Neural Network Approach for Estimation of Peak Over voltages Under Switching Transients

D. Thukaram, Senior *Member, IEEE,* H. P. Khincha, Senior *Member, IEEE* and Sulabh Khandelwal

Abstract— Intended transmission line switching operations are required for charging the lines for restoration of power following some disturbances. Though detailed transient studies carried out for the design of transmission lines, such studies are not common in a day-today operation of power systems. 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 overvoltages generated by switching transients. In the 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 results presented for a 400 kV system show that the proposed approach can estimate the peak values of switching overvoltages with good accuracy.

***Index Terms*— Artificial neutral networks, electromagnetic transients, switching surges.**

I. INTRODUCTION

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. These voltages may impose high stresses on the line and apparatus insulations. Network transients may result in disturbance of normal operating conditions and may cause catastrophic or protective interruption. Switching operations, faults, lightning surges and other intended or unintended disturbances cause temporary overvoltages and currents in power system. The simulation of transient phenomena is therefore very important for the proper coordination of insulation as well as for the proper design of protective devices and schemes. If the estimation of transients can be carried out at the design stage itself, proper precaution can be taken to minimize their effects.

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Severe overvoltages resulting from switching transients may cause flashover and serious damage to equipment. Switching transients are fast transients that occur in the process of energizing transmission line and bus load 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. The insulation level of apparatus should be capable for withstand at that switching transient overvoltages. Whenever a transmission line energization, re- energization and opening happens the generated switching surge magnitude depends on [1]:

- Point on the AC sinusoidal wave at the instant of opening or closing i.e. switching angle.
- Time span between closing of three phases i.e. pole-discrepancy.
- Strength of source i.e. fault level of the sending end bus.
- Transmission line length.

Digital computer tool such as Electro Magnetic Transients Program (EMTP) 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 consider arriving at the magnitude of maximation. These cases arise because of the sensitivity of the switching surge magnitude with respect to the parameter mention above.

The knowledge of switching overvoltages severity during the intended operations of transmission lines are important from the operator point of view to take safe decisions about the operations. In a day-to-day operation of power systems, EMTP simulations are not common due to enormous cases required to be carried out to estimate the worse switching overvoltages. This paper presents the ANN application for estimation of peak over voltages under switching transients during line charging. This will also helps in consolidation of number of case studies to be carried out using the conventional methods. ANN has attracted a great deal of attention because of their pattern recognition capabilities, and their ability to handle noisy data. They have been successfully applied to several classification problems in the area of speech and image processing, as well as in certain power engineering application [2]. It reflects a practical classification approach that can draw on the experience and knowledge of an engineer.

II. 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. Some of the most common types of transient phenomena in electric power system include [3],

- Lightning strokes on or near transmission lines
- Energization of transmission lines
- Capacitor switching (single capacitor switching, or "back-to-back" switching of one capacitor next to an energized capacitor)
- Interruption of small inductive currents (switching off reactors and unloaded transformers)
- Energization of transformer-termination lines ("temporary" overvoltages caused by a combination of transformer inrush currents and traveling waves on the line)
- Linear resonance at fundamental or at a harmonic frequency.
- Series capacitor switching and sub-synchronous resonance
- Load rejection
- Transient recovery voltage across circuit breakers
- Very fast transients in gas insulated bus ducts.

A load rejection accompanied by a fault can give rise to severe power frequency over voltages. 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 [1]. In general, the highest switching overvoltages in a high voltage network are caused by energizing and re-energizing of unloaded line. When the line is connected to the source, traveling 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. for a 400kV system [4] as shown in Fig. 1. In practical system a number of factors affect the overvoltages factors due to energization or re-closing. The influence of various factors can be grouped into three broad categories, such as strong, medium and weak [5] as given in Table 1.

On re-closer 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 [4]. Transient on re-closer can heavily damped by pre-insertion resister (PIR). The optimum size of the PIR depends on the surge impedance of line and particularly on its length. For an existing system PIR value and PIR duration timings remain fixed and the effect of trapped charge comes in medium category.

The shunt compensation effect is shown in the Fig. 2. A 50 MVAR shunt reactor is connected at the receiving end bus of a 400kV system, which cause the maximum overvoltage come down to the value 1.778 p.u. To arrive at the worse case peak overvoltages, shunt compensation and the frequency dependency of line parameter are neglected. So the factors, which strongly affect the switching overvoltages are switching angle, fault level of the sending end bus and transmission line length.

