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An Intelligent Estimator for Reactor Switching Studies

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Abstract. In this paper an intelligent approach is proposed to evaluate switching overvoltages caused by shunt reactor energization by applying analytical rules. In a small power system that appears in an early stage of a black start of a power system, an overvoltage could be caused by core saturation on the energization of a reactor with residual flux. An artificial neural network (ANN) has been used to estimate the overvoltages due to shunt reactor energization. Three learning algorithms, delta-bar-delta (DBD), extended delta-bar-delta (EDBD) and directed random search (DRS), were used to train the ANNs. Equivalent circuit parameters of network have been used as ANN inputs; thus developed ANN is applicable to every studied system. The developed ANN is trained with the worst case of the switching angle and remanent flux, and tested for typical cases. The simulated results for a partial of 39-bus New England test system show that the proposed technique can measure the peak values and duration of switching overvoltages with good accuracy and EDBD algorithm presents best performance.

Keywords: Harmonic index, power system restoration, extended delta-bar-delta, shunt reactor switching, switching overvoltages.

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1 Introduction

In high-voltage (HV) power systems usually power is transmitted through long high-voltage transmission lines. During the low demand periods (nights or weekends), excessive reactive power produced by the capacitance of these lines causes a voltage increase over 1.1 p.u. at the high-voltage/medium-voltage (HV/MV) substations. For the absorption of the surplus reactive power, HV shunt reactors are connected to the receiving end of the transmission lines. Switching of those shunt reactors produce transients that need to be carefully studied and, if required, limited [1-6].

If the frequency characteristic of the system shows resonance conditions around multiples of the fundamental frequency, very high and weakly damped temporary overvoltages (TOVs) of long duration may occur when the system is excited by a harmonic disturbance.

In this paper power system blockset (PSB), a MATLAB/Simulink-based simulation tool 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 Artificial Neural Network (ANN) application for estimation of peak and duration overvoltages under switching transients during reactor 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. Results of the studies are presented for a partial of 39-bus New England test system to illustrate the proposed approach.

2 Harmonic Overvoltages during Restoration

One of the major concerns in power system restoration is the occurrence of overvoltages as a result of switching procedures [7-9]. 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 non-harmonic resonance characterized by overvoltages whose waveforms are highly distorted and can cause catastrophic equipment damages [7].

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 reactors, power electronics, etc. They may lead to long lasting overvoltages resulting in arrester failures and system faults [10].

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., where 100 MVA is considered as a base power. Fig. 2 shows the switching transient at bus 2 when reactor is energized.

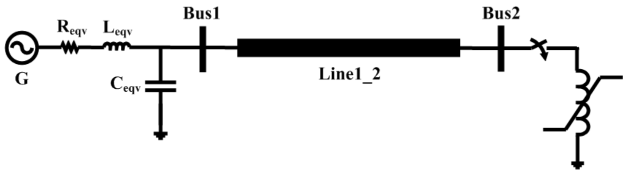

Fig. 1. Sample system for shunt reactor energization study.

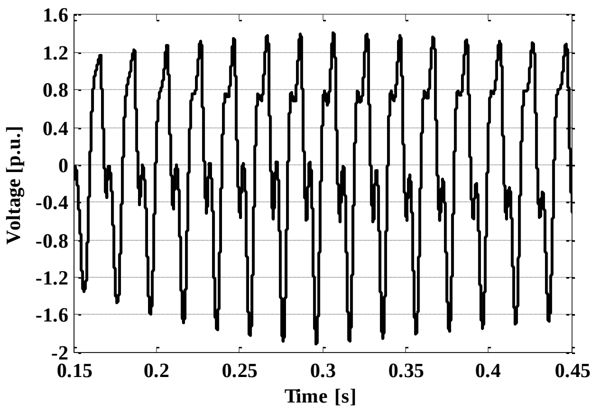

Fig. 2. Voltage at bus 2 after switching of shunt reactor.

