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An Approach to Evaluate Switching Overvoltages during Power System Restoration

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Abstract: Transformer switching is one of the important stages during power system restoration. This switching can cause harmonic overvoltages that might damage some equipment and delay power system restoration. Core saturation on the energisation of a transformer with residual flux is a noticeable factor in harmonic overvoltages. This work uses artificial neural networks (ANN) in order to estimate the temporary overvoltages (TOVs) due to transformer energisation. In the proposed methodology, the Levenberg–Marquardt method is used to train the multilayer perceptron. The developed ANN is trained with the worst case of switching condition, and tested for typical cases. Simulated results for a partial 39-bus New England test system, show the proposed technique can accurately estimate the peak values and durations of switching overvoltages.

Keywords: Artificial neural networks, Harmonic overvoltages, Inrush current harmonics, Power system restoration, Transformer energization.

1 Introduction

Power system blackouts are infrequent but their impacts are major and their repercussions can be very serious. After a blackout, power needs to be restored as quickly and reliably as possible and, consequently, detailed restoration plans are necessary [1, 2].

During the early stages of restoring high voltage overhead and underground transmission lines, concerns are with three related overvoltages: sustained power frequency overvoltages, switching transients (surges), and harmonic resonance. In the early stages of the restoration, the lines are lightly loaded; resonance therefore is lightly damped, which in turn means the resulting resonance voltages may be very high [3 – 7].

If the frequency characteristic of the system shows resonance conditions around multiples of the fundamental frequency, very high and weakly damped

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temporary overvoltages (TOVs) of long duration may occur when the system is excited by a harmonic disturbance, such as the switching of lightly loaded transformers or transformer saturation [8 – 11].

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 [2, 12].

In this paper power system blockset (PSB), a MATLAB/Simulink-based simulation tool [13, 14] is used for computation of temporary overvoltages. In order to study temporary overvoltages for a large number of possible system configurations, it is necessary to run many time-domain simulations resulting in a large amount of simulation time. A way to limit the overall calculation time is to reduce the number of simulations by applying analytical or knowledge-based rules to discard a number of system configurations before an actual time-domain simulation is carried out. This paper presents the ANN application for estimation of peak and duration overvoltages under switching transients during transformer energization. A tool such as proposed in this paper that can give the maximum switching overvoltage and it's duration will be helpful to the operator during system restoration. Also it can be used as training tool for the operators. In the proposed ANN we have considered the most important aspects, which influence the transient overvoltages such as source voltage, line length, switching angle, saturation curve slope and remanent flux. This information will help the operator to select the proper sequence of transformer to be energized safely with transients appearing safe within the limits. Results of the studies are presented for a partial of 39-bus New England test system to illustrate the proposed approach.

2 Modelling Issues

2.1 Power System Blockset (PSB)

Simulations presented in this paper are performed using the PSB [14]. The simulation tool has been developed using state variable approach and runs in the MATLAB/Simulink environment. This program has been compared with other popular simulation packages (EMTP and Pspice) in [13]. The user friendly graphical interfaces of PSB enable faster development for power system transient analysis.

2.2 Transmission-line model

Transmission lines are described by PI cells, the *R*, *L* and *C* parameters being derived from lumped-line models. One PI section is used for every 25 km line section [15] in order to correctly represent its exact impedance under the tenth harmonic. This model is also accurate enough for frequency-dependent parameters, because the positive sequence resistance and inductance are fairly constant up to approximately 1 kHz [16] which covers the frequency range of phenomena that this paper deals with.

2.3 Generator model

In [16], generators have been modeled by the generalized Park's model that electrical and mechanical parts are thoroughly modeled. In this work, generators are represented by a sinusoidal voltage source behind their subtransient reactances X''_d. Phases of voltage sources are determined by the load-flow results.

2.4 Load and shunt devices model

All of the loads and shunt devices, such as capacitors and reactors, are modeled as constant impedances.

2.5 Transformer model

The model takes into account the winding resistances (R_1, R_2) , the leakage inductances (L_1, L_2) as well as the magnetizing characteristics of the core, which is modeled by a resistance, R_m, simulating the core active losses and a saturable inductance, L_{sat}. The saturation characteristic is specified as a piece-wise linear characteristic [17].

