the system operating conditions, detect the bus or buses at which certain constraints have been violated, and select the appropriate control actions to alleviate the voltage violations. Therefore, ES decides and gives proper signals to perform the control actions of the power system.

References [8-10] presented fuzzy logic theory to optimal control of reactive power. Using fuzzy sets operators, the coefficient of the objective functions are calculated for each bus and membership functions are defined for bus voltages. The advantage of these techniques is to overcome the limit of bus voltage variations by adjusting one of the control devices.

The line outage contingency create the under and over voltage condition in the system. The most critical bus was identified by the voltage difference from the base case and contingency case. The most effected bus has been selected as the point where MVAR has to be injected. ANN technique [11] was implemented for predicting the injected MVAR at critical bus.

Reference [12] presented a review of computational intelligence techniques as applied in load shedding and discussed the relative merits and demerits of each against the others

Reference [13] presented the differential search algorithm for solving the reactive power planning. The technique designed to solve the problem of the non-feasibility solution of the fuel cost minimization problem where the IPM is applied, for a given operating point.

This paper proposes a new artificial neural network-based approach (ANN) for reactive power optimization of interconnected power systems. The training data is obtained by solving several abnormal conditions using Linear Programming (LP). The 220 kV network of the UPSE was used in this paper to test the suggested approach.

2. REACTIVE POWER OPTIMIZATION PROBLEM DEFINITION

The definition of reactive power optimization can be divided into four categories: network, controls, objectives, and constraints.

- **Network:** the model common in all functions that require a network definition. The optimal power flow must respect the physical constraints implied by the network definition. The primary network constraints are the bus real and reactive power mismatch equation, the same ones that the basic power flow solves.
- **Objectives:** the desirable solution attributes that are not specified as constraints. Many common objective functions, such as minimizing fuel cost, or finding a feasible solution with minimum control movements, can be expressed as cost function of the control. One common objective function, minimizing active power losses, cannot be directly expressed as cost function of the control. The job of the reactive power optimization is to optimize the objective function while meeting all constraints, if possible.
- **Controls:** the set of the power system controls (such as adjusting transformer taps, changing generator voltages and switching reactive power compensators) that the reactive power optimization is allowed to move to meet constraints and optimize objectives.
- **Constraints:** the limits defined by operating procedure that keep the power system within a safe, sustainable operating region. These are the equipment operating and system security limits, such as bus voltage magnitude or line flow limits and so on. Useful by-products of solving the reactive power optimization are the sensitivities of enforcing each constraints, relative to the objective (cost) function. This gives the user information on how much it is costing to hold each of the constraints at its present value.

It is important that the user understands how to translate real world operation problems into reactive power

optimization problem definitions, and how to interpret the reactive power optimization results. Defining the problem may require several iteration between definition and solution. As the user sees the results from one definition, it may be necessary to change that definition. For example if the reactive power optimization suggests unreasonable control recommendations due to inappropriate problem definition, it will be necessary to correct the problem definition and try again.

3. TRADITIONAL OPTIMIZATION TECHNIQUES.

Because reactive power optimization can be set up in so many different ways, this section will focus upon a few typical scenarios. To become familiar with how reactive power optimization functions, it is useful to look at typical power system problem definitions [10].

When the user specifies an empty set of controls, the optimization program effectively reduces to a power flow solution. This is a relatively inefficient way to run a power flow, but optimal power flow solves the bus mismatch equations and provides output similar to a power flow solution. Optimization program provides the same state solution, including bus voltage and branch flows, as the standard power flow.

- Also optimization program may be set up to run a constrained economic dispatch of the generation. For example, given the generation cost data, the network model and the load profile, the optimal power flow can be run to give a power flow solution with an economic generation profile. The optimization program can determine the lowest cost solution that does not cause network security problems.
- Optimization program can be used to minimize real power loss through reactive power dispatch. In this case, only reactive controls (e.g. transformer tap positions, shunt capacitors and reactors, and MVAR output of generating units) are used to minimize losses on the entire network, or on a subset of the network.
- Using a "minimum of control movements" from the starting point, the optimal power flow can be used to find a feasible solution (or determine if one exists). In this case the objective is to minimize the cost function based on control deviation from the base case. The user may define parabolic cost curves, with their minimum point centered on the base case control setting. Only those controls that must move to alleviate constraints violations will move, due to the resultant increase in cost.

Traditional optimization techniques have some disadvantages such as:

- data communications requirements.
 - algorithmic complicity.
 - execution time, which restrict their use in real-time
- voltage optimization or losses minimization strategies.

