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Research Note

Application of Artificial Neural Networks in Controlling Voltage and Reactive Power

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This paper presents an application of Artificial Neural Networks (ANN) to control the voltage and reactive power in power systems. The technique is based on using a feed-forward artificial neural network with an error back-propagation training algorithm, based on the Levenberg-Marquardt method to train the networks. The training data is obtained by solving several abnormal conditions using Linear Programming (LP). Generator voltages, reactive power sources and transformer taps are considered as control variables and load bus voltages and generator reactive powers as dependent variables. The method presented in this paper has been tested on IEEE 14-bus and 30-bus standard systems. The obtained results clearly indicate that the trained neural networks are capable of controlling the voltage and reactive power in power systems with a high level of precision and speed.

INTRODUCTION

One of the most important problems in power systems is the control of the voltage and reactive power for improving the quality, security and economy of the operation. So far, numerous methods have been presented in this field. Until about twenty years ago, the voltage and reactive power in power systems used to be controlled separately in a non-concentrated form by regulating the set point of the buses, which consisted of the local reactive power (generators, condensers and transformers with tap changers). This could be due to the limitations of the range and load of power systems in the past. However, through the development of power systems, it was felt necessary to create coordination among dispersed components of reactive power. Therefore, this topic displayed its strength in the form of an appearance of the second level of control of voltage and reactive power in power systems. In reality, the set point of the different reactive power equipment available in the system must be regulated under the supervision of a central control unit in such a way that the new objective of controlling the reactive power in the system may be achieved [1]. In order to achieve such an objective, an effective method of control is needed. This method will have to be simple, easily enforceable and have a short answering time. Respectively, in the past, many techniques have been developed and several methods have been initiated. These methods can be classified into two general categories, as follows:

a) Mathematical methods,
b) Artificial intelligence methods [2].

In mathematical methods, the issue of control and reactive power load flow is considered as an optimization case (a case of optimization with conditions). Among the mathematical methods, linear programming has been widely applied in voltage and reactive power control discussions in recent years [3,4]. In this method, first, the objective function is determined, which is generally the main subject for minimization of power loss. Then, the constraints available on system variables are explained as programming conditions. In spite of the fact that mathematical methods have had a lot of success, there are still problems, which prevent the finding of a complete general solution from these methods. Some of these problems are as follows:

a) Needing a database for reserving operator data,
b) Possibility of utilizing operator decisions,
c) Possibility of using experience,

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d) Possibility of considering problems such as the uncertainty of some quantities, load variations etc.

Therefore, a combination of Artificial Intelligence Methods and ordinary methods has been presented to control the optimal reactive power. Among the most important, one can point at the utilization of fuzzy set theories, expert systems and artificial neural networks. In [5,6], fuzzy based reactive power control has been presented. Application of fuzzy sets is within the upper and lower limits of variables and within the coefficients of the objective function. The difficulties of these methods lie in precise determination of the upper and lower limits and the coefficients of the objective function. Furthermore, because of using linear programming in the original solution, calculation time, in comparison with the application of neural networks, is longer. In [7], the expert system has been utilized to compensate the reactive power. The advantage of the expert system approach is the very high speed of answering time. However, in the case of large power systems, these techniques have problems, because the expected time saving will be decreased and, as the knowledge base is larger, the search time will be increased. Also in [8], utilization of mixed integer programming in solving the control of reactive power has shown that the length of time taken for full precision in the obtained results is one of the disadvantages of this method.

Artificial neural networks have emerged as a powerful pattern recognition technique. Since the need for pattern recognition arises whenever computers interact with the real world, ANNs are broadly useful in a range of applications. The networks can recognize spatial, temporal or other relationships and can perform such tasks as classification, prediction and function estimation. This can bridge the gap between individual examples and general relationships. This characteristic has encouraged various researchers to apply ANNs to solve various power system problems, such as load forecasting, security assessment, fault diagnosis, fault location, system protection and control systems etc.

In this paper, Artificial Neural Network (ANN) is applied to control the voltage and reactive power in power systems [9]. A three layer feed-forward ANN with back-propagation, based on the Levenberg-Marquardt training algorithm [10], is trained to give the proper control action required to achieve reactive power and voltage control. The training data is obtained by solving several abnormal conditions using Linear Programming (LP). The system losses are chosen as objective functions, so that the approach minimizes system losses and enhances voltage profile by making suitable variations in control variables. The proposed method has been tested on IEEE 14-bus and 30-bus standard systems, the obtained results from simulation are satisfactory and show a superior performance compared to other techniques.