3 Harmonic Overvoltages during Restoration

One of the major concerns in power system restoration is the occurrence of overvoltages as a result of switching procedures. These can be classified as transient overvoltages, sustained overvoltages, harmonic resonance overvoltages, and overvoltages resulting from ferro-resonance. Steady-state overvoltages occur at the receiving end of lightly loaded transmission lines as a consequence of line-charging currents (reactive power balance). Excessive sustained overvoltages may lead to damage of transformers and other power system equipment. Transient overvoltages are a consequence of switching operations on long transmission lines, or the switching of capacitive devices, and may result in arrester failures. Ferro-resonance is a nonharmonic resonance characterized by overvoltages whose waveforms are highly distorted and can cause catastrophic equipment damages [1].

This paper concentrates on the estimation of harmonic overvoltages. These are a result of network resonance frequencies close to multiples of the fundamental frequency. They can be excited by harmonic sources such as saturated transformers, power electronics, etc. They may lead to long lasting overvoltages resulting in arrester failures and system faults [2].

The major cause of harmonic resonance overvoltage problems is the switching of lightly loaded transformers at the end of transmission lines. The harmonic-current components of the same frequency as the system resonance frequencies are amplified in case of parallel resonance, thereby creating higher voltages at the transformer terminals. This leads to a higher level of saturation, resulting in higher harmonic components of the inrush current that again results in increased voltages This can happen particularly in lightly damped systems, common at the beginning of a restoration procedure when a path from a black-start source to a large power plant is being established and only a few loads are restored yet [1, 18].

Fig. 1 shows the sample system considered for explanation of the proposed methodology which is a portion of 39-bus New England test system. Fig. 2 shows a sample switching overvoltages at bus 39 when transformer is energized.

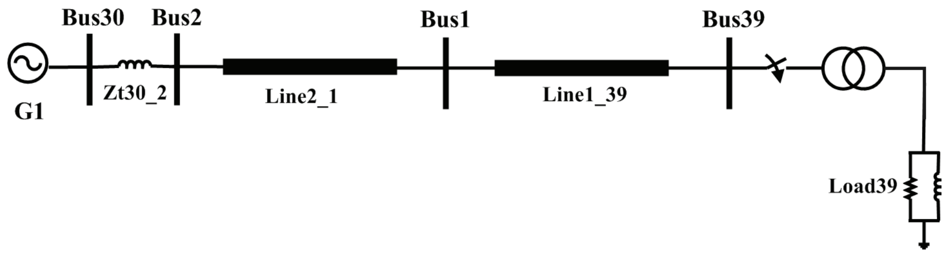


Fig. 1 – *Power system at the beginning of a restoration procedure.*

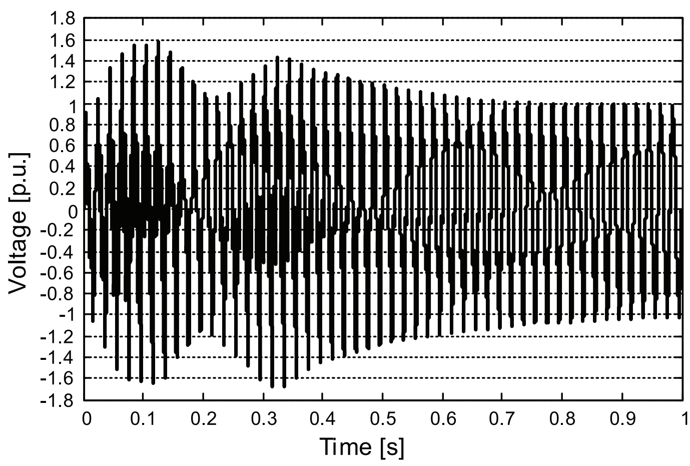


Fig. 2 – *Voltage at bus* 39 *after switching of transformer for worst case condition.*

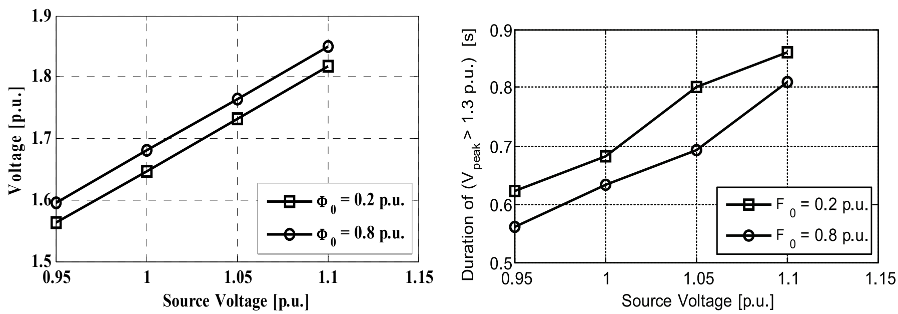
In practical system a number of factors affect the overvoltages factors due to energization or reclosing. In this paper following parameters is considered:

– Source voltage,

– Line length,

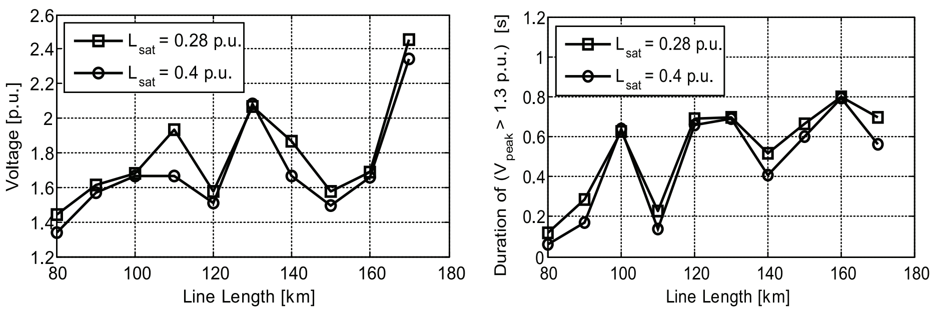
– Closing time of the circuit breaker poles,
– Saturation curve slope,
– Remanent flux.

Source voltage affects the overvoltage strongly. Fig. 3 shows the effect of source voltage on overvoltage peak and duration at different remanent flux. Fig. 4 shows the effect of line length on overvoltages at different saturation curve slope. The saturation curve, and especially the L_{sat} i.e. the final slope of this curve, is a key point for the computation of the inrush currents but is not very easy to obtain. The transformer manufacturer provides a L_{sat} slope value with a dispersion usually considered of ±20 %. Fig. 5 shows effect of remanent flux on overvoltages at different line length. Fig. 6 shows the effect of saturation curve slope on overvoltages at different source voltage.



(a) (b)

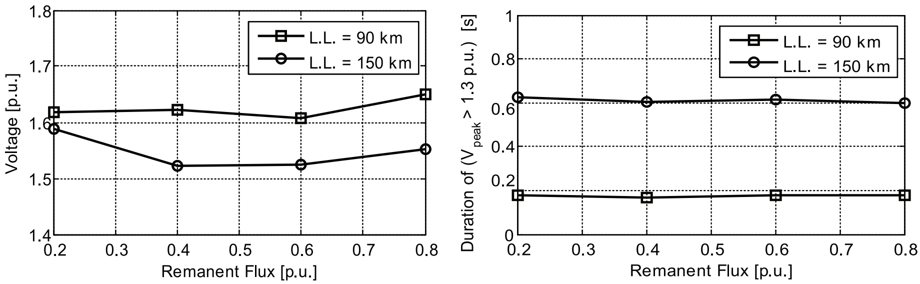
Fig. 3 – *Overvoltage at bus* 39 *vs. source voltage: with line length* = 100 km *and saturation curve slope* = 0.32 p.u. (a) *Peak*; (b) *Duration*.



(a) (b)

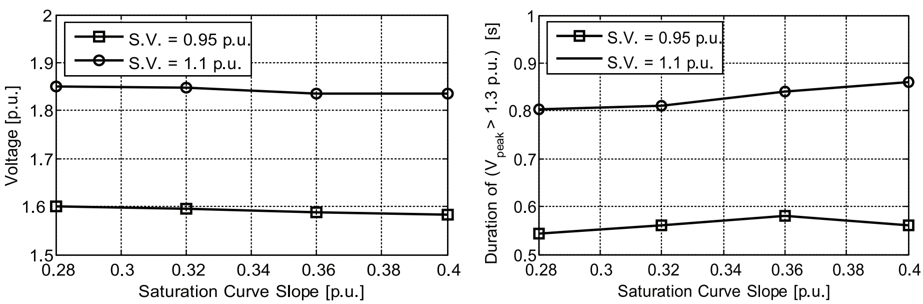
Fig. 4 – *Overvoltage at bus* 39 *vs. line length: with source voltage* =1 p.u. *and remanent flux* =0.8 p.u (a) *Peak*; (b) *Duration*.

