Available online at www.sciencedirect.com
SCIENCE DIRECT®

Electric Power Systems Research 76 (2006) 259–269

ELECTRIC POWER SYSTEMS RESEARCH

www.elsevier.com/locate/epsr

Estimation of switching transient peak overvoltages during transmission line energization using artificial neural network

D. Thukaram *, H.P. Khincha, Sulabh Khandelwal

Department of Electrical Engineering, Indian Institute of Science, Bangalore 560012, India

Received 7 March 2005; received in revised form 6 June 2005; accepted 12 July 2005
Available online 26 September 2005

Abstract

Overvoltages are one of the most frequently encountered problems during line energization. At the time of restoration transmission line switching is also one of the major causes, which creates overvoltage. The magnitude and shape of the switching overvoltages vary with the system parameters and network configuration and the point-on-wave where the switching operation takes place. Though detailed electromagnetic transient studies carried out for the design of transmission systems, such studies are not common in a day-to-day operation of power system. However it is important for the operator to ensure that peak overvoltages resulting from the switching operations are well within safe limits. This paper presents an Artificial Neural Network (ANN)-based approach to estimate the peak overvoltage generated by switching transients during line energization. In proposed methodology Levenberg–Marquardt method is used to train the multilayer perceptron. The developed ANN is trained with the extensive simulated results, and tested for typical cases. The simulated results presented clearly show that the proposed technique can estimate the peak values of switching overvoltages with good accuracy.
© 2005 Elsevier B.V. All rights reserved.

Keywords: Artificial neural networks; Restoration; Electromagnetic transients; Switching surges; Line energization

1. Introduction

The insulation level of EHV and UHV ac systems is largely determined by the magnitude of switching overvoltages. Switching overvoltages are therefore a focal point in studies of these systems. Switching transients are fast transients that occur in the process of energizing transmission line and busload capacitances immediately after a power source is connected to the network. Inductance of transmission line and power sources interacts with capacitance to cause very fast oscillations in the process [1]. In reintegration phase of restoration, it is desirable to energize as large a section of high-voltage transmission as switching transient voltages would allow. Energizing small sections tends to prolong the restoration process. During this phase of restoration of high voltage overhead transmission lines, transient voltages or switching surges are caused by energizing large segments of a transmission system or by switching capacitive elements [2]. The magnitude and shape of the switching overvoltages vary with the system parameters and network configuration. Even with the same system parameters and network configuration, the switching overvoltages are highly dependent on the characteristics of the circuit breaker operation and the point-on-wave where the switching operation takes place.

The reliable operation of any electrical power system is determine to a great extent by the amplitude, duration and frequency of the transient voltages appearing in different places in the network. Power transformers, surge arresters and circuit breakers will be the equipment earliest affected by overvoltages. Transient overvoltages are usually a significant factor at transmission voltages above 400 kV. At higher transmission voltages, overvoltages caused by switching may become significant, because arrester operating voltages are relatively close to normal system voltage and lines are usually long so that the energy stored on the lines may be large. Overvoltage will put the transformer into saturation, causing core heating and copious harmonic current generation. Circuit breaker called upon to operate during periods of high voltage will have reduced interrupting capability. At some voltage even the ability to interrupt line-charging current will be lost [1]. The energy stored in long high voltage lines is

* Corresponding author. Tel.: +91 80 22932362; fax: +91 80 23600444.
E-mail addresses: dtram@ee.iisc.ernet.in (D. Thukaram), hpk@ee.iisc.ernet.in (H.P. Khincha), sulabh@ee.iisc.ernet.in (S. Khandelwal).

0378-7796/$ – see front matter © 2005 Elsevier B.V. All rights reserved.
doi:10.1016/j.epsr.2005.07.001

large causing significant transient overvoltages, must carefully be considered during line energization.

Extensive EMTP simulation studies are carried out during planning stage of transmission system. A line energization is an intended operation, certain initial condition are required in the studies and the main purpose of studies is to provide proper protection system, such as lightning arrester, shunt reactor etc. to limit the overvoltages to specified design limits as per the utility practice. However during system operation, a large disturbances or a partial blackout, the system condition can be very abnormal. Thus during such situation many transmission lines indented to be energized. At this stage the operator should follow the switching sequence, which is safe and lead to successful energization.

Digital computer tool such as Electro Magnetic Transients Program (EMTP) [3,4] is universally accepted as industry standard for computation of both switching and temporary over voltages. At the planning stage the insulation level of apparatus is decided on the basis of peak value of transient over voltages, but enormous numbers of cases have to considered to arrive at the maximum magnitude. However during day-to-day operation such studies, by the operators are prohibitive due to actual detail data required and also large computational time involved. During power system restoration there is a need for real time tool, which can provide crucial values of peak overvoltages, generated during energization of transmission line.

This paper presents the ANN application for estimation of peak over voltages under switching transients during line charging. A tool such as proposed in this paper that can give the maximum switching overvoltage will be helpful to the operator. It can be used as training tool for the operators. The proposed ANN is expected to learn many scenarios of operation. To give the maximum peak overvoltage in a shortest computational time which is the requirement during online operation of power systems. In the proposed ANN we have considered the most important aspects, which influence the transient overvoltages such as line length, switching angle, source strength and receiving end reactor. This information will help the operator to select the proper sequence of transmission line to be energized safely with transients appearing safe within the limits. Results of the studies are presented for a sample system and also for an equivalent EHV system of Indian southern grid to illustrate the proposed approach.

2. Switching transients

An electrical transient is the outward manifestation of the sudden change in circuit conditions, as when a switch opens or close or a fault occurs on a system. Generally a switching operation in a power system changes the state of the system from those conditions existing prior to switching to those existing after the operation, this generates transient phenomena. The power frequency voltage before and after the switching operation may be of a different value due to the change in the state of the system. This means that the total amplitude of the overvoltage due to switching may be considered in two parts; namely a transient component which is superimposed on a power frequency component. A load rejection accompanied by a fault can give rise to severe power frequency over voltages [5]. In an interconnected system the effect of this cause is some what alleviated. Full load rejection on an interconnected system is not likely since there are other lines or real load, which offer some outlet for power. In general, the highest switching overvoltage in a high voltage network is caused by energizing and re-energizing of unloaded line. When the line is connected to the source, travelling wave will start to travel along the line towards the receiving end and double there at the open end with an overvoltage near to 2 p.u. [6]. Switching transients usually exhibit complex waveforms for which the fundamental frequency usually lies in the range 100 to −1000 Hz but in some cases a very steep voltage rise or collapse can occur. In EHV and UHV systems there are a number of switching operations, which require special consideration as they may lead to magnitudes of the switching transient, which influence the choice of the system insulation level. However the overvoltages produced during the switching of reactors and transformers may readily be limited by surge diverters [5] and are therefore not considered here. Of the other switching operations, line closing and reclosing generally produce the larger overvoltages and consequently we concentrate on line energization in this paper.