OPTIMAL REACTIVE POWER CONTROL BASED ON LINEAR PROGRAMMING

The power system model is described by a well-known power flow equation [3]:

$$P_i = \sum_j V_i V_j \left(B_{ij}\sin(\delta_i-\delta_j) + G_{ij}\cos(\delta_i-\delta_j)\right),$$

$$Q_i = \sum_j V_i V_j \left(-B_{ij}\cos(\delta_i-\delta_j) + G_{ij}\sin(\delta_i-\delta_j)\right), \tag{1}$$

in which G_{ij} and B_{ij} stand for conductance and susceptance from bus i to bus j, respectively; P_i, Q_i for active and reactive power injected to bus i, respectively, and V_i, δ_i for voltage magnitude and angle of bus i, respectively.

The active power loss of the system is also calculated from the following equation [3]:

$$P_L = \sum_{k=1}^{N_L} G_k \left(V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i-\delta_j)\right), \tag{2}$$

in which N_L stands for the number of lines and G_K for conductance of the k line from bus i to bus j.

In this paper, the objective function is the power loss of lines and the goal is to minimize them. Also, in order to apply linear programming, the objective function is described in terms of control variables and the restrictions of control and depending variables are considered as the constraints of programming, i.e.:

$$\begin{array}{ll} \text{minimize} & P_L, \\ \text{subject to:} & X_{\min} \le X \le X_{\max}, \\ & Y_{\min} \le Y \le Y_{\max}, \end{array} \tag{3}$$

in which:

$$X = \begin{bmatrix} V_G & T & Q_c \end{bmatrix}^T, \quad Y = \begin{bmatrix} V_L & Q_G \end{bmatrix}^T, \tag{4}$$

and:

X = control variable vector,
Y = dependent variable vector,
V_G = generators voltage vector,
T = transformers tap vector,
Q_c = reactive power source vector,
V_L = load buses voltage vector,
Q_G = generations reactive power vector.

According to Equations 1 and 2, since P_L has a non-linear relation with the control variables, in order to optimize the reactive power by using LP, P_L must be linearized on the primary state condition (x, y).

Then, ΔP_L should be optimized in any iteration as the new objective function. The power system, which is introduced by Equations 1 and 2 can be represented by a matrix equation as follows:

$$Y = S.X, \tag{5}$$

in which S is the sensitivity matrix. Then, the optimization problem introduced by Equation 3 is converted to a case of linear programming, as shown below [3]:

$$\begin{aligned} &\text{minimize} && \Delta P_L = C^T \Delta X, \\ &\text{subject to:} && \Delta X_{\min} \le \Delta X \le \Delta X_{\max}, \\ & && \Delta Y_{\min} \le \Delta Y \le \Delta Y_{\max}. \end{aligned} \tag{6}$$

In this equation,

$$C = \left. \frac{\partial P_L}{\partial X} \right|_{\substack{X=X_0 \\ Y=Y_0}} .$$

Based on the aforementioned linear programming method, the variations required in control variables will be obtained. The status of these variables is then modified and the NR load flow is performed. This completes one iteration of the VAR control problem. Iterations are repeated until all the restrictions are removed and the losses are minimized. Figure 1 depicts the corresponding flowchart of voltage and reactive power control by utilizing linear programming and offers a method of using LP to generate the training data for neural networks.

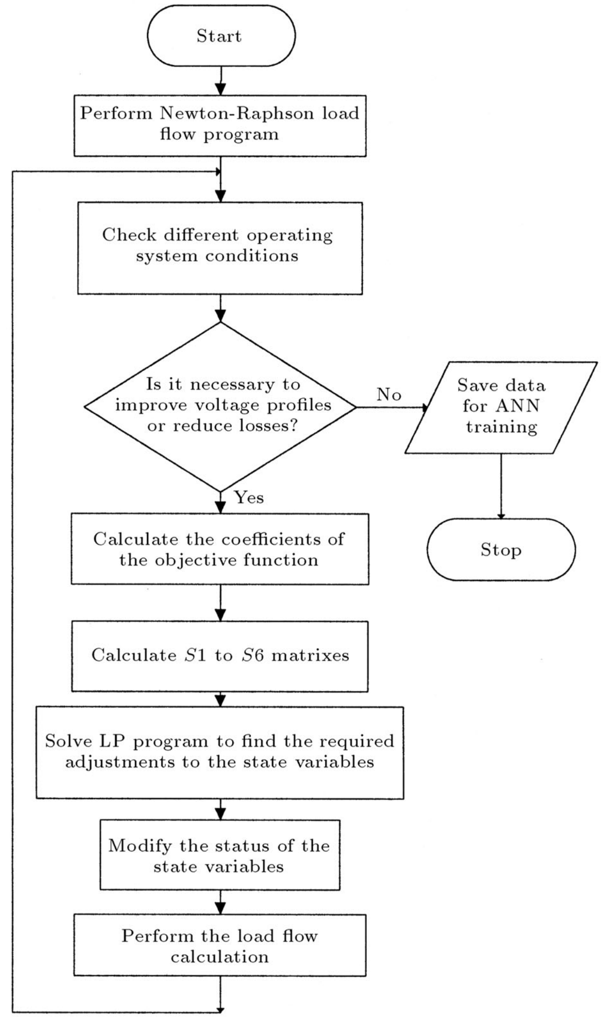

Figure 1. Flowchart for optimal reactive power and voltage control and storing data for ANN training.