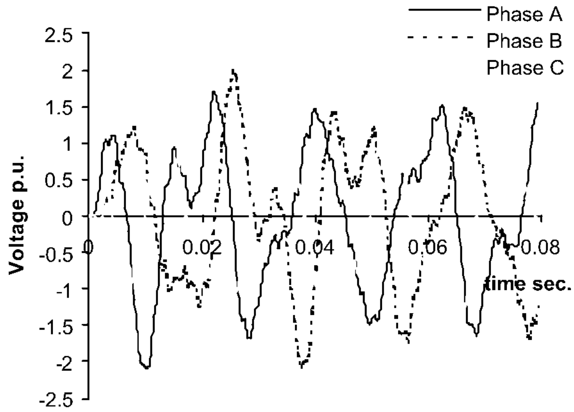

Fig. 1. Switching transient overvoltage at bus 3 without reactor at bus 3. Max peak absolute value is 2.08, 2.06 and 2.02p.u. in phase A,B and C respectively with switching angle 90°

Table-1

	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.	Trapped charges when PIR is used	M
6.	Line parameters	M
7.	Frequency dependence of line parameter	M
8.	Corona of lines	W
9.	Saturation of reactor	M
10.	Total pole closing span	M
11.	Value of closing resistors	S
12.	Insertion times of closing resistors	S
13.	Pole closing instants	S
14.	Nature of source-inductive or complex	S
15.	Total short circuit level	S

S: Strong, **M**: Medium and **W**: Weak

System size affect the overvoltage strongly, overvolatge 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. Fig. 4 shows the effect of source strength on overvoltage at different line length. As the source become stronger it will keep the transient voltage low. If switching take place at the voltage maximum i.e. at 90° the voltage at first oscillate along the whole the lne length to almost twice the value of the system voltage [4] as shown in Fig. 1. Overvoltage can be limited by controlled switching of circuit breaker as shown in the Fig. 3, in which line closing is done at 0°. Fig. 5 shows that for a particular line length and source strength transient voltage will be more at 90° than 0°. The effect of transmission line length is shown in Fig. 4 and Fig. 6.

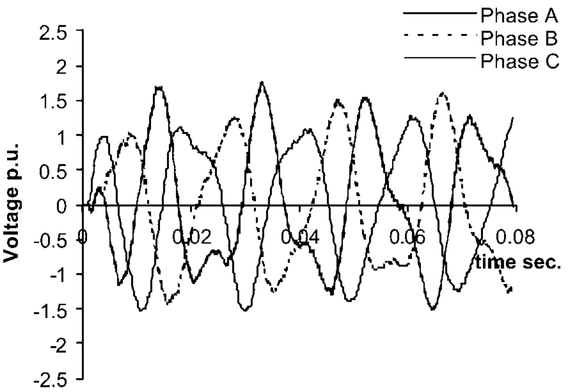

Fig. 2. Switching transient overvoltage at bus 3 with 50 MVAR reactor at bus 3. Max peak absolute value is 1.563, 1.602 and 1.778p.u. in phase A,B and C respectively with switching angle 90°

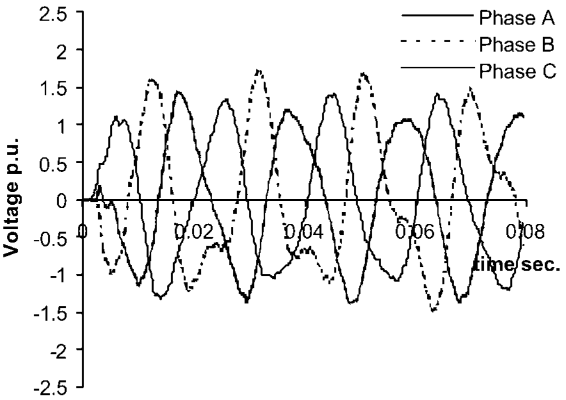

Fig. 3. Switching transient overvoltage at bus 3 with 50 MVAR reactor at bus 3. Max peak absolute value is 1.411, 1.749 and 1.426p.u. in phase A,B and C respectively with switching angle 0°