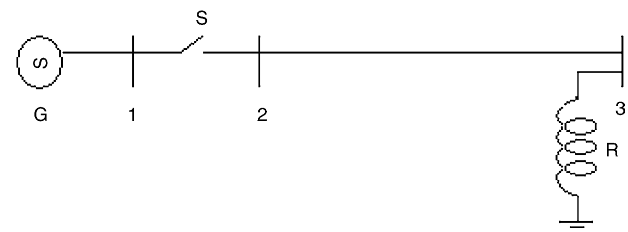

Fig. 1. Sample system G: generator S: switch R: reactor.

The sample system considered for explanation of the proposed methodology is a 400 kV EHV network shown in Fig. 1. The normal peak value of any phase voltage is $400\sqrt{2}/\sqrt{3}$ kV and this value is taken as base for voltage p.u. In the system studies 400 kV line-to-line base voltage and 100 MVA as a base power is considered. Fig. 2 shows the switching transient at bus 3 when line is energized. In practical system a number of

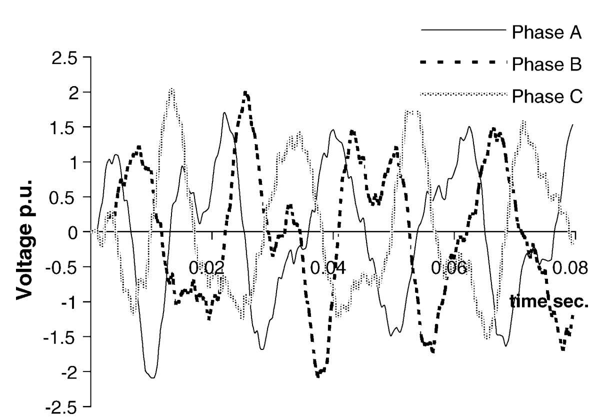

Fig. 2. Switching transient overvoltage at bus 3 without reactor at bus 3. Max peak absolute value is 2.08, 2.06 and 2.02 p.u. in phase A, B and C, respectively with switching angle 90°.

Table 1
Parameters inherent to the network and the circuit breaker influencing the switching overvoltages

	Factor/parameter	Influence
1.	Line length	S
2.	Degree of shunt compensation	S
3.	Line termination	S
4.	Trapped charges when PIR is not used	S
5.	Value of closing resistors	S
6.	Insertion times of closing resistors	S
7.	Pole closing instants	S
8.	Nature of source-inductive or complex	S
9.	Total short circuit level	S
10.	Total pole closing span	M
11.	Trapped charges when PIR is used	M
12.	Line parameters	M
13.	Frequency dependence of line parameter	M
14.	Saturation of reactor	M
15.	Corona of lines	W

S: strong, M: medium and W: Weak.

factors affect the overvoltages factors due to energization or reclosing. The influence of various factors can be grouped into three broad categories, such as strong, medium and weak as given in Table 1 [5]. On re-closure the power frequency voltage on the feeding point side across the breaker gap is superimposed on the voltage corresponding to the trapped charges, the transient is correspondingly increase and result in a higher overvoltage [6].

Transient on re-closure can heavily be damped by pre-insertion resister (PIR). The optimum pre insertion resistance is not only a function of the line shunt compensation but also the short circuit power of the feeding network and the line length [5]. For an existing system PIR value and PIR duration timings remain fixed and the effect of trapped charge comes in medium category. On the other hand the resistor equipped circuit breaker are more expensive. These complex breakers shows mechanical mal functions as the most common cause of circuit breaker failures. Reduction of mechanical complexity should greatly improve reliability. So in this paper study is done without PIR. The metal oxide surge arrester is a good substitute of PIR to control the overvoltages.

The shunt compensation effect is shown in Fig. 3. A 50 MVAR shunt reactor is connected at the receiving end bus of a 400 kV system, which cause the maximum overvoltage come down to the value 1.778 p.u. [7,8], which was 2 p.u. without shunt reactor. The effect of variation in receiving end reactor value is shown in Fig. 7. The study is performed with fully transposed lines. So the factors, which strongly affect the switching overvoltage are switching angle, fault level of the sending end bus, transmission line length and receiving end reactor [9].

System size (source strength) affect the overvoltage strongly, overvoltage reduces as the size of system increases. This reduction is due to the superposition of a number of different frequencies not due to the damping of switching overvoltage [10,11]. Figs. 4 and 5 show the effect of source strength on overvoltage at different line length and switching angle, respectively. As the source become stronger it will keep the transient voltage low.

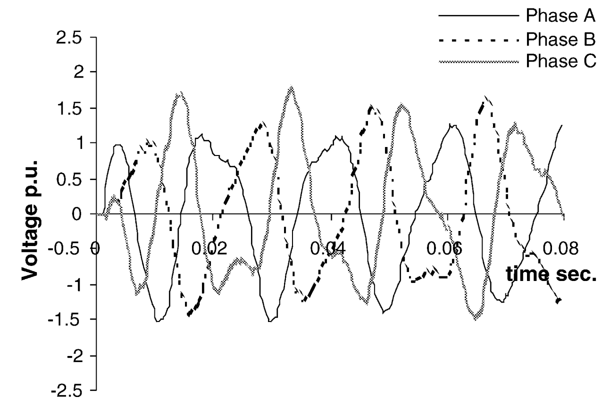

Fig. 3. Switching transient overvoltage at bus 3 with 50 MVAR reactor at bus 3. Max peak absolute value is 1.563, 1.602 and 1.778 p.u. in phase A, B and C, respectively with switching angle 90°.

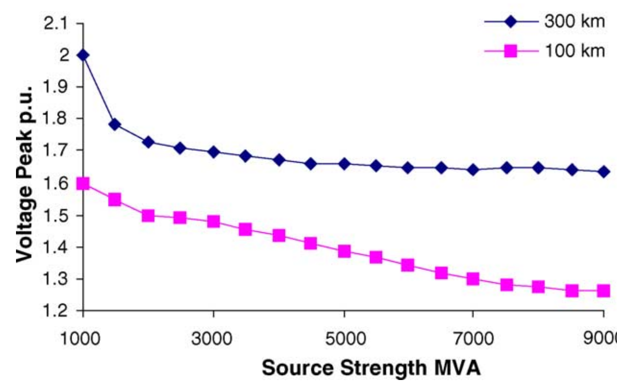

Fig. 4. Voltage peak at bus 3 as source strength increases, while the switching angle is kept fixed at 50° with PIR.