CONTROLLING THE VOLTAGE AND REACTIVE POWER BY USING ANN

The block diagram of the ANN-based algorithm for voltage and reactive power control in power systems is shown in Figure 2. The method is based on using a 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. Furthermore, 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 conditions).

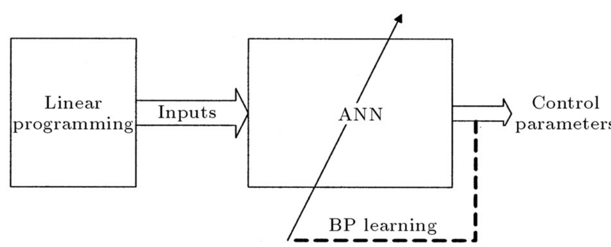

Figure 2. Block diagram of the ANN-based algorithm for reactive power and voltage control.

Training the Artificial Neural Networks

Training is a stage at which all the weighting factors and thresholds are regulated according to a specific rule, in such a way that the objective function may be minimized. The usual method for training of a multi-layer feed-forward neural network is the method of error back-propagation. In order to use this method, both the desired output and the real output of the network must be available. The difference between desired output and real output is called error. The algorithm of error back-propagation is based on the learning rule of error correction. This algorithm is an iterative method designed for minimizing the average of the squared error [10].

The primary algorithm for operational problems has a low speed. In order to increase training speed, numerous methods of the error back-propagation algorithm have been presented (which have more capabilities, ten times or even a hundred times faster than the primary algorithm). In [11], for example, it has been shown that among these methods, Levenberg-Marquardt is the fastest from the viewpoint of the number of iterations and convergence time.

The Levenberg-Marquardt method is a generalization of the Newton method, in which there is no need to calculate the Hessian Matrix. In this case, the network's standard function is considered as the total of squared errors (as is the case for multi-layer feed-forward networks). The Hessian Matrix can be written with an approximation in the following form:

$$H = J^T.J. \tag{7}$$

Also, the error gradient is obtained from the following relation:

$$g = J^T.e, \tag{8}$$

in which:

J = the Jacobian Matrix, which consists of the first derivative of the network's error with respect to weights and biases,

E = Network's error vector.

Calculation of the Jacobian Matrix is much easier than that of the Hessian Matrix (second order derivative) [10]. The following equation also performs an adjustment of the weighting factors and biases:

$$X_{k+1} = X_k - [J^T.J + \mu I]^{-1}.J^T.e, \tag{9}$$

in which μ is a scalar number and X represents the network's parameters, which must be adjusted (weighting factors and biases). In this paper, the Levenberg-Marquardt method has been utilized for training the neural network.

Extraction of Training Data by Utilizing Linear Programming Algorithm

Training data can be obtained by real measurement using the operators' experimental rules or via simulation results. These data must have particular conditions. For example, the training data must cover all the working conditions of the system (including both normal and abnormal operating conditions). In order to improve the performance and speed of the training process, it is very important to reduce the number of training data. In a real power system, the working conditions of the system change by variations in the scale of load demand. The load variations themselves bring about variations in the load bus voltages and sometimes cause buses to violate their voltages and cause the voltages to violate their authorized limits. In this paper, in order to control the voltage against load variations in IEEE 14-bus and IEEE 30-bus, by varying the scale of bus loads and using the method of linear programming for issuance of reasonable controlling orders (desired output) in each of the above situations, reasonable training data are obtained.

By changing the load of each bus from zero to 120%, with step 20% and, also, by simultaneous changing of all the load, from 75 to 115%, with step 10%, the results of linear programming for voltage and reactive power control have been achieved so that by using this input and output data, the neural network may be trained. The single line diagrams of these two power systems are shown in Figures 3 and 4.

Structure of Artificial Neural Networks

The aim of voltage and reactive power control discussions is to maintain the voltage of load buses within authorized limits, as well as decreasing system losses. This is done by regulating the control variables (generator voltages, transformer taps and VAR sources). Therefore, to design the neural network, the number of inputs to the network must be equal to the number of load buses and the number of outputs must be equal to the number of control variables. In this paper, in order to control the voltage and reactive power in IEEE 14-bus and 30-bus systems, two multi-layer networks, with eight neurons in the hidden layer and a sigmoid transfer function, have been utilized. The structure of these networks has been shown in Figures 5 and 6 and their neural specifications have been presented in Table 1.