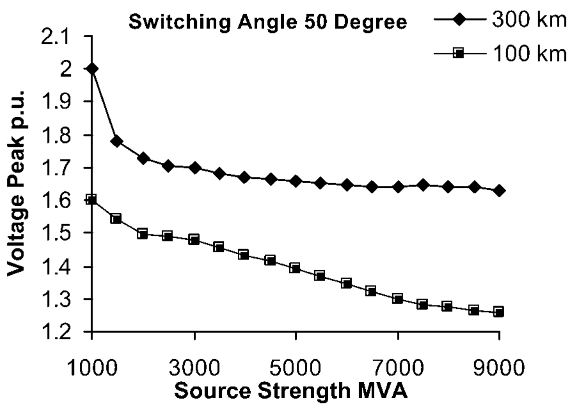

Fig. 4. Voltage peak at bus 3 as source strength increases, while the switching angle is kept fixed at 50°

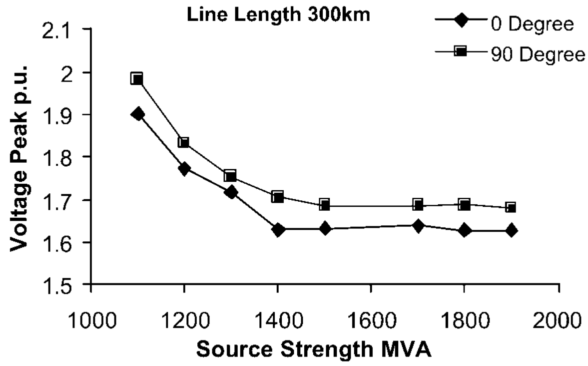

Fig. 5. Voltage peak at bus 3 as source strength increases, while line length is 300km.

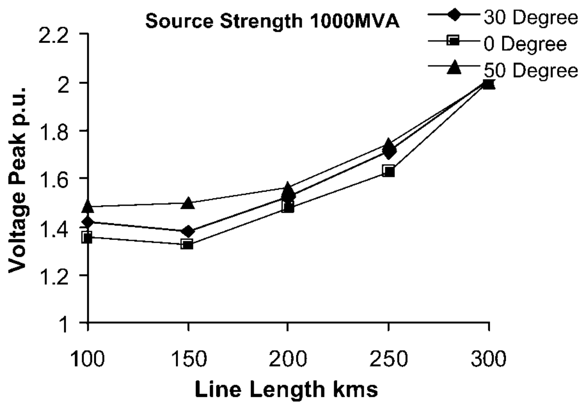

Fig. 6. Voltage peak at bus 3 as line length increases, while the source strength is 1000 MVA

The switching overvoltage values which may occur during the operations of transmission line like energization, re- energization and opening are important from the operator point of view to take decision about the operation. In late 1960s Herman Dommel developed the Electromagnetic Transients Program (EMTP) at Bonneville Power Administration. The EMTP is a general-purpose computer program for simulating high-speed transient effects in electric power systems. The trapezoidal rule was chosen for integrating the ordinary differential equations of lumped inductance and capacitances, which reduces the numerical instability [6]-[9]. The EMTP method cannot give an online solution because to reach the solution lot of cases has to be carried out. As discuss above for a existing system the main factor witch affect the switching overvoltage are switching angle, line length and source strength. An ANN can help to take the online decision for switching operation. 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. Its ability to perform well is affected by the chosen training data as well as training scheme. In next section a ANN based approach is describe 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

III. The Proposed Artificial Neural Network

The proposal in this work considers the adoption of forward multilayer perceptron (MLP) architecture. A simple MLP neural network composed of single hidden layer and output layer is capable of solving difficult and complex problems [10]. Non-linear hyperbolic tangent function is used for the hidden units while linear activation function is used for the output units.

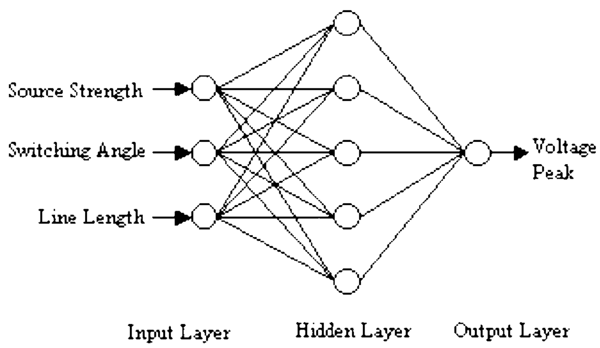

Fig. 7. Proposed MLP based ANN architecture

The schematic diagram of the proposed MLP neural networks architecture is shown in Fig. 7. The composition of the input variables for the proposed neural networks has been carefully selected. The following data has been considered in the input:

- Switching angle.
- Source strength.
- Transmission line length.