Controlled switching of high-voltage ac circuit breakers has become a commonly accepted means of reducing switching transients in power systems. The primary motivation for using controlled switching of transmission lines is to minimize the switching overvoltages during energization. If switching take place at the voltage maximum i.e. at 90° the voltage at first oscillate along the whole the line length to almost twice the value of the system voltage [7] as shown in Fig. 2. Overvoltage can be limited by controlled switching of circuit breaker as shown in Fig. 5, in which line closing is done at 0°. Fig. 6 shows that for a

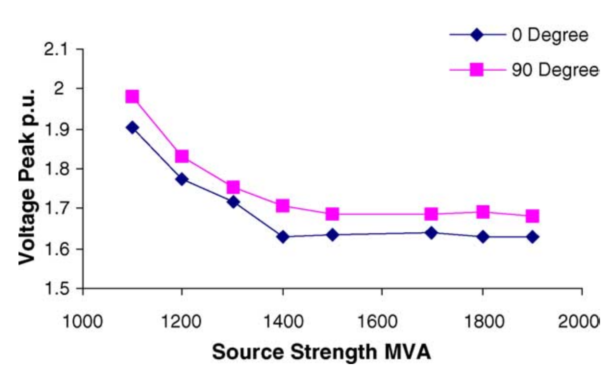

Fig. 5. Voltage peak at bus 3 as source strength increases, while line length is 300 km with PIR.

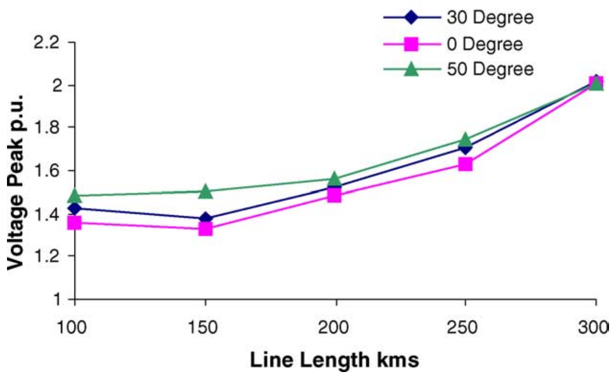

Fig. 6. Voltage peak at bus 3 as line length increases, while the source strength is 1000 MVA with PIR.

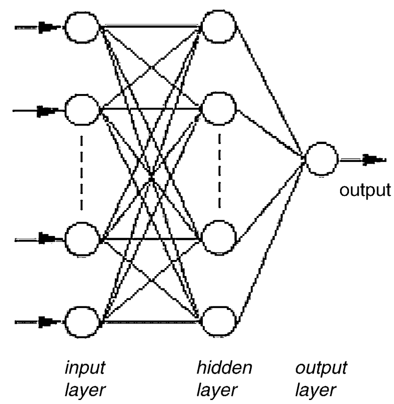

Fig. 8. Proposed MLP-based ANN architecture.

particular line length and source strength transient voltage will be more at 90° than 0°. The effect of transmission line length is shown in Figs. 4, 6 and 7, as line length increases charging current also increases which creates higher overvoltage at receiving end bus.

As discussed above for an existing system the main factors witch affect the peak value of switching overvoltage are switching angle, line length, source strength and shunt reactor. Here it should be mentioned that a single parameter often cannot be regarded independently from the other important influencing factors. The magnitude of the overvoltages normally does not depend directly on any single isolated parameter and a variation of one parameter can often alter the influence of another parameter, in other words there exists an interaction between the various system and breaker parameters. This forbids the derivation of precise generalized rule of simple formulae applicable to all cases [5]. So an ANN can help to estimate the peak value of switching overvoltages generated during line energization. An ANN is programmed by presenting it with training set of input/output patterns from which it then learns the relationship between the inputs and outputs. In next section a ANN-based approach is described which can give a acceptable solution of switching transients by the help of which an operator can take a quick decision at the time of operation.

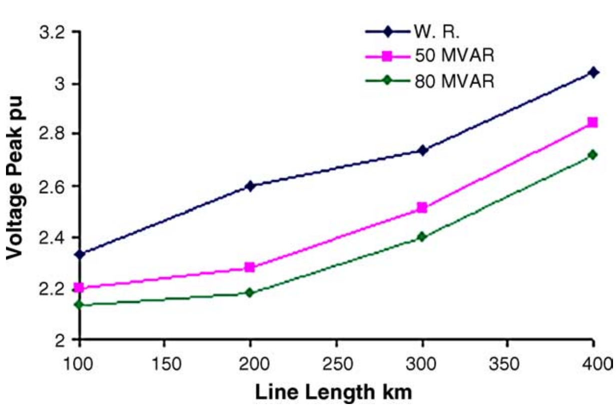

Fig. 7. Voltage peak at bus 3 at various values of receiving end reactor and without PIR, source strength is 1000 MVA and switching angle 90°. W.R. = without reactor.

3. The artificial neural network

The proposal in this work considers the adoption of feed forward Multilayer Perceptron (MLP) architecture. A MLP trained with the back-propagation algorithm may be viewed as a practical vehicle for performing a nonlinear input–output mapping of a general nature. Function approximation by feed forward MLP network is proven to be very efficient, considering various learning strategies like simple back propagation or the robust Levenberg–Marquardt. Its ability to perform well is affected by the chosen training data as well as training scheme. A simple MLP neural network composed of single hidden layer and output layer is capable of solving difficult and complex problems [12]. The schematic diagram of the proposed MLP neural networks architecture is shown in Fig. 8. The composition of the input variables for the proposed neural networks has been carefully selected. In proposed methodology two schemes are adopted to estimate the peak overvoltages.

3.1. Scheme 1

In this scheme it is assumed that the receiving end reactor has fixed value. Then the parameters, which influence the voltage peak are:

- switching angle;
- source strength;
- transmission line length.

In this scheme input vector consist only three variables as mention above as shown in Fig. 9. In case of with and without receiving end reactor different neural network is trained

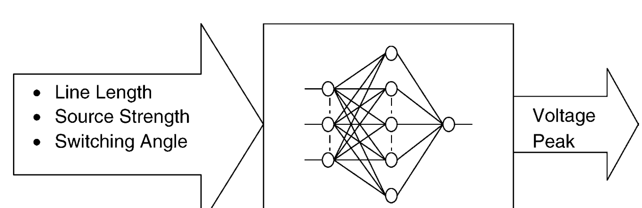

Fig. 9. Proposed Scheme 1.

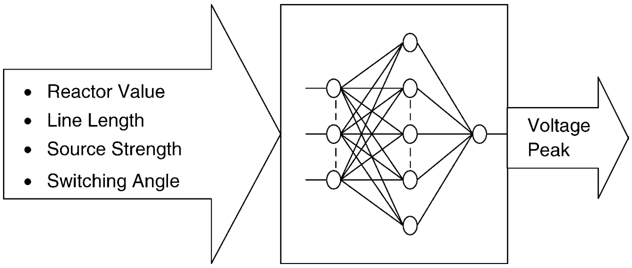

Fig. 10. Proposed Scheme 2.

and for different value of reactor different neural network is used.