4. NEW BACK PROPAGATION NEURAL NETWORK (BPNN) SYSTEM FOR REACTIVE POWER OPTIMIZATION

Artificial neural networks (ANNs) have the potential advantage over conventional techniques in significantly improving the performance of the other techniques. The artificial neural networks (ANNs) have been recognized as useful tools for the identification and control of the system with different nonlinearities. This is so by virtue of the fact that ANNs have the capability of non-linear mapping, parallel processing and learning; these attributes make them ideally suited for power system control application. In the power systems (ANNs) have been successfully used for short term load forecasting, power system control, fault detection, harmonic propagation, and so on. The block diagram of the new back propagation neural network (BPNN) system for reactive power optimization is shown in Fig.1. The method is based on using linear programming technique to generate different training patterns and obtain the input data to ANN. In this respect, the ANN is trained to determine the proper adjustment of the control variables required to alleviate over-voltages, under-voltages and generator reactive power limit violations. More details about the complete system in section eight.

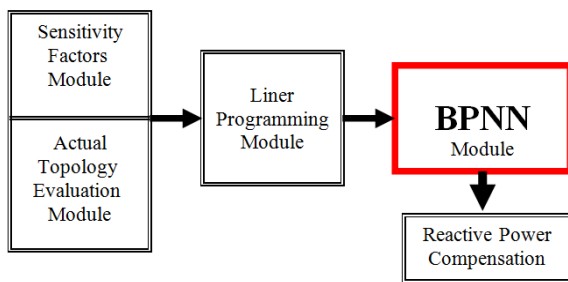


Fig. 1. The block diagram of the back propagation neural network (BPNN) system for reactive power optimization.

5. LEARNING IN ARTIFICIAL NEURAL NETWORKS

Among the many interesting properties of a neural network, the property that is of primary significance is the ability of the network to learn from its environment, and

to improve its performance through learning. The improvement in performance takes place over time in accordance with some prescribed measure. A neural network learns about its environment through an iterative process of the adjustments applied to its synaptic weights and thresholds. Ideally, the network becomes more knowledgeable about its environment after each iteration of the learning process. Research in learning has been conducted/on animals of different intelligence levels and on humans of different ages and intelligence levels. Learning is not a unique process; there are different learning processes, each suitable to different species.

Not all learning processes are equally efficient. In artificial neural networks, the concepts of learning process have been borrowed from the behaviorist's lab and ported in actual electronic circuitry. Learning is a process by which the free parameters of a neural network we adapted through a continuing process of stimulation by the environment in which the network is embedded. The type of learning is determined by the manner in which the parameter changes take place. This definition of the learning process implies the following sequence of events [7]:

- the neural network is stimulated by an environment
- the neural network undergoes changes because of this stimulation
- the neural network responds in a new way to the environment, because of the changes that have occurred in its internal structure

6. A BACK-PROPAGATION

Back-propagation technique was created by generalizing the Widrow-Hoff learning rule to multiple layer networks and non-linear differentiable transfer, functions. Input vectors, and the corresponding output vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by user. Networks with biases, at least one sigmoid neuron layer, and a linear output neuron layer are capable of approximating any reasonable function [14].

The back-propagation learning rules are used to adjust the weights and biases of networks to minimize the mean squared error of the network. This is done by continually changing the values of the network weights and biases in the direction of steepest descent with respect to error. This is called a Levenberg-Marquardt (trainlm) procedure. Changes in each weight and bias are proportional to that element's effect on the mean squared error of the network [14, 15].

Trained back-propagation networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input will lead to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results for new inputs without training the network on all possible input/output pairs [16].

The back-propagation training may lead to a local rather than a global minimum. The local minimum that has been found may be satisfactory, but if it is not, a network with more layers and neurons may do a better job. However, the number of neurons or layers to add may not be obvious. Alternatively, one might run the problem using several different set of initial conditions to see if they led to the same or different solution.

7. GENERATION OF TRAINING DATA

To design a neural network it is very important to train and test the network. The well trained neural network should give the right decision for both normal and abnormal operating conditions. To achieve this important goal, the training data should be selected carefully. In this case, the training data should cover the expected range of operation for each bus (including both normal and abnormal operating condition).

8. A NEW BACK PROPAGATION NEURAL NETWORK (BPNN) SYSTEM FOR REACTIVE POWER OPTIMIZATION CONFIGURATION DETAILS

In this section, a description of the proposed (BPNN) system components and its operation is introduced. The block diagram of the proposed system is shown in Figure 1. The system consists of four fundamental components which are: Sensitivity Factor Module (SFM), Actual Topology Evaluation Module (ATEM), Linear Programming Module (LPM), and Back propagation Neural Network (BPNN). More details about each one is as follows.

8.1. ACTUAL TOPOLOGY EVALUATION MODULE (ATEP)

The term "Actual Topology" is meant to cover the nodes and impedance bearing branches necessary for a physical description of the system with reference to the switching state at a certain point in time. And the term "Potential Topology" is meant to cover all existing switchable and fixed connecting elements of a network between and within substations, fields, etc.