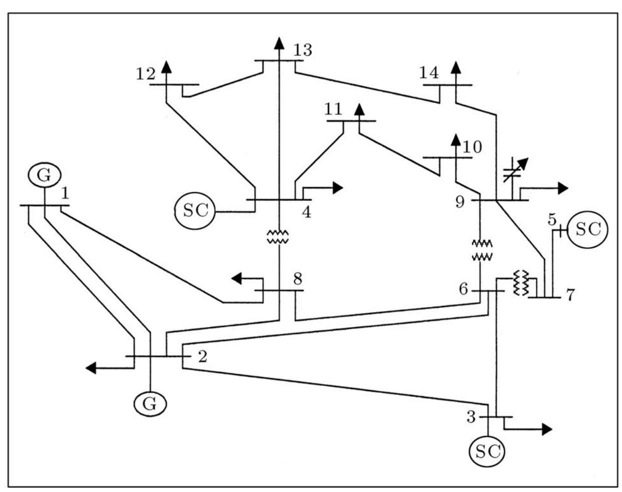

Figure 3. One-line diagram of IEEE 14-bus system.

Table 1. Specifications of neural networks used in this paper.

ANN	IEEE 14-BUS	IEEE 30-BUS
Number of input neurons	9	24
Number of output neurons	9	20
Number of hidden layers	1	1
Number of neurons of hidden layer	8	8
Stimulating of hidden neurons	Hyperbolic Tangent	Hyperbolic Tangent
Stimulating of output neurons	Sigmoid	Sigmoid
Training algorithm	Levenberg-Marquardt	Levenberg-Marquardt

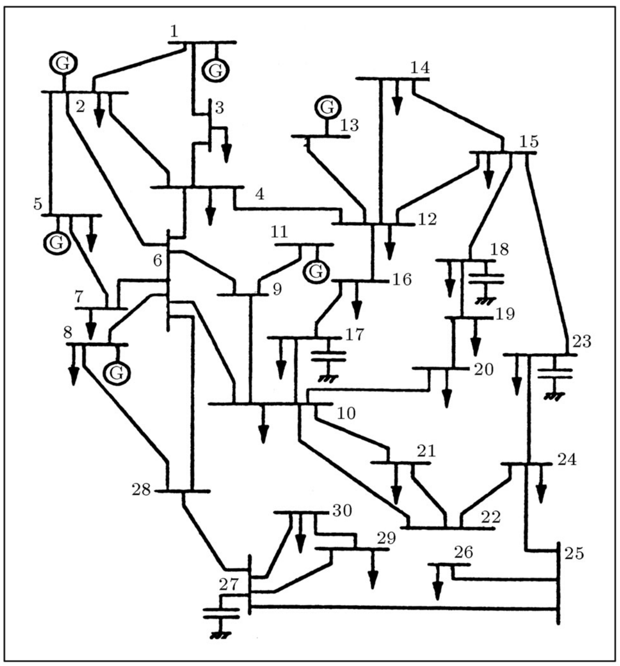

Figure 4. One-line diagram of IEEE 30-bus system.

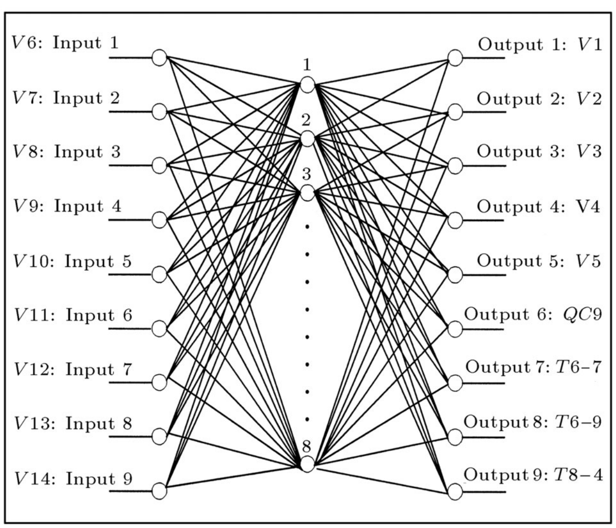

Figure 5. Structure of neural network concerning IEEE 14-bus system.

TEST RESULTS

Both methods of linear programming and artificial neural networks have been simulated in a Matlab Software [12] environment and have been applied to the two systems: IEEE 14-bus and 30-bus. Therefore, separate sets of test patterns were supplied for each system as inputs to the ANN involved, in order to evaluate their performance. The results obtained from numerous tests clearly show the capability of these networks in controlling the voltage and reactive power in both systems. In order to test the validity of each ANN structure, several tests have been performed. For the sake of brevity, only three test cases for each system are presented in this paper.