3.2. Scheme 2

In this Scheme it is assumed that the receiving end reactor is switchable and has various values. In this condition reactor also affect the voltage peak, so the value of receiving end reactor also considered as the input parameters as shown in Fig. 10. This scheme consist only one neural network with the parameters in input vector are:

- switching angle;
- source strength;
- transmission line length;
- receiving end reactor value.

In both the schemes output is the absolute maximum value of peak voltage of any phase at the receiving end bus. The other parameters which influence the switching overvoltage are kept constant. ANN can predict the peak value in each phase also but we have to modify the ANN architecture. This aspect is discussed briefly in Appendix A. However our concern in the present scope is to obtain the worst peak overvoltage irrespective of the phase so the ANN is trained for peak value among three phases.

Supervised training of ANN is a usual training paradigm for MLP architecture. Fig. 11 shows the supervised learning of ANN for which input is given to EMTP to get the peak values of transient overvoltages and the same data is used to train the ANN. Error is calculated by the difference of EMTP output and ANN output. This error is used to adjust the weight of connection. Since the switching transient demands a solution with high precision, the neural network has to be trained considering a very small stopping criterion. Output values of the trained neural networks must be capable of computing the voltages with very good precision. Gradient-based training algorithms, like back-propagation, are most commonly used for training procedures. They are not efficient due to the fact that the gradient vanishes at the solution. Hessian-based algorithms allow the network to learn more subtle features of a complicated mapping. The training process converges quickly as the solution is approached, because the Hessian does not vanish at the solution. To benefit from the advantages of Hessian based training, we focused on the Levenberg–Marquardt (LM) algorithm reported in [13].

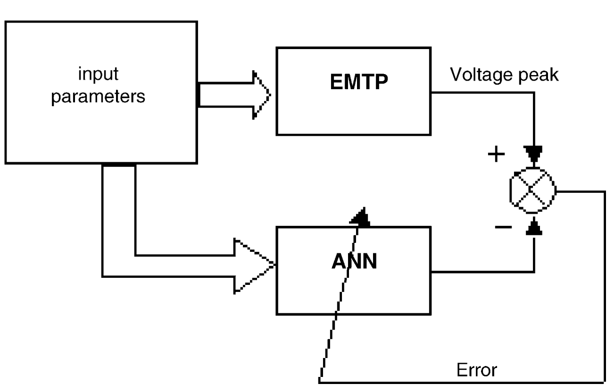

Fig. 11. Supervised learning of ANN.

3.3. Levenberg–Marquardt (LM) algorithm

Suppose that we have a function $\xi(\mathbf{x})$ which we want to minimize with respect to the parameter vector $\mathbf{x}$, where

$$\xi(\mathbf{x}) = \sum_{i=1}^{N} {e_i}^2(\mathbf{x})$$

Then the Marquardt–Levenberg modification to the Gauss–Newton method is

$$\Delta\mathbf{x} = [\mathbf{J}^{\mathrm{T}}(\mathbf{x})\,\mathbf{J}(\mathbf{x}) + \mu\mathbf{I}]^{-1}\mathbf{J}^{\mathrm{T}}(\mathbf{x})\,\mathbf{e}(\mathbf{x})$$

The parameter μ is multiplied by some factor β whenever a step would result in an increased $\xi(\mathbf{x})$. When a step reduces $\xi(\mathbf{x})$, μ is divided by β. Notice that when μ is large the algorithm becomes steepest descent; while for small μ the algorithm becomes Gauss–Newton. The LM algorithm is very efficient when training networks have up to few hundred weights. Although the computational requirements are much higher for the each iteration of the LM algorithm, this is more than made up for by the increased efficiency. This is especially true when high precision is required.

In order to get good generalization capability of the neural networks, the composition of training data consider different source levels, various switching angles and line lengths. Depending on the analysis to be conducted it is possible to increase or decrease the quantity of training cases. The PIR values and duration time is not considered for the training data.

4. Simulated studies and results

4.1. System study

The proposed scheme is tested with a sample three-bus 400 kV system. Single line diagram is shown in Fig. 1. The case of power system restoration stage is taken as an example for the proposed methodology. The source is an inductive type source and remains fixed in study. Studies are carried out with and without the receiving end reactor at bus 3. Switching transients are simulated for various combinations of system parameters as follows:

- source strength: 1000–10000 MVA in step of 1000 MVA
- line length: 100–400 km in step of 50 km
- switching angle: 0–90° in step of 30°

In the case of reactor presence at bus 3, the standard reactor values 50, 63 and 80 are considered.

4.2. Generalization and normalization

One of the most critical problems in constructing the ANN is the choice of the number of hidden layers and the number of neurons. Using too few neurons in the hidden layer may prevent the training process to converge, while using too many neurons would produce long training time, and/or result in the ANN to lose its generalization attribute. In this study, a number of tests were performed varying with the one or two hidden layers as well as varying the number of neurons in each hidden layer. A MLP with one hidden layer and 10 hidden units is found to be sufficient to get good accuracy and generalization for proposed both schemes.

Neural networks learn more quickly and give better performance if the input variables are pre-processed before being used to train the network. Using zero mean inputs can minimize the learning time. The inputs presented after first hidden layer should also be zero mean to speed up the learning. An antisymmetric activation function like the hyperbolic tangent function is better than logistic function which permits the output of neurons in the interval (−1, 1), in which case it is likely for its mean to zero [14]. Input variables have different range like line length is in the order of 100 km, switching angle is in the order of 10° and source strength is in the order of 1000 MVA. Normalization of data is done to preprocessed inputs and single output, which is peak voltage in the range of 1–3 p.u. and which scaled into the range of (−1, 1). As the dimension of input vector is three and four in Scheme 1 and 2, respectively, curse of dimensionality do not affect the convergence of learning. The hyperbolic tan sigmoid function is used in hidden neurons and linear activation function is used at output neuron.

4.3. Training

A set of training data is obtained for numerous cases by using EMTP developed by Prof. D. Thukaram at Indian Institute of Science, Bangalore, India which has all features like frequency dependence, saturation of reactors, lighting arrestors, nonlinearity of various components, etc. This program has been extensively used in planning studies of Indian EHV system. We have used this EMTP program to generate results for various cases.

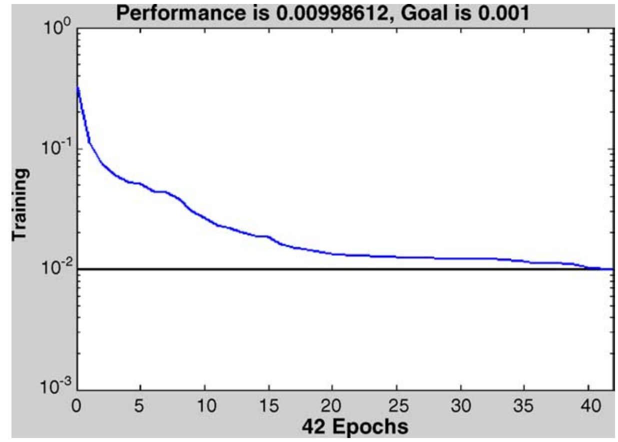

Fig. 12. Squared error against epoch curve for the data with 50 MVAR in Scheme 1.