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

- Voltage at shunt reactor bus before switching
- Equivalent resistance of the network
- Equivalent inductance of the network
- Equivalent capacitance of the network
- Line length
- Closing time of the circuit breaker poles
- Shunt reactor capacity
- Saturation curve slope
- Remanent flux

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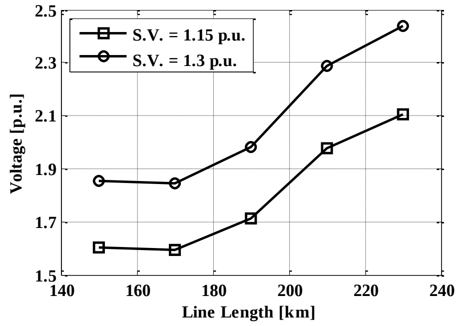
In this paper, ANN training is based on Fig. 1 that includes equivalent circuit parameters. In fact, ANN is trained just once for Fig. 1. Therefore, it's possible to use developed ANN for estimation of overvoltages in every studied system. In section 4 that developed ANN is tested for 39-bus New England test system, this issue is better understood.

Also, a novel method based on worst case condition determination is proposed in section 3 to reduce time-domain simulations.

Source voltage affects the overvoltage strongly. Fig. 3 shows the effect of line length on overvoltage at different source voltage. Fig. 4 shows the effect of saturation curve slope on overvoltages at different equivalent inductance. 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. The reactor manufacturer provides a L_{sat} slope value with a dispersion usually considered of ±20%. Fig. 5 shows effect of shunt reactor capacity on overvoltages at different equivalent resistance. Also, Fig. 6 shows the effect of equivalent capacitance on overvoltages at different remanent flux.



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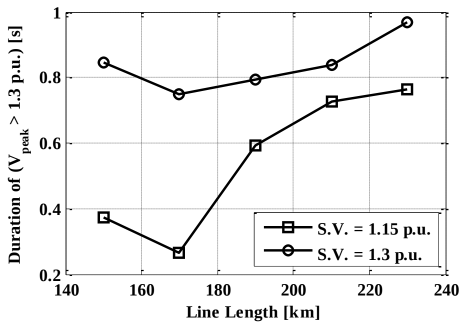


(b)

Fig. 3. Overvoltage at bus 2 as line length while equivalent resistance 0.003 p.u., equivalent inductance 0.03 p.u., equivalent capacitance 1.282 p.u., switching angle 60°, shunt reactor capacity 20 MVAR, saturation curve slope 0.28 p.u., and remanent flux 0.8 p.u. S.V. is source voltage. (a) Peak, (b) Duration.

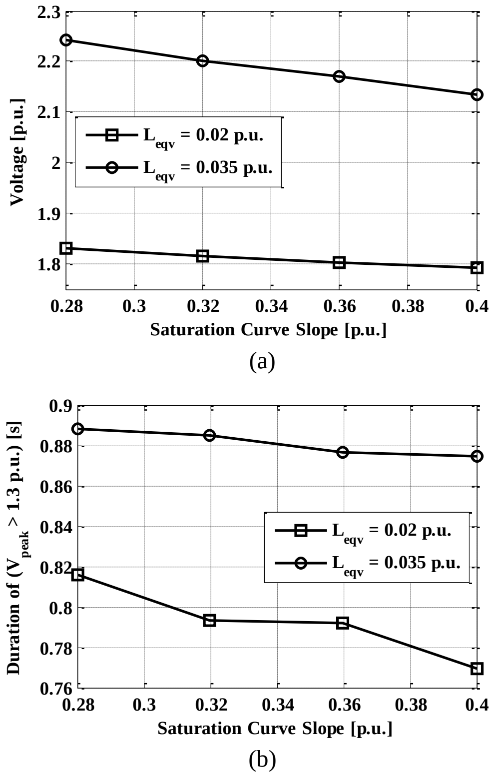


Fig. 4. Overvoltage at bus 2 as saturation curve slope while source voltage 1.25 p.u, equivalent resistance 0.003 p.u., equivalent capacitance 1.282 p.u., line length 210 km, switching angle 60°, shunt reactor capacity 20 MVAR, and remanent flux 0.8 p.u. L_{eqv} is equivalent inductance. (a) Peak, (b) Duration.