In order to accelerate the neural network training the input variables must be normalized. Output is the absolute maximum value of peak voltage of any phase at the receiving end bus. The other parameter like preinsertion resister (PIR) value, PIR duration time is kept constant.

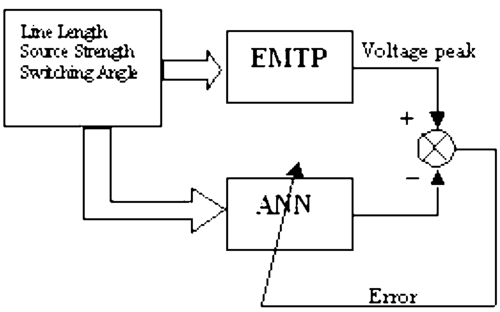

Fig. 8. Supervised Learning of ANN

Supervised training of ANN is a usual training paradigm for MLP architecture. Fig. 8 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 [11]. The LM algorithm is basically a Hessian-based algorithm for nonlinear least squares optimization.

Levenberg-Marquardt (LM) Algorithm

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

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

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 devided 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 variation in reactor values at buses, PIR values and duration time is not considered for the training data.

IV. Simulated Studies And Results

A. System Study

The proposed scheme is tested with three-bus 400kV system. Single line diagram is shown in Fig. 9. Equivalent source generator G is connected at bus 1, switch S is placed between buses 1 and 2, a 400 kV transmission line is represented between bus 2 and bus 3. This system is simulated for various combination of switching angle, source strength and line length. Minimum and maximum switching angle, source strength and line length have been considered as follow:

- Source strength :1000 - 9000 MVA in step of 500 MVA
- Line length : 100kms - 300 kms in step of 50 kms
- Switching angle : 0° - 90° in step of 30°

B. 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 for each layer. 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 five hidden unit is sufficient to get good accuracy and generalization for proposed methodology. Input vector contain three feature switching angle, line length and source strength. Neural networks learn more quickly and give better performance if the input variables are pre-processed before being used to train the network [12]. Input variable has different range like line length is in the order of 100kms, switching angle is in the order of 10^{o} and source strength is in the order of 1000MVA. Normalization of data is done to preprocessed inputs and targets and which scaled into the range of [-1, 1]. As the dimension of input vector is three so no need to reduce the dimension of input vector. The hyperbolic tan sigmoid function is used in hidden units and linear activation function used at output node. Whole simulation is run for 1000 epoch with 350 training patterns at each epoch. Network is trained with the goal of Mean Square Error (MSE) 1e-3.

C. Training

A set of training data is generated with the variation of input data by using EMTP program. Switching angle is varied in steps of 30°, fault MVA in steps of 500 MVA and Line length in steps of 50kms. PIR is chosen 5.33p.u. at base of 100MVA (300Ω). Switching sequence are 0-2-4ms and PIR duration sequence are 8ms chosen for all the cases. The total numbers of generated pattern are 350 The Neural Network is trained using the results of simulated conditions. The second order Levenberg-Marquardt training method is adopted to get high precision accuracy as mention in section III.

D. Testing

Testing of ANN is done by varying the line length in steps of 10kms, switching angle in steps of 10^{o} and source strength in steps of 100MVA. Results for testing data is shown in Figs. 10-12. In Fig. 10 shown the voltage peak at bus3 with the variation in source strength both ANN and EMTP values are shown, line length is constant at 300km and switching angle at 90^{o}. Fig. 11 shows the voltage peak at bus 3 find by both ANN and EMTP change with line length at constant source strength 1000MVA and switching angle 90^{o} and Fig. 12 shows the voltage peak at bus 3 as switching angle varies in step of 10^{o} with constant line length and source level. .