If we use the frequency dependency of line parameters during switching studies the transient wave shape will contain less harmonics and peak overvoltages will also have less magnitude as compared to when frequency dependency of line parameters are not considered in the study. Considering the higher value of peak overvoltages for training the ANN will lead to safer estimation. Two sets of data are generated one without reactor and also with reactor of three standard values of 50, 63 and 80 MVAR used in the Indian southern grid. The total numbers of patterns obtained for training are about 1120.

4.3.1. Scheme 1

Four different neural network of same architecture are trained using the results of simulated conditions one for without reactor and other three for the different values of reactor. The second order Levenberg–Marquardt training method is adopted to get high precision accuracy as mentioned in Section 3. Each Neural Network is trained with the goal of mean square error (MSE) 1e-2. Fig. 12 shows the training of ANN2 Neural Network. Table 2 shows the learning time and number of epoch for each ANN in Schemes 1 and 2.

4.3.2. Scheme 2

Single neural network ANN5 is used with additional input the reactor value. Neural Network is trained with the goal of Mean Square Error (MSE) 1e-2 which takes more time in learning and number of epochs as the number of sample is increased and also now the input vector has four input variable which has increased the dimensionality of problem. Fig. 13 shows the training of ANN5.

Table 2
Number of epoch and learning time for various ANN

	ANN 1	ANN 2	ANN 3	ANN 4	ANN5
Shunt reactor at bus 3 (MVAR)	No reactor	50	63	80	Without and with 50, 63, 80
Time (s)	7.797	7.844	7.797	7.812	20.75
No. of epoch	45	42	44	46	72

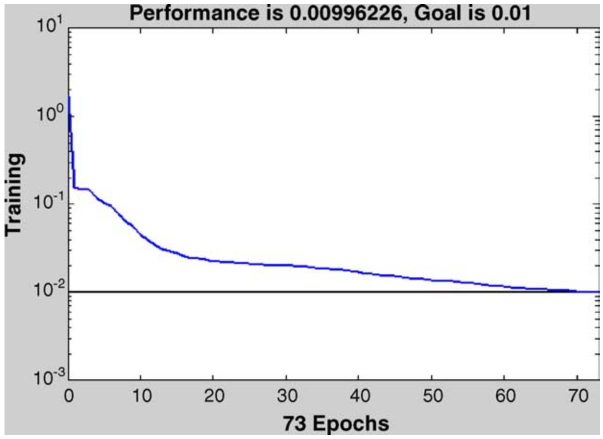

Fig. 13. Squared error against epoch curve for the data of Scheme 2.

4.4. Testing

All experiments have been repeated for different system parameters. After learning, all parameters of the trained networks have been frozen and then used in the retrieval mode for testing the capabilities of the system on the data not used in learning. The testing data samples have been generated through the EMTP program by placing the parameter values not used in learning, by applying different source strength values, and different switching angle and line length. A large number of testing data have been used to check the proposed solution in the most objective way at practically all possible parameters variation. Line length varied in steps of 25 km, switching angle in steps of 10° and source strength in steps of 500 MVA. Results for a sample test data are presented in Tables 3 and 4 and also shown in Figs. 15–19. Table 3 contains the some sample result of test data of Scheme 1 and Table 4 has some sample test data of Scheme 2. Values in column EMTP are the absolute values of peak voltage at bus 3 calculated by EMTP program where the ANN values are the values simulated by trained network. Error and percentage error are calculated as:

Table 3
Scheme 1 some sample testing data and output

L.L. (km)	S.S. (MVA)	S.A. (°)	EMTP	ANN	Error	Error (%)
ANN1						
125	1500	0	2.165	2.095	0.070	3.222
225	5500	45	2.469	2.537	0.068	2.755
225	5500	50	2.521	2.580	0.059	2.345
ANN2						
125	1500	0	2.017	2.046	0.029	1.450
375	1500	0	2.463	2.488	0.025	1.001
225	5500	40	2.322	2.388	0.066	2.835
ANN3						
325	5500	90	2.524	2.478	0.046	1.830
375	5500	90	2.845	2.853	0.008	0.267
225	5500	75	2.563	2.554	0.009	0.366
325	2500	0	2.149	2.222	0.073	3.413
ANN4						
225	1500	90	2.256	2.301	0.045	1.992
225	5500	60	2.439	2.482	0.043	1.780
375	9500	90	2.679	2.685	0.006	0.241

L.L. = line length, S.S. = source strength and S.A. = switching angle.

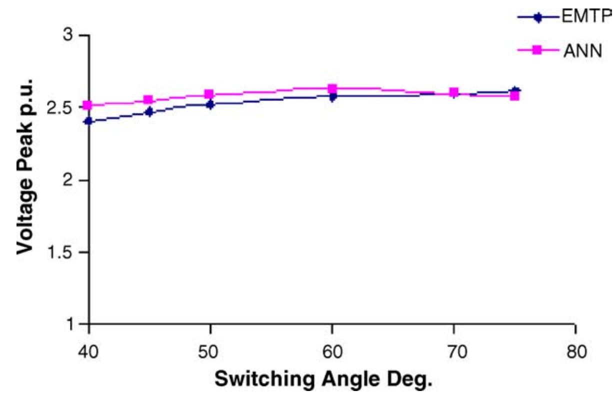

Fig. 14. ANN1 output: voltage peak at bus 3 simulated by ANN and EMTP while source strength 1500 MVA and line length 225 km without receiving end reactor.

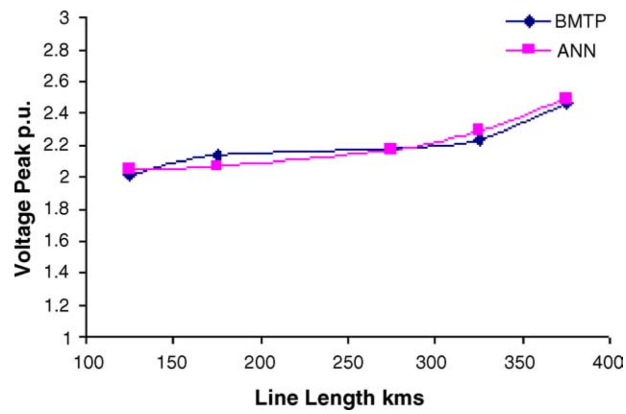

Fig. 15. ANN2 output: voltage peak at bus 3 simulated by ANN and EMTP while source strength 1500 MVA and switching angle 0° with 50 MVAR receiving end reactor.

$$\text{error} = \frac{|\text{ANN} - \text{EMTP}|}{\text{EMTP}},$$

$$\text{percentage error (\%)} = \text{error} \times 100$$

The proposed model tested with 11-bus system. Various cases of line energization are taken into account and corresponding peak values estimated from trained model. Detailed result is shown in Section 4.5.