IEEE 14-Bus System

A one-line diagram for the 14-bus system is shown in Figure 5. The specifications of this system have been shown in Appendix A. The simulation results for three different situations of a 14-bus system are presented in Table 2.

First Status

In the first status, the system operates with its full (100%) nominal load. The first results obtained from the load flow have been shown in Table 2 in the first column under the title “initial”. Under these circumstances, the system experiences a low voltage limit violation in bus no. 12. The variations proposed by the LP and ANN methods have been displayed in columns concerning LP and ANN methods in the section of depending variables (Table 2). The results presented in Table 2 indicate that by applying the variations proposed by LP and ANN methods, the violation of a low voltage restriction has been removed, the voltage profile has improved and the power losses have decreased.

Second Status

In the second status, the system works with 75% of its nominal load. Under these circumstances, the lower

Table 2. Simulation results of reactive power and voltage control for IEEE 14-bus system.

	First Status			Second Status			Third Status		
	Initial	LP	ANN	Initial	LP	ANN	Initial	LP	ANN
Control Variables									
$V1$	1.0600	1.0809	1.0777	1.0600	1.0705	1.0684	1.0600	1.0612	1.0723
$V2$	1.0450	1.0672	1.0558	1.0450	1.0429	1.0422	1.0450	1.0310	1.0315
$V3$	1.0100	1.0380	1.0330	1.0100	1.0248	1.0280	1.0100	1.0150	1.0210
$V4$	1.0700	1.0649	1.0630	1.0700	1.0578	1.0523	1.0700	1.0413	1.0468
$V5$	1.0900	1.0750	1.0771	1.0900	1.0527	1.0650	1.0900	1.0478	1.0730
$QC9$	0.0000	0.2000	0.2000	0.0000	0.2000	0.2000	0.0000	0.200	0.200
$T6-7$	0.9780	1.0150	1.0084	0.9780	0.9861	0.9932	0.9780	1.0043	1.0530
$T6-9$	0.9690	0.9898	0.9940	0.9690	0.9752	0.9810	0.9690	0.9875	1.0300
$T8-4$	0.9320	0.9796	0.9687	0.9320	0.9821	0.9784	0.9320	0.9913	0.9830
Dependent Variables									
$Q1$	-0.1515	-0.2145	-0.0427	-0.0358	0.1875	0.1538	-0.0199	-0.1877	1.7850
$Q2$	0.4884	0.3824	0.1664	0.2527	-0.1991	-0.2047	0.5109	0.4701	0.4950
$Q3$	0.2739	0.2829	0.3379	0.0906	0.2129	0.2440	0.4000	0.400	0.400
$Q4$	0.2290	0.2371	0.2187	0.1069	0.1825	0.1286	0.2400	0.240	0.240
$Q5$	0.2528	0.1576	0.1765	0.2067	0.0247	0.0893	0.3354	0.300	0.300
$V6$	1.0120	1.0419	1.0339	1.0196	1.0282	1.0295	0.9386	0.9479	0.9670
$V7$	1.0492	1.0492	1.0482	1.0566	1.0486	1.0502	1.0268	1.0354	1.0230
$V8$	1.0160	1.0461	1.0374	1.0228	1.0341	1.0336	1.0117	1.0275	1.0312
$V9$	1.0324	1.0462	1.0434	1.0438	1.0498	1.0489	1.0013	1.0170	1.0250
$V10$	1.0315	1.0420	1.0394	1.0428	1.0456	1.0439	1.0007	1.0410	1.0350
$V11$	1.0469	1.0498	1.0476	1.0536	1.0491	1.0455	1.0105	1.0405	1.0400
$V12$	1.0533	1.0495	1.0476	1.0577	1.0468	1.0416	1.0212	1.0315	1.0471
$V13$	1.0467	1.0443	1.0423	1.0529	1.0433	1.0384	1.0168	1.0317	1.0395
$V14$	1.0195	1.0263	1.0239	1.0336	1.0328	1.0302	0.9715	1.0413	1.0450
PL	0.1359	0.1283	0.1298	0.0706	0.0695	0.0697	0.1987	0.1899	0.1791

voltage limit is violated at buses 7, 11, 12 and 13. The results from Table 2 clearly show that by applying the variations proposed by LP and ANN methods, while voltage restrictions have been removed, the voltage profile has improved and power losses are decreased.

Third Status

In the third status, the system works with 125% of its nominal load. Also, to put the system into critical emergency conditions, the upper limit of reactive power in generator no. 5 is reduced to 30 Mvar (or 0.3 pu). Under such circumstances, bus no. 6 has already violated an amount of the lower limit of the bus voltage. Bus 14 is also in critical condition and the amount of power loss will be equal to 0.1987 pu. This is shown in Table 2 in the column labeled “initial”. The results available in the table show that by applying the variations proposed by the LP method, the limit violation of bus no. 6 has not yet been alleviated. However, the proposed ANN technique suggests proper control actions. Also, in the LP method, the amount of power loss will be equal to 0.1899 pu, while the amount of this loss, by employing the ANN algorithm, reduces to 0.1791 pu. This shows more desirable deviations in variables.