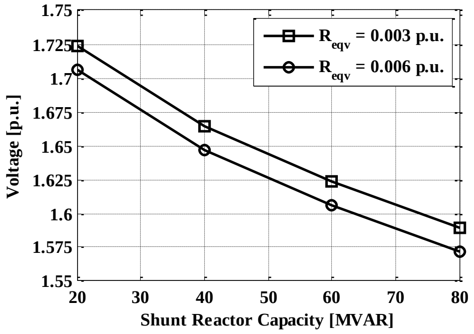
3 Proposed Method for Harmonic Overvoltages Study

3.1 Worst Case Condition Determination for Overvoltages Simulation

Normally for harmonic overvoltages analysis, the worst case of the switching angle and remanent flux must be considered which it is a function of switching time, reactor characteristics and its initial flux condition, and impedance characteristics of the switching bus [11]. Using the worst switching angle and remanent flux, the number of simulations for each case can be reduced significantly.

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

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



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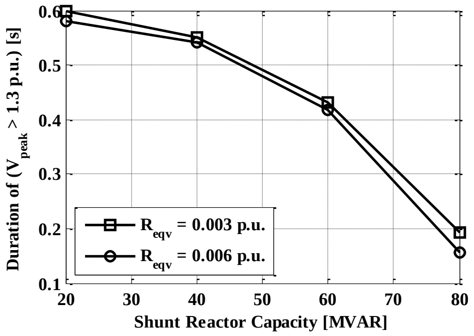

(b)

Fig. 5. Overvoltage at bus 2 as shunt reactor capacity while source voltage 1.2 p.u., equivalent inductance 0.025 p.u., equivalent capacitance 1.8912 p.u., line length 190 km, switching angle 45°, saturation curve slope 0.32 p.u., and remanent flux 0.8 p.u. R_{eqv} is equivalent resistance. (a) Peak, (b) Duration.

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

Fig. 7 shows the result of the PSB frequency analysis at bus 2. The magnitude of the Thevenin impedance, seen from bus 2, Zbus2 shows a parallel resonance peak at 174 Hz. Fig. 8 shows changes of W index with respect to the current starting angle and remanent flux. Fig. 2 shows voltage at bus 2 after reactor switching for the worst-case condition (i.e., switching angle 20° and remanent flux 0.27 p.u.). For temporary overvoltages, the overvoltage duration has to be taken into account in addition to the amplitude. Table 1 summarizes the results of overvoltages simulation for four different switching angle and remanent flux that verify the effectiveness of W index.

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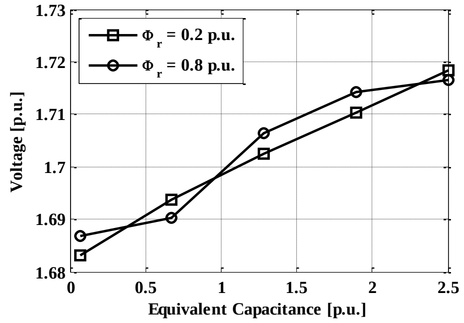
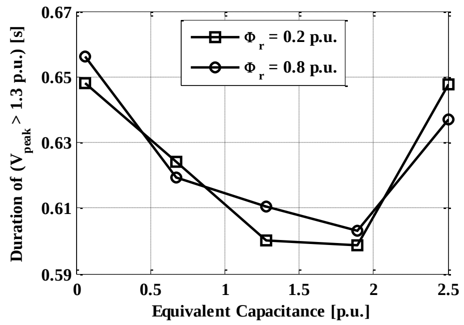


(a)



(b)

Fig. 6. Overvoltage at bus 2 as equivalent capacitance while source voltage 1.2 p.u, equivalent resistance 0.004 p.u., equivalent inductance 0.025 p.u., line length 190 km, switching angle 45°, shunt reactor capacity 20 MVAR, and saturation curve slope 0.32 p.u. Φ_r is remanent flux. (a) Peak, (b) Duration.

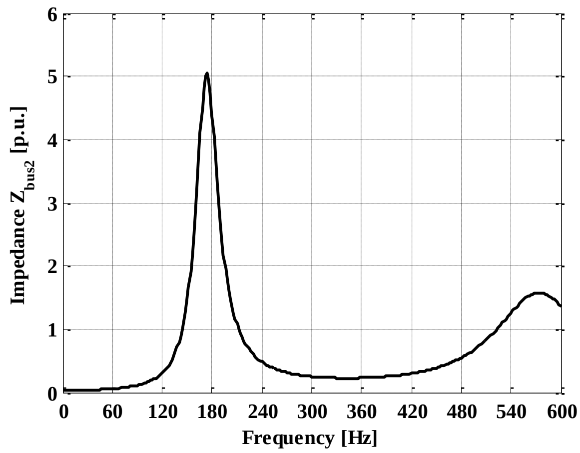


Fig. 7. Voltage at bus 2 after switching of shunt reactor.