As discussed above for an existing system the main factors which affect the peak and duration values of switching overvoltage are source voltage, line length, switching angle, saturation curve slope and remanent flux. Here it should be mentioned that a single parameter often cannot be regarded independently from the other important influencing factors. The magnitude and duration 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 [19]. So an ANN can help to estimate the peak and duration values of switching overvoltages generated during transformer 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.



(a) (b)

Fig. 5 – *Overvoltage at bus* 39 *vs. remanent flux: with source voltage* = 1 p.u. *and saturation curve slope* = 0.32 p.u. (a) *Peak*; (b) *Duration*.



(a) (b)

Fig. 6 – *Overvoltage at bus* 39 *vs. saturation curve slope: with line length* = 100 km *and remanent flux* = 0.8 p.u. (a) *Peak*; (b) *Duration*.

4 Proposed Method for Harmonic Overvoltages Study

4.1 Worst switching condition determination for overvoltages simulation

Normally for harmonic overvoltages analysis, the worst case of the switching condition must be considered which it is a function of switching time, transformer characteristics and its initial flux condition, and impedance characteristics of the switching bus [17]. Using the worst switching condition, the number of simulations for each case can be reduced significantly.

In order to determine worst-case switching time, the following index is defined as:

$$W = \sum_{h=2}^{10} Z_{jj}(h) I_j(h, t_0, \varphi_0)\,, \tag{1}$$

where t_0 is the switching time and φ_0 is initial transformer flux. This index can be a definition for the worst-case switching condition. Using a numerical algorithm, one can find the switching time for which W is maximal (i.e., harmonic overvoltages is maximal).

Fig. 7 shows the result of the PSB frequency analysis at bus 39. The magnitude of the Thevenin impedance, seen from bus 39, Zbus39 shows a parallel resonance peak at 293 Hz. Fig. 8 shows changes of harmonic currents and W index with respect to the current starting angle [20], where k is harmonic number. Fig. 2 shows voltage at bus 39 after transformer switching for the worst-case condition (i.e., 17°) in one case. For temporary overvoltages, the overvoltage duration has to be taken into account in addition to the amplitude [18]. **Table 1** summarizes the results of overvoltages simulation for three different switching conditions that verify the effectiveness of W index.

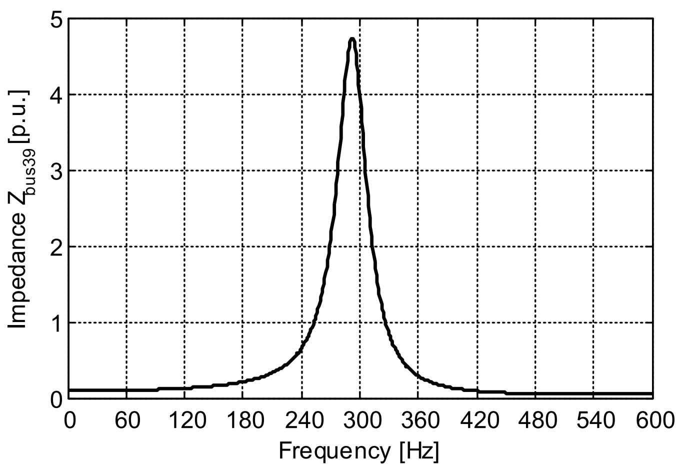


Fig. 7 – *Impedance vs. frequency at bus* 39.

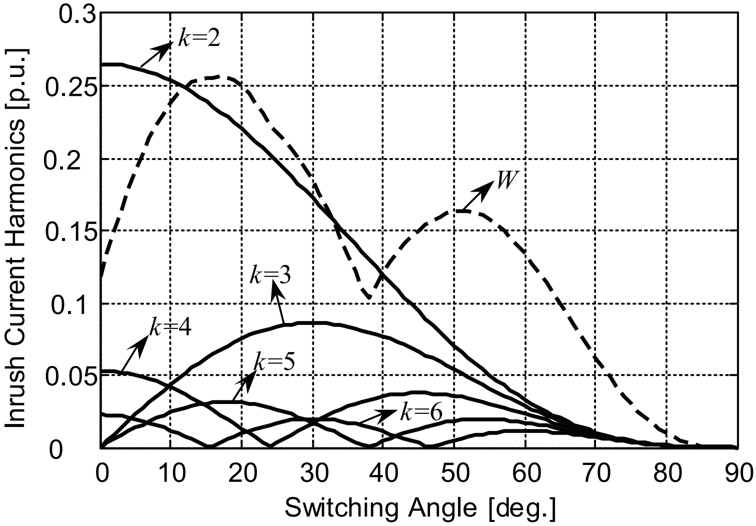


Fig. 8 – *Changes of harmonic currents and W index vs. switching angle.*

Table 1

Effect of switching time on the maximum of overvoltage and duration of $V_{peak} > 1.3$ p.u.