IEEE 30-Bus System

Figure 6 shows the one-line diagram of a modified IEEE 30-bus system. In Tables B1 and B2 of Appendix B, the specifications of this system have also been explained. In Table 3, the simulation results

Table 3. Simulation results of reactive power and voltage control for IEEE 30-bus system.

	First Status			**Second Status**			**Third Status**		
	Initial	**LP**	**ANN**	**Initial**	**LP**	**ANN**	**Initial**	**LP**	**ANN**
Control Variables									
$V1$	1.060	1.060	1.060	1.060	1.060	1.060	1.060	1.060	1.060
$V2$	1.045	1.045	1.045	1.045	1.045	1.045	1.045	1.045	1.045
$V5$	1.010	1.010	1.010	1.010	1.010	1.010	1.010	1.010	1.010
$V8$	1.010	1.015	1.023	1.010	1.010	1.010	1.010	1.025	1.031
$V11$	1.082	1.082	1.082	1.082	1.072	1.081	1.082	1.082	1.082
$V13$	1.071	1.071	1.071	1.071	1.071	1.071	1.071	1.071	1.071
$QC17$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$QC18$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$QC23$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$QC27$	0.000	0.045	0.008	0.000	0.000	0.000	0.000	0.074	0.086
$T1-3$	0.9610	0.9610	0.9610	0.9540	0.9540	0.9540	1.0500	1.0500	1.0500
$T2-4$	0.9560	0.9560	0.9560	0.9680	0.9680	0.9680	1.0700	1.0700	1.0700
$T5-7$	0.9650	0.9650	0.9650	0.9440	0.9440	0.9440	1.0300	1.0300	1.0300
$T8-28$	0.9700	0.9700	0.9700	0.9650	0.9650	0.9650	1.0750	1.0750	1.0750
$T9-10$	0.9635	0.9635	0.9635	0.9685	0.9685	0.9685	1.0450	1.0470	1.0490
$T10-17$	0.9590	0.9590	0.9590	0.9390	0.9390	0.9390	1.0300	1.0300	1.0300
$T12-13$	0.9850	0.9850	0.9850	0.9710	0.9710	0.9710	0.9900	1.0300	1.0500
$T18-19$	0.9655	0.9655	0.9655	0.9575	0.9575	0.9575	1.0130	1.0130	1.0130
$T23-24$	0.9810	0.9910	0.9950	0.9690	0.9690	0.9690	1.0230	1.0230	1.0230
$T27-29$	0.9530	0.9730	0.9850	0.9410	0.9410	0.9410	1.0550	1.0450	1.0550
Dependent Variables									
$Q1$	0.091	0.085	0.068	0.230	0.265	0.280	0.089	0.080	0.065
$Q2$	0.087	0.065	0.015	0.105	0.128	0.153	0.081	0.025	-0.021
$Q5$	0.120	0.112	0.095	-0.085	-0.058	-0.063	0.120	0.115	0.101
$Q8$	0.038	0.058	0.235	0.085	-0.047	-0.011	0.054	0.124	0.458
$Q11$	0.410	0.415	0.385	0.145	0.140	0.172	0.480	0.450	0.410
$Q13$	0.475	0.458	0.430	0.031	-0.084	-0.113	0.490	0.478	0.451
$V3$	1.035	1.035	1.037	1.032	1.027	1.025	1.021	1.028	1.030
$V4$	1.028	1.031	1.033	1.024	1.020	1.021	1.025	1.026	1.033
$V6$	1.019	1.005	1.008	1.021	1.018	1.017	1.010	1.013	1.022
$V7$	1.010	1.008	1.008	1.011	1.012	1.010	0.995	1.012	1.017
$V9$	1.003	1.010	1.015	1.058	1.044	1.045	0.989	0.995	1.002
$V10$	0.982	0.985	0.990	1.048	1.039	1.041	0.965	0.977	0.981
$V12$	1.008	1.005	1.008	1.062	1.044	1.041	0.990	0.997	1.003
$V14$	0.990	0.998	1.003	1.056	1.040	1.038	0.975	0.975	0.983
$V15$	0.984	0.991	0.995	1.048	1.039	1.035	0.970	0.976	0.990
$V16$	0.985	0.990	0.994	1.058	1.042	1.040	0.980	0.984	0.991
$V17$	0.971	0.985	0.986	1.044	1.034	1.021	0.965	0.971	0.983

Table 3. Continued.