The topology evaluation routine is able to read the data-base, to calculate the actual topology and to generate special lists of network elements as:

- nodes.
- branches (lines and transformers).
- loads.

The actual topology consists of all nodes and branches with impedances, which are connected with a synchronized power unit. The data available from the listing after the actual topology evaluation are:

- R [Ohm], X [Ohm], G [Siemens] and B [Siemens].
- maximum power [MVA].
- connectivity.

8.2. SENSITIVITY FACTORS MODULE

The sensitivity factor module assists the system during the solution of the problem. In order to calculate the changes in the load bus voltages and generator reactive power outputs for a given increment in control variables sensitivity factors can be employed.

8.3. LINEAR PROGRAMING MODULE

To use the linear programming approach to compute the required control actions, an objective function to be minimized and a set of constraints must be first defined. In the literature, several objectives function such as minimizing the total amount of adjustments or minimizing transmission losses have been employed. Before the objective function for this work was chosen, a discussion with operators at Egyptian unified power network (EUP) has been made. After these discussions the impression that the operators favor a control action that requires least number of switchings of capacitors/inductors and/or an adjustment to transformer taps had been got. The main reason why they favor such a control action is that capacitor/inductor switching and tap adjustment tend to reduce the life expectancy of these devices and increase the maintenance cost. Based on these practical considerations, we propose to use the objective function of minimizing the total number of required switching/adjustments to control the voltage in this paper. In other words, the objective is to

$$\text{Minimize } Z = \sum_i x_i \quad (1)$$

where X_i is the number of capacitors/inductors that have to be switched on/off or the number of steps that the transformer tap should adjusted to at bus i . Note the other objective functions can also be employed if desired. The constraints in the linear programming formulation include the following:

- Constraints on control variables.

$$\Delta Q_i \min \leq \Delta Q_i \leq \Delta Q_i \max \quad (2)$$

$$\Delta t_{pq} \min \leq \Delta t_{pq} \leq t_{pq} \max \quad (3)$$

- Constraints in bus voltage

$$V_i \min \leq V_i \leq V_i \max \quad (4)$$

Where:

ΔQ_i is the increment of the reactive power of switchable Capacitors/Inductors at bus i ,

Δt_{pq} is the increment of the transformer tap between buses p and q

9. APPLICATION EXAMPLES

In real world operating conditions of the system are changed due to the change in the load demand. This will lead to changes in the load bus voltage violation. The developed system has been applied on the 220 KV network of the Unified Power System of Egypt (UPSE) in order to demonstrate its effectiveness. The single line diagram of the (UPSE) is shown in the appendix A1. A final voltage profile characterized by minimum and maximum voltage levels of 1.0 pu, and 1.05 pu., respectively was considered for this study. In all the following figures which represent different case studies, the continuous line represents the initial voltages profile and the dashed line represents the final voltages profile.

9.1. CASE ONE

The results of the application of the new back propagation neural network system on the 220 KV network of the Unified Power System of Egypt (UPSE) are shown in Fig 2. Over-voltages observed at two buses, and under-voltages observed at five buses. After applying the proposed system one can see from the results in Fig 2. that, all the bus voltage violations are alleviated. On the other hand the amount of reactive power required to reach the optimal solution is equal to 7.8 pu.

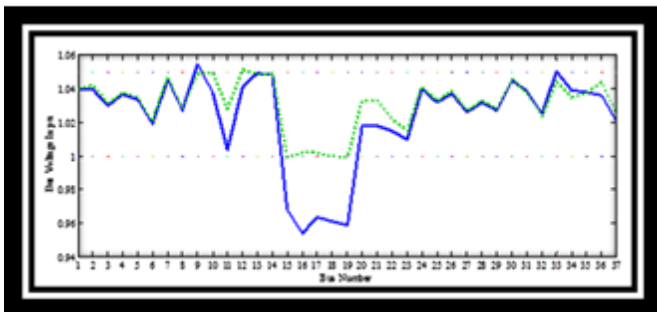


Fig. 2. Initial and final voltage profile for the 220 KV Network of the UPSE.

9.2. CASE TWO

In this case after voltage correction (refer to the results of section (9.1) the lines between buses (19-20) and (8-27) in the 220 KV network of UPSE is switched off, resulting in distortion in the system voltage profile as in Fig 3.

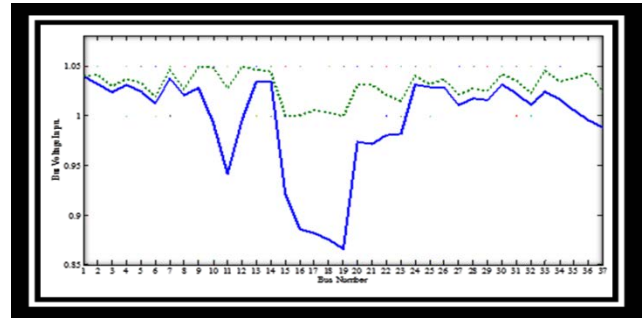


Fig. 3. Final voltage profile if the lines between buses (19-20) and (8-27)37 in the 220 kV network of the UPSE is switched off.