4.4.1. Scheme 1

Fig. 14 shows the voltage peak at bus 3 against the switching angle, other parameters like line length, source strength, constant at 225 km, 1500 MVA, respectively and without receiving end reactor. Fig. 15 shows the voltage peak as line length varies from 125 to 375 km at constant source strength, switching angle and with 50 MVAR reactor at bus 3. Fig. 16 shows the voltage peak at bus 3 as source strength varies in step of 1000 MVA from 1500 to 5500 MVA with constant line length, switching angle with 63 MVAR reactor. Fig. 17 shows the results of ANN4 with varying source strength from 5500 to 9500 MVA, line length and

Table 4
Scheme 2 some sample testing data and output

R.R. (MVAR)	L.L. (km)	S.S. (MVA)	S.A. (°)	EMTP	ANN	Error	Error (%)
0	125	1500	0	2.165	2.128	0.037	1.732
0	325	5500	90	2.598	2.570	0.028	1.061
0	225	5500	45	2.469	2.462	0.007	0.275
50	275	1500	0	2.178	2.178	0.000	0.012
50	225	5500	45	2.391	2.407	0.016	0.675
63	375	1500	75	2.649	2.680	0.031	1.158
63	225	5500	50	2.421	2.451	0.030	1.237
63	325	8500	90	2.394	2.411	0.017	0.698
80	125	1500	0	1.977	1.981	0.004	0.194
80	225	5500	10	2.044	2.059	0.015	0.734
80	225	5500	70	2.515	2.468	0.047	1.860
80	375	6500	90	2.783	2.818	0.035	1.241

R.R. = receiving end reactor, L.L. = line length, S.S. = source strength and S.A. = switching angle.

switching angle are kept constant and with 80 MVAR reactor value.

4.4.2. Scheme 2

Figs. 18 and 19 show the output of ANN5 with the variation of various input parameter. Fig. 18 shows the voltage peak at bus 3 simulated by ANN and EMTP while source strength 5500 MVA line length 225 km with 50 MVAR receiving end reactor. Fig. 19 shows the results with varying line length while source strength and switching angle are kept constant without receiving end reactor. Table 4 shows some sample testing data.

4.5. An equivalent EHV system studies

The proposed ANN approach is also tested with an 11-bus system (Fig. 20), which is an equivalent EHV system of

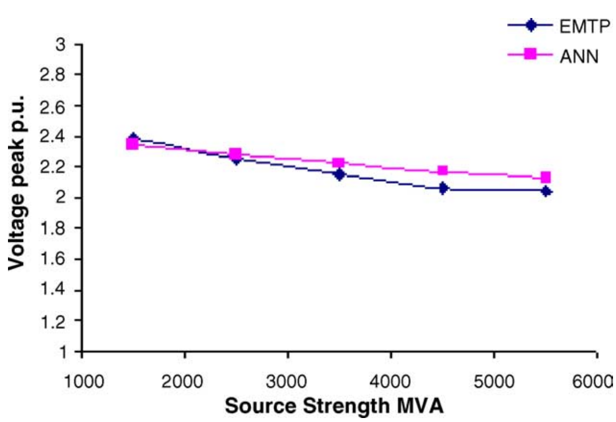

Fig. 16. ANN3 output: voltage peak at bus 3 simulated by ANN and EMTP while switching angle 90° and line length 325 km with 63 MVAR receiving end reactor.

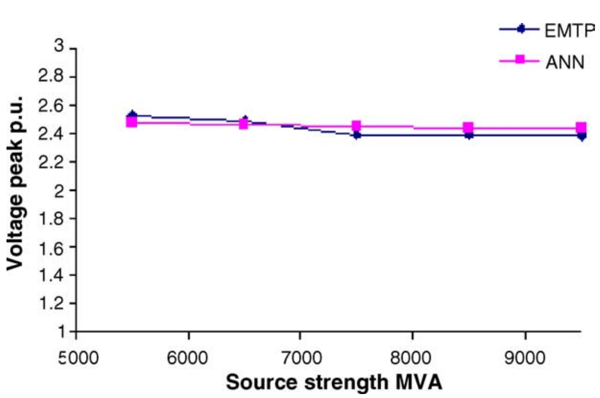

Fig. 17. ANN4 output: voltage peak at bus 3 simulated by ANN and EMTP while switching angle 0° and line length 375 km with 80 MVAR receiving end reactor.

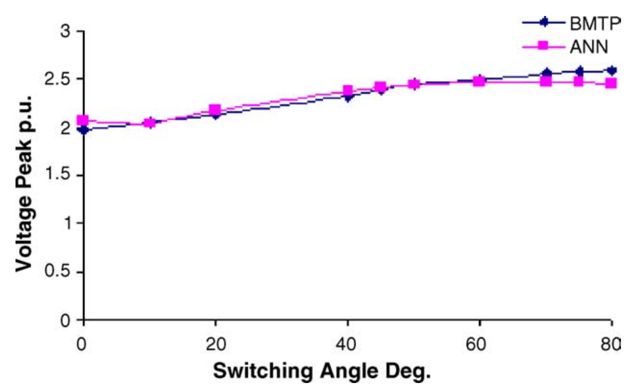

Fig. 18. ANN5 output: voltage peak at bus 3 simulated by ANN and EMTP while source strength 5500 MVA line length 225 km with 50 MVAR receiving end reactor.

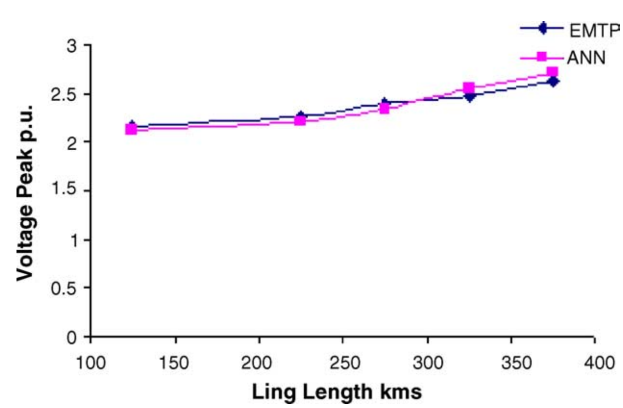

Fig. 19. ANN5 output: voltage peak at bus 3 simulated by ANN and EMTP while source strength 1500 MVA and switching angle 0° without receiving end reactor.