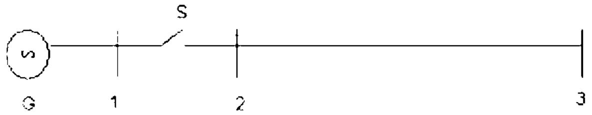

Fig. 9: Sample system
G: Generator S: Switch

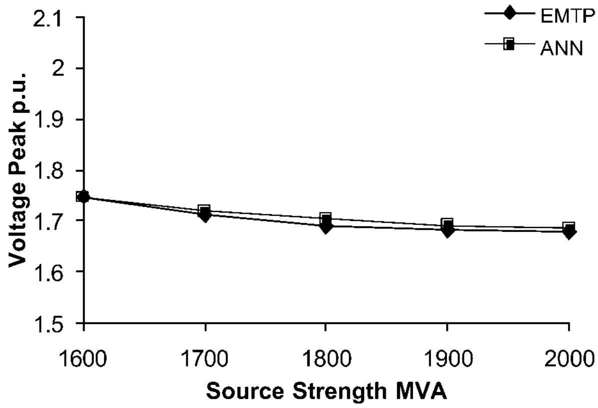

Fig. 10. Voltage peak at bus 3 simulated by ANN and EMTP while switching angle 90^{o} and line length 300km

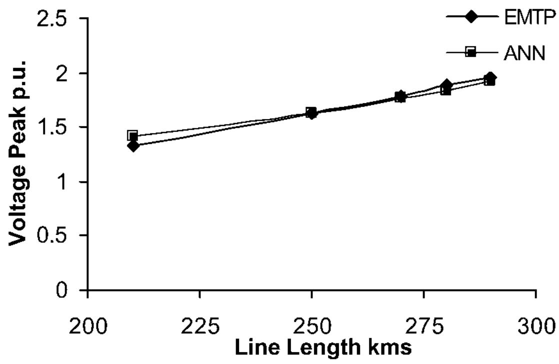

Fig. 11. Voltage peak at bus 3 simulated by ANN and EMTP while switching angle 90^{o} and source strength is 1000 MVA

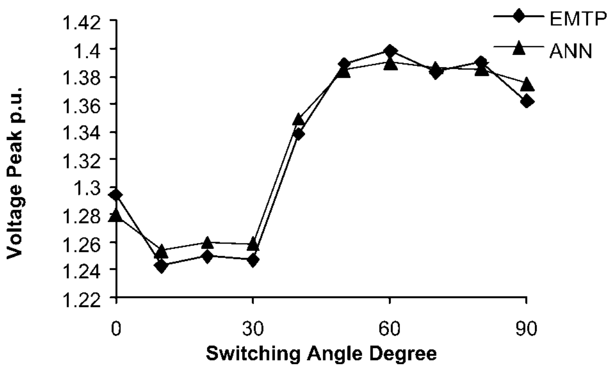

Fig. 12. Voltage peak at bus 3 simulated by ANN and EMTP while source strength is 5000MVA and line length 100km

E. Optimal PIR

The data pattern of various cases obtained for the training in proposed methodology PIR value (300Ω) was maintained constant. The PIR 300Ω is optimal for around 200 km line length, which shows the clustering of peak voltages data close to the value 1.45 p.u. 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. The parameters like presence of shunt reactor at receiving end and sending end of different sizes can also be considered.

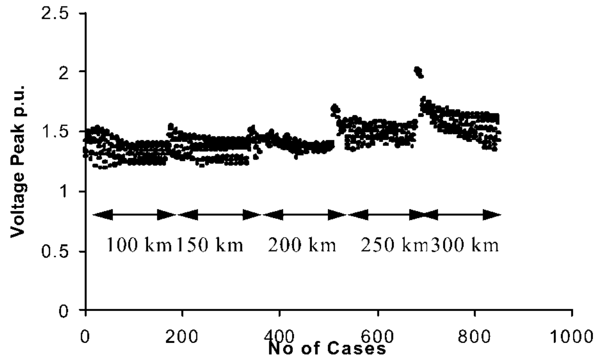

Fig.. 13. Data Pattern generated by 850 cases

V. CONCLUSION

A Neural Network approach to estimate the peak over voltages under switching transient was proposed and implemented. The Levenberg-Marquardt second order training method has been adopted for obtaining small MSEs without losing generalization capability of ANN. This approach also helps in reduction of the number of case studies to be carried out for the insulation coordination. The results from this scheme are near to conventional method and helpful in predicting the over voltage of the other case studies within the range of training set.

A three bus 400kV system has been used to test the proposed ANN based switching transients estimation. The simulated results clearly shows that the proposed technique can estimated the peak values of switching overvoltages with good accuracy. Further work can be carry out by taking the various optimal values of PIR and PIR duration time. Additional parameters in input like presence of shunt reactor of different sizes at receiving end and sending end can also be considered.

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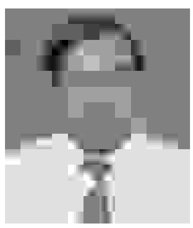

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