	First Status			Second Status			Third Status		
	Initial	**LP**	**ANN**	**Initial**	**LP**	**ANN**	**Initial**	**LP**	**ANN**
Dependent Variables									
$V18$	0.972	0.981	0.982	1.044	1.037	1.031	0.932	0.983	0.985
$V19$	0.965	0.964	0.965	1.043	1.039	1.030	0.968	0.973	0.975
$V20$	0.960	0965	0.967	1.045	1.030	1.021	0.953	0.961	0.969
$V21$	0.960	0.968	0.970	1.042	1.031	1.028	0.955	0.965	0.973
$V22$	0.959	0.965	0.968	1.038	1.034	1.023	0.961	0.973	0.981
$V23$	0.968	0.977	0.997	1.045	1.047	1.041	0.971	0.977	0.989
$V24$	0.945	0.968	0.968	1.038	1.033	1.027	0.932	0.974	0.984
$V25$	0.943	0.987	0.985	1.034	1.031	1.021	0.909	0.965	0.972
$V26$	0.931	0.965	0.966	1.035	1.028	1.027	0.935	0.991	0.990
$V27$	0.956	1.003	1.001	1.041	1.043	1.041	0.942	0.985	0.981
$V28$	1.012	1.021	1.023	1.015	1.024	1.024	1.003	1.015	1.025
$V29$	0.935	0.998	1.001	1.030	1.021	1.020	0.890	0.995	1.003
$V30$	0.925	0.988	0.985	1.025	1.068	1.035	0.915	0.970	0.988
PL	0.0480	0.0391	0.0378	0.0660	0.0565	0.0532	0.0790	0.0610	0.0580

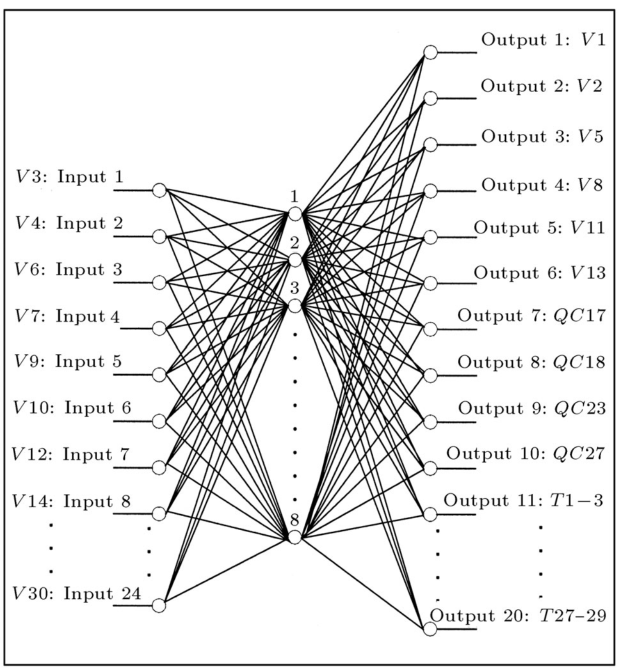

Figure 6. Structure of neural network concerning modified IEEE 30-bus system.

have been shown for an IEEE 30-bus system, in three different states.

First Status

In the first status, the system works with its full nominal load. As observed, under these circumstances, bus numbers 24, 25, 26, 29 and 30 have violated the restriction fault of a lower voltage limit and the amount of power loss will be equal to 0.0480 pu. In order to remove this fault, the LP method has suggested variations in each of the six controlling variables that have been displayed in Table 3, in the column concerning the LP method, in the section of controlling variables. In addition, the variations proposed by the ANN method have been explained in this table in the column pertaining to ANN methods in the section of controlling variables. Also, by applying these variations, which can be seen in the same table in the columns concerning LP and ANN methods in the section of depending variables, while removing the limit violations of the buses, the total voltage profile of the system has been improved. Furthermore, in the LP method, the amount of power loss will be equal to 0.0391 pu, while the amount of this loss, employing the control action by the ANN algorithm, reduces to 0.0378 pu. In this respect, the ANN method shows more desirable deviations in variables.

Second Status

In the second status, the system operates with 50% of its nominal load. Under such circumstances, bus numbers 9, 12, 14, and 16 have violated a slight amount of the high limit of bus voltage (1.05 pu). The results presented in Table 3 show that by applying the variations proposed by LP and ANN methods, while limit violation of the buses has been alleviated, the voltage profile has improved and the power losses have decreased.

Third Status

In the third status, the system is fully connected and operates at 110% of full load. This results in a low limit violation at buses 18, 24 to 27, 29, and 30, shown in Table 3 under case 3 in the column labeled "initial". In these situations, both techniques suggest proper control actions. Therefore, the voltage violation is alleviated and the voltage profile is improved, as shown in Table 3. However, ANN gives this decision in almost no time.