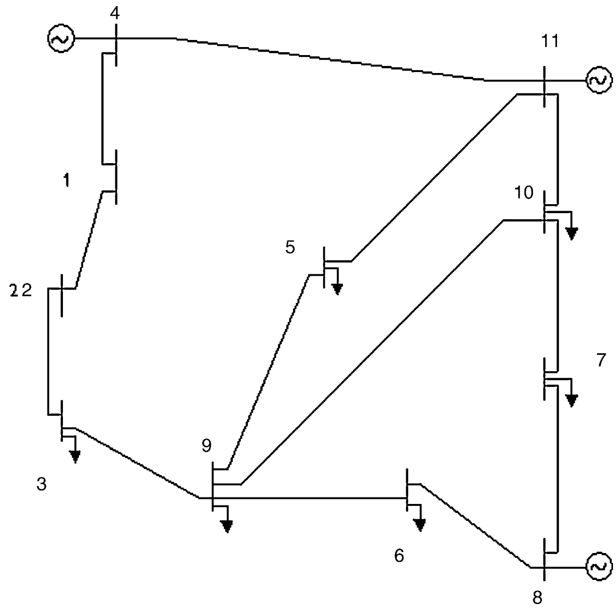

Fig. 20. An equivalent 11-bus EHV system of Indian southern grid.

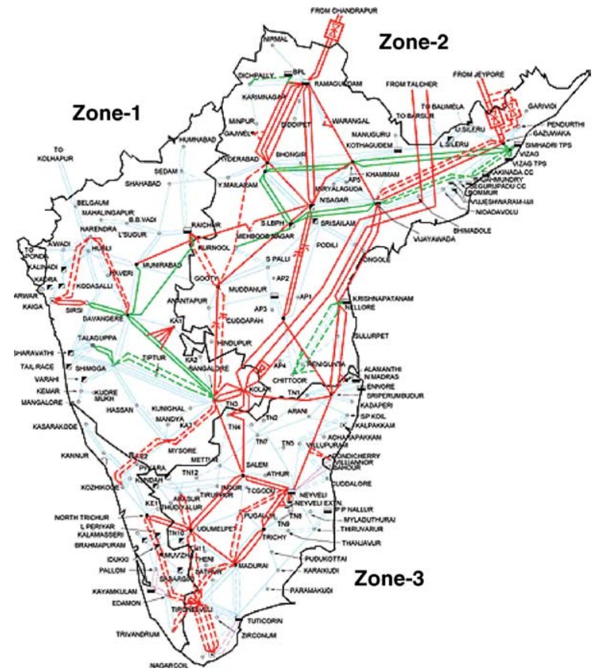

Fig. 21. Indian southern grid.

Indian southern grid shown in Fig. 21. The various cases of line energization are taken into account and corresponding peak overvoltages are computed from EMTP program. Equivalent source strengths were obtained at all buses for various conditions. Energization of lines from either end of a transmission line is considered. Typical system scenarios are considered for exhaustive training patterns for proposed ANN. Scheme 2 of the proposed ANN is used to train the generated data. Summary of few results are presented in Table 5. It can be seen from the results that the ANN is able to learn the patterns and give results to acceptable accuracy.

4.6. Optimal PIR

The system used for study in proposed methodology is an equivalent system of Indian southern grid. For a particular system the PIR values remain constant. When a line is energized through single step preinsertion resistors two temporally separated transients occur.

- The transients generated when the line is energized through the resistor.
- The transients generated when the resister is short-circuited.

Table 5
Results for equivalent 11-bus EHV system

Line	Switching end bus no.	R.R. (MVAR)	L.L. (km)	SS (MVA)	SA (°)	EMTP	ANN	Error (%)
11-5	11	0	295	4756	0	2.38	2.29	3.58
		0	295	4756	60	2.56	2.54	0.62
		63	295	4756	60	2.37	2.41	1.56
		63	295	4756	90	2.27	2.34	3.09
	5	0	295	1007	60	2.64	2.60	1.31
		0	295	1007	90	2.64	2.68	1.58
11-4	11	0	257	4188	90	2.51	2.49	0.96
		0	257	4188	60	2.69	2.70	0.59
		50	257	4188	00	2.01	2.06	2.79
		50	257	4188	90	2.40	2.37	1.24
	4	0	257	3000	0	2.20	2.21	0.22
		0	257	3000	60	2.58	2.58	0.20
11-10	11	0	282	4555	00	2.22	2.27	2.27
		0	282	4555	90	2.37	2.38	0.14
		50	282	4555	00	2.25	2.18	2.89
		50	282	4555	90	2.35	2.35	0.06
	10	0	282	1289	60	2.52	2.61	3.82
		0	282	1289	90	2.59	2.71	4.72

R.R. = receiving end reactor, L.L. = line length, S.S. = source strength and S.A. = switching angle.

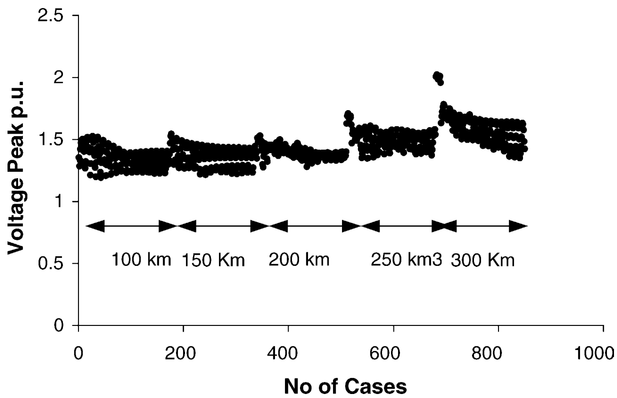

Fig. 22. Data pattern generated by 850 cases with PIR of 300 Ω.

So an optimal value of PIR requires for switching to keep overvoltage low. The optimum value of PIR is the function of line shunt compensation, short-circuit power of the feeding network and the line length to be energized. As the system conditions vary the optimal value will also vary and one should be careful about the PIR value.

The data pattern of various cases obtained with PIR value (300 Ω) maintained constant. The PIR 300 Ω is optimal for around 200 km line length, which cause the clustering of peak voltages data close to the value 1.45 p.u. (Fig. 22). If the optimal value of PIR used for each line length then the peak voltage data pattern will be different. Hence further work needs to be carried out by taking the various optimal values of PIR and PIR duration time.

5. Conclusion

A Neural Network approach to estimate the peak over voltages under switching transient is proposed and implemented. The Levenberg–Marquardt second order training method has been adopted for obtaining small mean square errors (MSEs) without losing generalization capability of ANN. The results from this scheme are close to results from the conventional method and helpful in predicting the over voltage of the other case studies within the range of training set. A three-bus 400 kV system has been used to explain the proposed ANN-based estimator for switching transient overvoltages. The proposed ANN approach is also tested on an equivalent EHV system of Indian southern grid. The simulated results clearly show that the proposed approach can estimate the peak values of switching overvoltages with good accuracy. The ANN application can be used an operator-training tool for estimation of switching overvoltages during power system restoration. Further work can be carried out by taking the various optimal values of PIR and PIR duration timing. Additional parameters in input like presence of trapped charges also can be considered.