Switching Angle [deg.]	V_{peak} [p.u.]	Duration of ($V_{peak} > 1.3$ p.u.) [s]
17	1.6791	0.3494
51	1.6318	0.2746
74	1.2847	0

4.2 Steps of assessment and estimation of temporary overvoltages

The steps for harmonic overvoltages assessment and estimation follow.

1) Determine the characteristics of transformer that must be energized.
2) Calculate the $Z_{ii}(h)$ at the transformer bus for $h = 2f_0,\ldots,10f_0$.
3) Calculation of worst switching condition for simulation.
4) Run PSB simulation.
5) Calculation overvoltage peak and duration.
6) Repetition of above steps with various system parameters to learning artificial neural network.
7) Testing artificial neural network with different system parameters.

5 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 [4, 21]. 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. The schematic diagram of the proposed MLP neural networks architecture is shown in Fig. 9. The composition of the input variables for the proposed neural networks has been carefully selected.

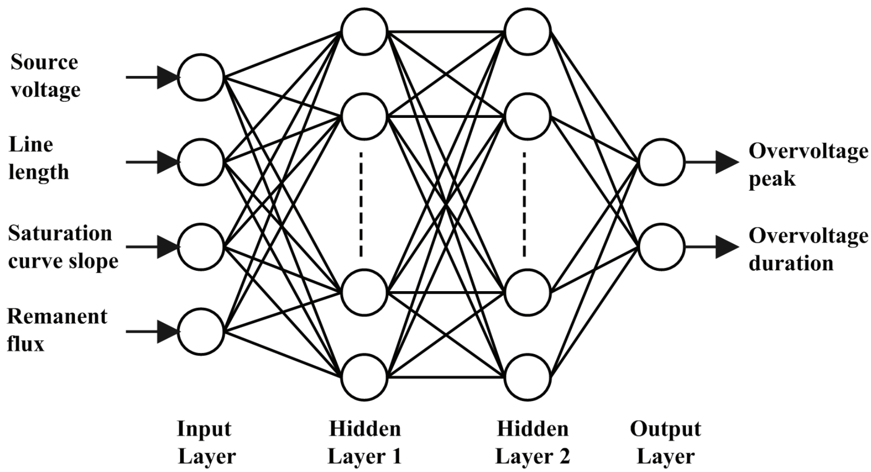


Fig. 9 – *Proposed* MLP-*based* ANN *architecture*.

Supervised training of ANN is a usual training paradigm for MLP architecture. Fig. 10 shows the supervised learning of ANN for which input is given to PSB to get the peak and duration values of transient overvoltages and the same data is used to train the ANN. Error is calculated by the difference of PSB 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 [22].

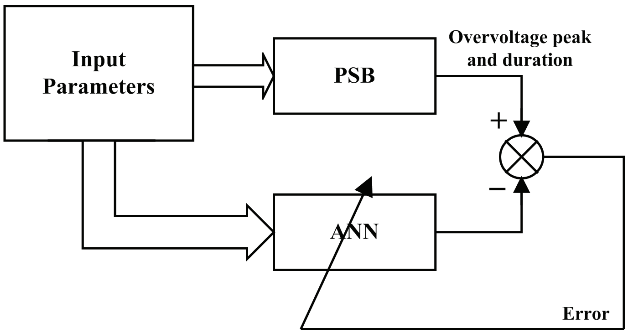


Fig. 10 – *Supervised learning of* ANN.

5.1 Levenberg-Marquardt (LM) Algorithm

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

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

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

$$\Delta \boldsymbol{x} = \left[\boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\boldsymbol{J}(\boldsymbol{x}) + \mu \boldsymbol{I}\right]^{-1} \boldsymbol{J}^{\mathrm{T}}(\boldsymbol{x})\boldsymbol{e}(\boldsymbol{x}) \,. \tag{3}$$

The parameter μ is multiplied by some factor β whenever a step would result in an increased $\xi(\boldsymbol{x})$. When a step reduces $\xi(\boldsymbol{x})$, 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 voltages, line lengths, saturation curve slopes and remanent fluxes. Depending on the analysis to be conducted it is possible to increase or decrease the quantity of training cases.