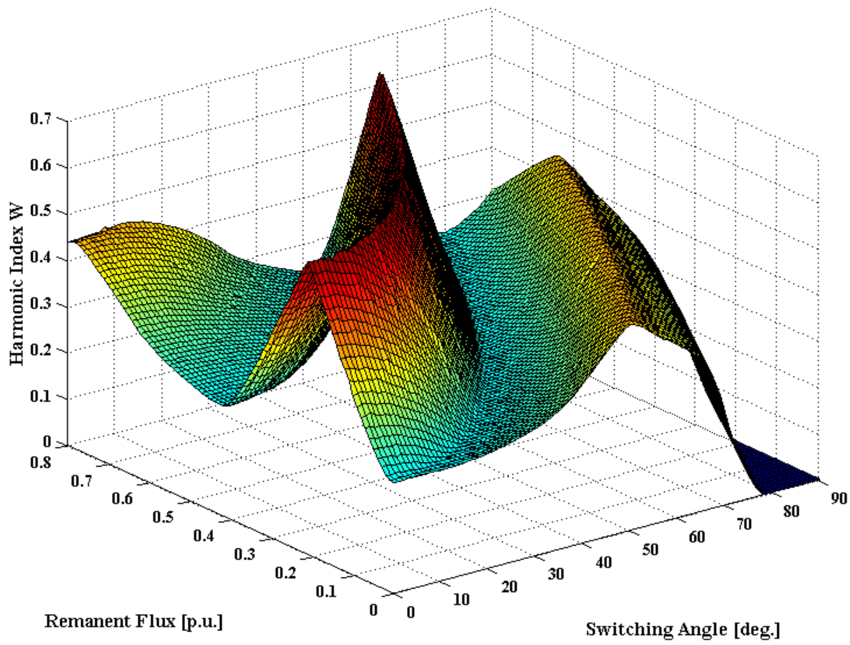


Fig. 8. Changes of *W* index with respect to current starting angle and remanent flux.

Table 1. Effect of switching time and remanent flux on the maximum of overvoltages and duration of V_{peak} > 1.3 p.u.

Switching Angle [deg.]	Remanent Flux [p.u.]	V_{peak} [p.u.]	Duration of (V_{peak} > 1.3 p.u.) [s]
20	0.27	1.9205	0.5628
20	0.65	1.5841	0.3394
75	0.27	1.6537	0.3064
60	0.5	1.5293	0.2675

3.2 Training of Artificial Neural Network

Multilayer perceptron (MLP) are the simplest and therefore most commonly used artificial neural network architectures. The basic structure of the MLP is shown in Fig. 9. The MLP consists of three layers namely, the inputs layer, the hidden layer, and the output layer. Training a network consists of adjusting weights of the network using a different learning algorithm. In this work, ANNs are trained with the two supervised and one reinforcement learning algorithms. In this paper, the delta-bar-delta (DBD), the extended delta-bar-delta (EDBD) and the directed random search (DRS) were used to train the MLP-ANN [12]. To improve the performance of ANNs, tangent hyperbolic activation function was used. A learning algorithm gives the change $\Delta w_{ji}(k)$ in the weight of a connection between neurons *i* and *j*.