Under-voltages are observed at several buses. After applying the proposed system one can see from the results in Fig 3. that, all the bus voltage violations are alleviated. On the other hand the amount of reactive power required to reach the optimal solution is equal to 10.2 pu.

9.3. CASE THREE

In this case after voltage correction (refer to the results of section (9.1) the load at bus (19) in the 220 KV network of the UPSE is switched off, resulting in distortion in the system voltage profile as in Fig 4.

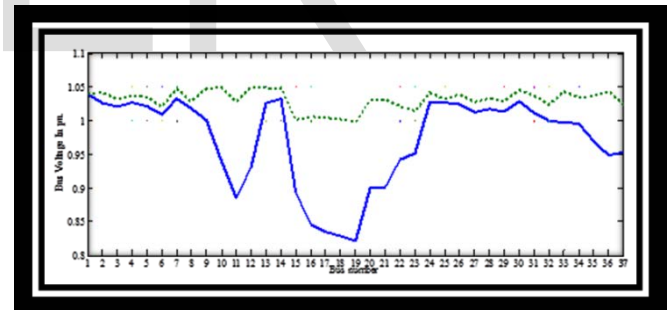


Fig. 4. Final voltage profile if the load at node 19 in the 220 kV UPSE is doubled.

Under-voltages are observed at several buses. After applying the proposed system one can see from the results in Fig 4. that, all the bus voltage violations are alleviated. On the other hand the amount of reactive power required to reach the optimal solution is equal to 9.27 pu.

9.4. CASE FOUR

In this case after voltage correction (refer to the results of section (9.1) the load at bus (17) in the 220 KV network of

the Unified Power System of Egypt is doubled, resulting in distortion in the system voltage profile as in Fig 5.

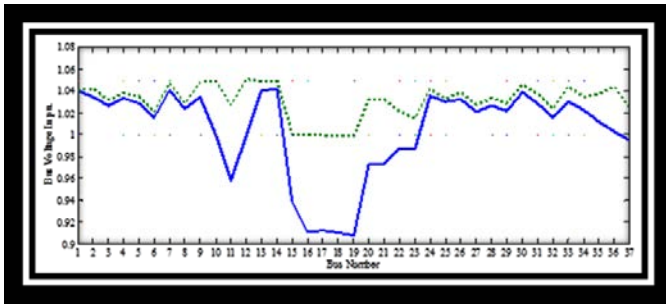


Fig. 5. Final voltage profile if the load at node (17) in the 220 UPSE is doubled.

Under-voltage are observed at several buses. After applying the proposed system one can see from the results in Fig 5. that, all the bus voltage violations are alleviated. On the other hand the amount of reactive power required to reach the optimal solution is equal to 7.5 pu.

9.5. CASE FIVE

In this case after voltage correction (refer to the results of section (9.1) the load at bus (16) in the 220 KV network of the UPSE is switched off, resulting in distortion in the system voltage profile as in Fig 5.

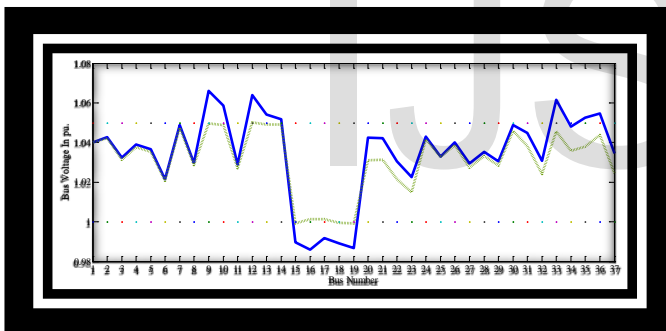


Fig. 6. Final voltage profile if load at node 16 in the 220 kV network of the UPSE is switched off.

Over-voltage are observed at several buses. After applying the proposed approach one can see from the results in Fig 6. that, all the bus voltage violations are alleviated. On the other hand the amount of reactive power required to reach the optimal solution is equal to 6.35 pu.

10. CONCLUSION

A new Back Propagation Neural Network (BPNN) system for reactive power optimization is developed in this paper. The (BPNN) system was tested on the 220 KV network of

the unified power system of Egypt and proved to be efficient. The (BPNN) system results proved the high accuracy and the suitability for the on line applications. The (BPNN) system is an excellent model that can be integrated in an open SCADA/EMS environment. Using the system in an actual control center will enable the control of the system voltage profile in a tracking mode.

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APPENDIX A1: The single line diagram of the 220 KV Network of the Unified Power System of Egypt