5.2 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 two hidden layer and 10 hidden units per layer is found to be sufficient to get good accuracy and generalization for proposed scheme.

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 anti-symmetric 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 [21]. Input variables have different range like source voltage is in the order of 0.5 p.u., line length is in the order of 10 km, saturation curve slope is in the order of 0.4 p.u. and remanent flux is in the order of 0.2 p.u. 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). The hyperbolic tan sigmoid function is used in hidden neurons and linear activation function is used at output neuron.

5.3 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 PSB program by placing the parameter values not used in learning, by applying different parameters. 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. Percentage error is calculated as:

$$\mathrm{error}(\%) = \frac{|\mathrm{ANN} - \mathrm{PSB}|}{\mathrm{PSB}} 100 \,. \tag{4}$$

The proposed model tested with portion of 39-bus New England test system. Various cases of transformer energization are taken into account and corresponding peak and duration values estimated from trained model.

5 Case Study

In this section, the proposed algorithm is demonstrated for two case studies that are a portion of 39-bus New England test system, of which its parameters are listed in [23]. The simulations are undertaken on a single phase representation.

4.6 Case 1

Fig. 1 shows a one-line diagram of a portion of 39-bus New England test system which is in restorative state. The generator at bus 30 is a black-start unit. The load 39 shows cranking power of the later generator that must be restored by the transformer of bus 39. When the transformer is energized, harmonic overvoltages can be produced because the transformer is lightly loaded.

Switching transients are simulated for various combinations of system parameters as follows:

– Source voltage: 0.95-1.1 p.u. in step of 0.05 p.u.
– Line length: 80-170 km in step of 10 km
– Saturation curve slope: 0.24-0.4 p.u. in step of 0.04 p.u.
– Remanent flux: 0.2-0.8 p.u. in step of 0.2 p.u.

Neural network is trained with the goal of mean square error (MSE) 1e–3. Fig. 11 shows the training of neural network. Results for a sample test data are presented in **Table 2** and also shown in Figs. 12–13. **Table 2** contains the some sample result of test data of Case 1. Values in column V_{PSB} are the absolute values of peak voltage at bus 39 calculated by PSB program where the V_{ANN} values are the values simulated by trained network (both in p.u.). Also Values in column T_{PSB} are the values of overvoltage duration calculated by PSB program and T_{ANN} values are the values simulated by trained network (both in seconds).

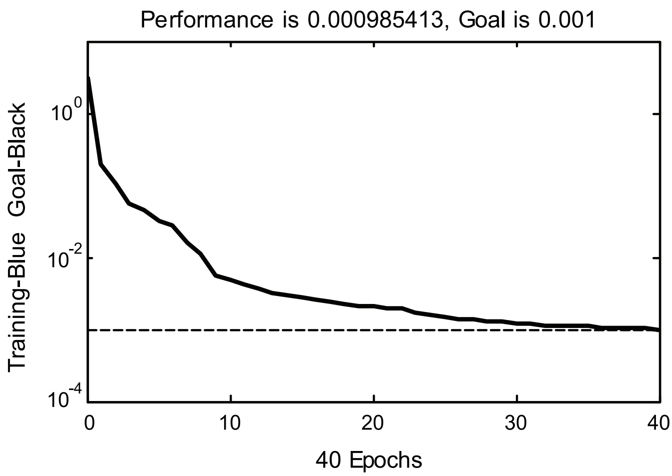


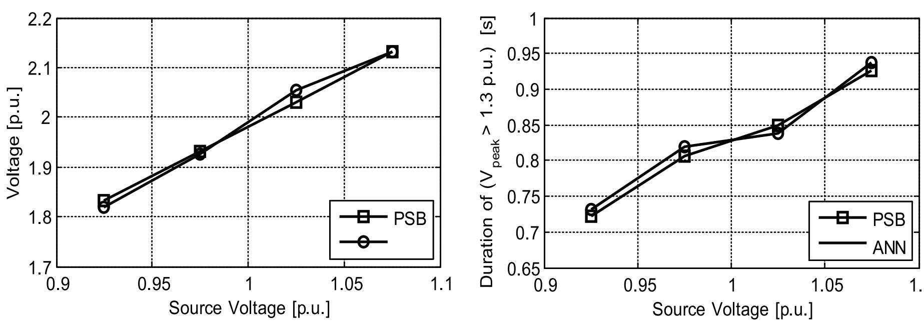
Fig. 11 – *Squared error against epoch curve during* ANN *training.*