Appendix A

The peak occurrence in the different phases depends on the instant of switching and other initial conditions. ANN can be trained for the maximum peak absolute value of each phase. Fig. A.1 shows the ANN architecture for the estimation of peak

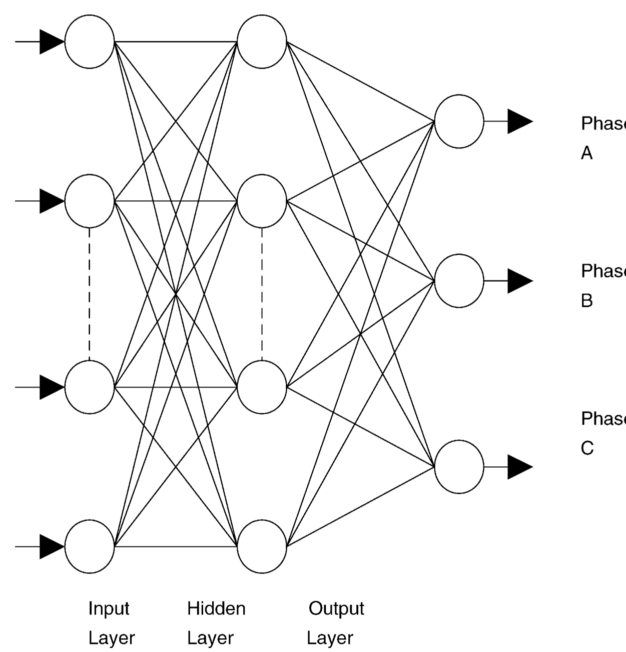

Fig. A.1. Proposed MLP-based ANN architecture to estimate the voltage peak of each phase (Scheme 3).

Table A.1
Results for modified Scheme 3

R.R. (MVAR)	L.L. (km)	S.S. (MVA)	S.A. (°)	EMTP	ANN	Phase	Error = |ANN-EMTP|	Error (%)
0	125	1500	0	2.165	2.128	B	0.037	1.732
0	325	5500	90	2.598	2.570	B	0.028	1.061
0	225	5500	45	2.469	2.462	C	0.007	0.275
50	275	1500	0	2.178	2.178	B	0.000	0.012
50	225	5500	45	2.391	2.407	C	0.016	0.675
63	375	1500	75	2.649	2.680	C	0.031	1.158
63	225	5500	50	2.421	2.451	C	0.030	1.237
63	325	8500	90	2.394	2.411	B	0.017	0.698
80	125	1500	0	1.977	1.981	B	0.004	0.194
80	225	5500	10	2.044	2.059	B	0.015	0.734
80	225	5500	70	2.515	2.468	C	0.047	1.860
80	375	6500	90	2.783	2.818	B	0.035	1.241

R.R.: receiving end reactor, L.L.: line length, S.S.: source strength and S.A.: switching angle.

overvoltage of each phase. The results of this modified scheme (Scheme 3) are shown in Table A.1. For the modified scheme the input vector is same as the previous schemes, but the output contains maximum peak absolute value of three phases. In Table A.1 results are shown for this Scheme 3. It can be seen that results obtained for peak values are same as in Scheme 2, but now we have information of phase also in which phase peak occurs.

References

[1] M.M. Adibi, R.W. Alexander, B. Avramovic, Overvoltage control during restoration, IEEE Trans. Power Syst. 7 (4) (1991) 1464–1470.

[2] M.M. Adibi, R.J. Kafka, Power system restoration issues, IEEE Comput. Appl. Power (1991) 19–24.

[3] Hermann W. Dommel, Techniques for analyzing electromagnetic transients, IEEE Comput. Appl. Power (1997) 18–21.

[4] Hermann W. Dommel, Digital computer solution of electromagnetic transient in single and multiphase networks, IEEE Trans. PAS-88 (1969) 388–398.

[5] Cigre Working Group, Switching overvoltages in EHV and UHV systems with special reference to closing and reclosing transmission lines, Electra 30 (1973) 70–122.

[6] A. Greenwood, Electrical Transients in a Power System, 2nd ed., Wiley, 1991.

[7] K. Joseph, et al., Controlling switching surges on 1100 kV transmission systems, IEEE Trans. Power Apparatus System PAS-89 (8) (1970) 1752–1762.

[8] Alessandro Clerici, G. Ruckstuhl, A. Vian, et al., Influence of shunt reactors on switching surges, IEEE Trans. Power Apparat. Syst. PAS-89 (8) (1970) 1727–1736.

[9] M.M. Adibi, et al., Energizing high and extra-high voltage lines during restoration, IEEE Trans. Power Syst. 14 (3) (1999) 1121–1126.

[10] K. Ragaller, Surges in High Voltage Networks, Plenum Press, 1980.

[11] D. Thukaram, H.P. Khincha, Sulabh Khandelwal, Neural network approach for estimation of peak over voltages under switching transients, in: Proceedings of the 13th National Power System Conference, December 27–30, India, 2004, pp. 624–629.

[12] V. Leonardo Paucar, Marcos J. Rider, Artificial neural network for solving the power flow problem in electric power system, Electr. Power Syst. Res. 62 (2002) 139–144.

[13] M.T. Hagan, M.B. Menhaj, Training feedforward networks with the Marquardt algorithm, IEEE Trans. Neural Network 5 (6) (1994) 989–993.

[14] S. Haykin, Neural Network: A Comprehensive Foundation, 2nd ed., Prentice Hall, 1998.

D. Thukaram received the B.E. degree in Electrical Engineering from Osmania University, Hyderabad, India in 1974, M.Tech. degree in Integrated Power Systems from Nagpur University in 1976 and Ph.D. degree from Indian Institute of Science, Bangalore in 1986. Since 1976 he has been with Indian Institute of Science as a research fellow and faculty in various positions and currently he is Professor. His research interests include computer aided power system analysis, reactive power optimization, voltage stability, distribution automation and AI applications in power systems.

H.P. Khincha received the B.E. degree in Electrical Engineering from Bangalore University in 1966. He received M.E. degree in 1968 and Ph.D. degree in 1973 both in Electrical Engineering from the Indian Institute of Science, Bangalore. Since 1973 he has been with Indian Institute of Science, Bangalore as faculty where currently he is Professor. His research interests include computer aided power system analysis, power system protection, distribution automation and AI applications in power systems.

Sulabh Khandelwal received the B.E. degree in Electrical Engineering from University of Rajasthan, Rajasthan, India in 2002. Currently he is pursuing his M.Sc. (Eng.) degree in Electrical Engineering at the Indian Institute of Science, Bangalore. His research interests include power system dynamic security, transients, AI techniques and applications.