A comparison between the computational time of the proposed ANN technique and LP is shown in Table 4. It is clearly shown that the ANN technique requires very small computational time to alleviate voltage violations for both IEEE 14 and 30-bus systems. Furthermore, the results indicate that the LP computational time increases considerably by increasing the size of the network, whereas the computational time of ANN remains approximately unchanged. These results have been achieved by using a computer with Pentium 2000, 512 MB RAM specifications.

As is clear from simulation results, the other advantages of ANN, as compared with linear programming in reactive power control, is that one can refer to the ability of the trained neural network at high and low limits of load. That is, with respect to the fact that the designed neural network has been trained in a specified percentage of load variations, it is, however, capable of controlling the network's voltage and reactive power permanently and favorably in the minimum to maximum range of load variation percentages of the network at a very high speed.

For example, in the first status of the results of the 14-bus system, this system has been trained with the full load of 100% for all buses, but the neural network can control the reactive power in a desired manner. In other words, it can put the voltage of bus no. 12, which had exceeded its authorized limits, within its authorized limits, by changing the transformer tap and the reactive power of the generators. Furthermore, by application of this technique, in spite of the voltage control, the voltage profile has improved and system losses have decreased.

Table 4. Computation times for LP and ANN methods with full load state.

System	LP	ANN
14-bus	9.8 Sec.	0.08 Sec.
30-bus	37.3 Sec.	0.14 Sec.

CONCLUSIONS

A new technique for voltage and reactive power control based on ANN is proposed in this paper. The training data is obtained by solving several abnormal conditions using the LP technique. The results obtained clearly show that the ANN approach is capable of alleviating voltage violations in power systems. The trained network is capable of controlling the power system voltage and reactive power in the minimum to maximum range of load variations at very high speed. A comparison with the LP technique shows the clear superiority of the proposed ANN in achieving the proper control action in a shorter computational time. Furthermore, since neural networks have a more simple structure and operation as compared with the linear programming method, it makes the widespread utilization of this network possible in the application of power systems. Therefore, it is possible to use the ANN technique on real time and implement it on a real power system.

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APPENDIX A

Specification of Standard IEEE 14-Bus System

The standard IEEE 14-bus system (see Figure 5) is considered to consist of five generators, three tap-changer transformers and 20 transmission lines. The system parameters are given in [13]. Also, the upper and lower limits of control variables, such as the voltage magnitude limits of PV buses, tap changer limits and the reactive power limits of the compensator, are illustrated in Table A1. Furthermore, the minimum and maximum values of dependent variables (voltage magnitude limits of PQ buses and reactive power limits of generators) are shown in Table A2.

APPENDIX B

Specification of Modified IEEE 30-Bus System

Similar to Appendix A, the second test system is a modified IEEE 30-bus system (see Figure 6). Lines, transformers and buses data can be observed in [5,13]. Also, in Tables B1 and B2, the upper and lower limits of control variables and dependent variables are illustrated, respectively.

Table A1. The upper and lower limits of control variables for IEEE 14-bus system.

	$V1$ (pu)	$V2$ (pu)	$V3$ (pu)	$V4$ (pu)	$V5$ (pu)	$T67$	$T69$	$T84$	$QC9$ (Mvar)
Minimum	1.000	1.000	1.000	1.000	1.000	0.900	0.900	0.900	0.00
Maximum	1.100	1.100	1.100	1.100	1.100	1.100	1.100	1.000	20.00

Table A2. The upper and lower limits of dependent variables for IEEE 14-bus system.

	$V6$ to $V14$ (pu)	$QG1$ (Mvar)	$QG2$ (Mvar)	$QG3$ (Mvar)	$QG4$ (Mvar)	$QG5$ (Mvar)
Minimum	0.950	-30.00	-40.00	0.00	-6.00	-6.00
Maximum	1.050	100.00	50.00	40.00	24.00	40.00

Table B1. The upper and lower limits of control variables for IEEE 30-bus system.

	$V1, V2, V5, V8, V11, V13$ (pu)	All Taps	$QC17$ (Mvar)	$QC18$ (Mvar)	$QC23$ (Mvar)	$QC27$ (Mvar)
Minimum	0.95	0.900	-5.00	0.00	-5.00	-5.5
Maximum	1.100	1.100	5.00	5.5	5.5	5.5

Table B2. The upper and lower limits of dependent variables for IEEE 30-bus system.

	$V3, V4, V6, V7, V9, V10, V12, V14$ to $V30$ (pu)	$QG1$ (Mvar)	$QG2$ (Mvar)	$QG5$ (Mvar)	$QG8$ (Mvar)	$QG11$ (Mvar)	$QG13$ (Mvar)
Minimum	0.950	-20.00	-20.00	-15.00	-15.00	-10.00	-15.00
Maximum	1.050	250.00	100.00	80.00	60.00	50.00	60.00