Table 2
Case 1: *Some sample testing data and output.*

S.V.	L.L.	L_{sat}	Φ_0	V_{PSB}	V_{ANN}	E_V	T_{PSB}	T_{ANN}	E_T
0.925	95	0.34	0.1	1.4322	1.4524	1.4126	0.0896	0.0904	0.9462
0.925	105	0.34	0.7	1.5868	1.5801	0.4222	0.5813	0.5862	0.8429
0.925	135	0.38	0.5	2.0273	2.0407	0.6581	0.5694	0.5531	2.8624
0.925	155	0.26	0.3	1.4626	1.4789	1.1117	0.4218	0.4167	1.2091
0.975	85	0.34	0.3	1.3773	1.3717	0.4097	0.1219	0.1236	1.3946
0.975	115	0.34	0.1	1.5817	1.5527	1.8313	0.1217	0.1234	1.4251
0.975	145	0.3	0.7	1.7852	1.7891	0.2196	0.4779	0.4751	0.5844
0.975	175	0.3	0.5	2.4214	2.4415	0.8287	0.5937	0.5962	0.4211
1.025	105	0.38	0.3	1.7533	1.7589	0.3184	0.7681	0.7724	0.5649
1.025	135	0.38	0.7	2.2154	2.2393	1.0805	0.8989	0.8802	2.0842
1.025	155	0.34	0.1	1.5835	1.5829	0.0372	0.8713	0.8646	0.7648
1.075	85	0.3	0.7	1.5817	1.6016	1.2581	0.4178	0.4254	1.8249
1.075	95	0.26	0.7	1.7605	1.7724	0.6759	0.4727	0.4651	1.6033
1.075	135	0.34	0.1	2.2708	2.2976	1.1802	0.9399	0.9404	0.0537
1.075	175	0.38	0.1	2.8332	2.8728	1.3965	0.9418	0.9338	0.8463

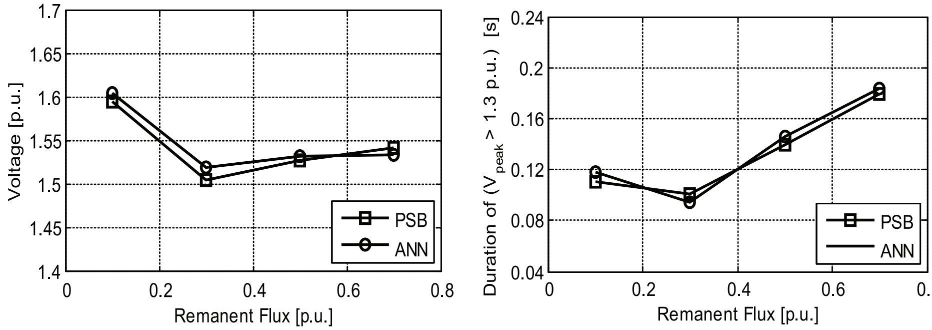
S.V. = source voltage [p.u.], L.L. = line length [km], L_{sat} = saturation curve slope [p.u.], Φ_0 = remanent flux [p.u.], E_V = voltage error [%] and E_T = duration time error [%].

Fig. 12 shows overvoltage peak and duration at bus 39 vs. the source voltage while other parameter like line length, saturation curve slope and remanent flux, constant at 125 km, 0.34 p.u. and 0.5 p.u., respectively. Fig. 13 shows overvoltage peak and duration at bus 39 vs. the remanent flux when other parameter like source voltage, line length, saturation curve slope, constant at 1.025 p.u., 95 km and 0.26 p.u., respectively.



(a) (b)

Fig. 12 – *Overvoltage vs. source voltage at bus* 39 *simulated by* ANN *and* PSB *while line length* 125 km, *saturation curve slope* 0.34 p.u. *and remanent flux* 0.5 p.u. (a) *Peak*; (b) *Duration*.



(a) (b)

Fig. 13 – *Overvoltage vs. remanent flux at bus* 39 *simulated by* ANN *and* PSB *while source voltage* 1.025 p.u., *line length* 95 km *and saturation curve slope* 0.26 p.u. (a) *Peak*; (b) *Duration*.

6.2 Case 2

As another example, the system in Fig. 14 is examined. It represents the same system as the one in Fig. 1, but a few restoration steps later. In the next step of the restoration, unit at bus 29 must be restarted. In order to provide cranking power for this unit, the transformer at bus 29 should be energized. In this condition, harmonic overvoltages can be produced because the load of the transformer is small.

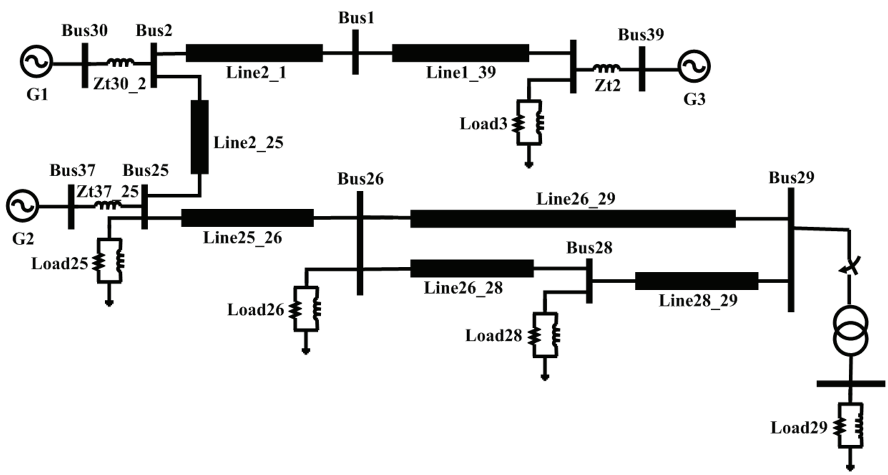


Fig. 14 – *Studied system for* Case 2.

The various cases of transformer energization are taken into account and corresponding peak and duration overvoltages are computed from PSB program. Summary of few result are presented in **Table 3**. It can be seen from the results that the ANN is able to learn the pattern and give results to acceptable accuracy.

Table 3
Case 2: *Some sample testing data and output.*

S.V.	L.L.	L_{sat}	Φ_0	V_{PSB}	V_{ANN}	E_V	T_{PSB}	T_{ANN}	E_T
0.925	95	0.26	0.5	1.4995	1.5132	0.9137	0.6195	0.6272	1.2439
0.925	115	0.34	0.3	1.6319	1.6365	0.2767	0.8014	0.7953	0.7631
0.925	135	0.38	0.1	2.0581	2.0304	1.3478	0.5218	0.5256	0.7325
0.925	165	0.3	0.7	1.8396	1.8673	1.5084	0.3015	0.2963	1.7318
0.975	95	0.38	0.3	1.5387	1.5105	1.8351	0.7996	0.7984	0.1534
0.975	125	0.34	0.3	1.9377	1.9469	0.4762	0.8617	0.8697	0.9308
0.975	155	0.34	0.5	2.0493	1.9636	4.1813	0.3821	0.3743	2.0379
0.975	175	0.26	0.7	2.0351	2.0031	1.5709	0.3422	0.3473	1.4968
1.025	95	0.38	0.3	1.6183	1.6043	0.8637	0.8071	0.8025	0.5699
1.025	125	0.34	0.3	2.0372	2.0443	0.3471	0.8969	0.9064	1.0559
1.025	155	0.3	0.5	2.2047	2.1734	1.4197	0.4748	0.4729	0.3941
1.075	95	0.26	0.5	1.7396	1.7185	1.2095	0.8021	0.8147	1.5709
1.075	115	0.34	0.7	1.8967	1.9076	0.5742	0.7906	0.7821	1.0751
1.075	145	0.38	0.5	2.3236	2.3214	0.0933	0.8749	0.8682	0.7638
1.075	165	0.38	0.7	2.1047	2.0809	1.1308	0.5435	0.5346	1.6392

S.V. = source voltage [p.u.], L.L. = line length [km], L_{sat} = saturation curve slope [p.u.], Φ_0 = remanent flux [p.u.], E_V = voltage error [%] and E_T = duration time error [%].

7 Conclusion

This paper proposed an artificial neural network based method to estimate the peak and duration overvoltages due to transformer energization. The Levenberg–Marquardt second order training method has been adopted for obtaining small mean square error (MSE) without losing generalization capability of ANN. The results from this scheme are close to results from the conventional method and helpful in predicting the overvoltage of the other case studies within the range of training set. The proposed ANN approach is tested on a partial 39-bus New England test system.

This method omits time-consuming time-domain simulations and it is suitable for real time applications during system restoration. Also it can be used as a training tool for the operators.

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