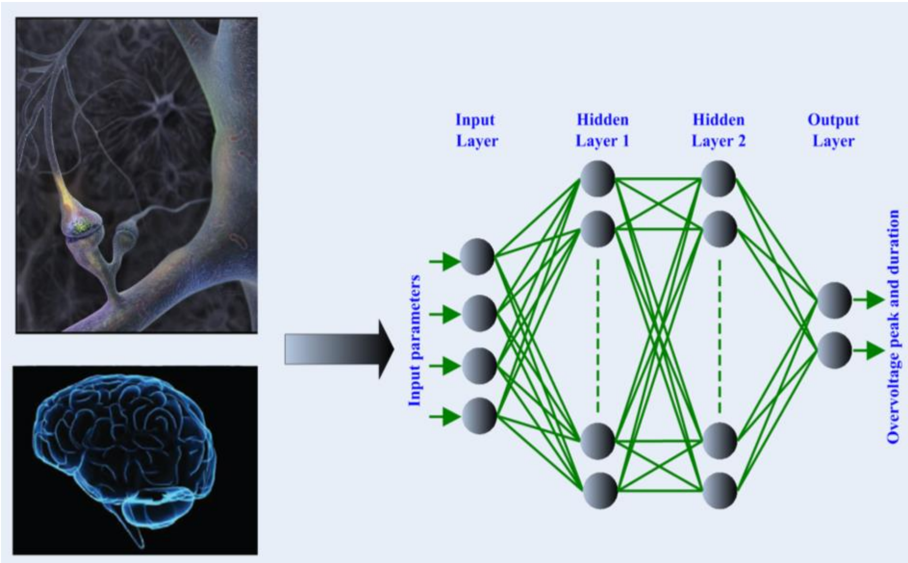


Fig. 9. Proposed MLP-based ANN architecture.

To train ANNs, 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. Relative error is calculated by the difference of PSB output and ANN output:

$$\mathrm{Er}_{\mathrm{Relative}}(\%) = \frac{|\mathrm{ANN}-\mathrm{PSB}|}{\mathrm{PSB}} \times 100. \tag{2}$$

and absolute error is calculated as:

$$\mathrm{Er}_{\mathrm{Absolute}} = |\mathrm{ANN}-\mathrm{PSB}|. \tag{3}$$

3.3 Steps of Assessment and Estimation of Switching Transient Overvoltages

The steps for harmonic overvoltages assessment and estimation follow.

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

Schematic diagram of shunt reactor energization study during power system restoration is illustrated in Fig. 10.

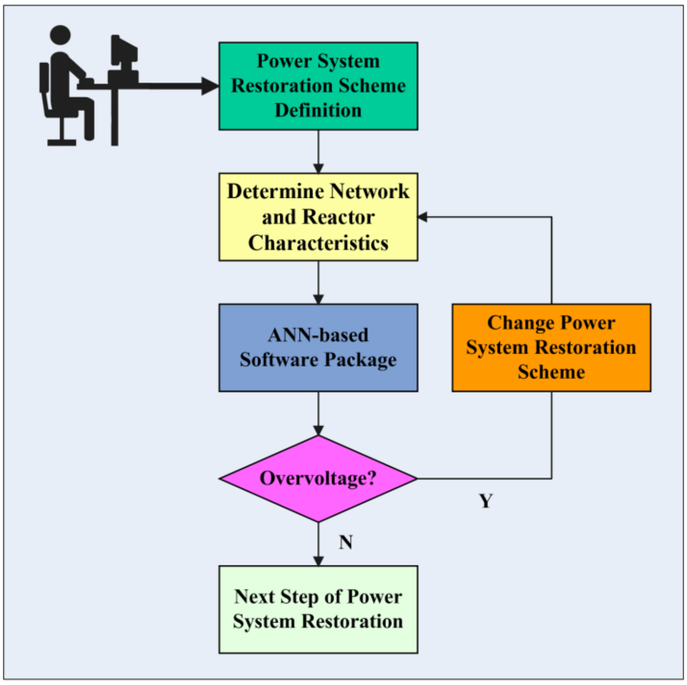


Fig. 10. ANN-based approach to analyze switching overvoltages during shunt reactor energization.

4 Case Study

In this section, the proposed algorithm is demonstrated for a case study that is a portion of 39-bus New England test system, of which its parameters are listed in [13]. The simulations are undertaken on a single phase representation. In proposed method, first, studied system must convert to equivalent circuit of Fig. 1. In other words, values of equivalent resistance, equivalent inductance, and equivalent capacitance are determined and used in trained artificial neural network to estimate overvoltages peak and duration.

Fig. 11 shows a one-line diagram of a portion of 39-bus New England test system which is in restorative state. In this step of the restoration, unit at bus 6 must be restarted. In order to reduce the steady state overvoltage of no load transmission lines, the reactor at bus 6 should be energized. In this condition, harmonic overvoltages can be produced.

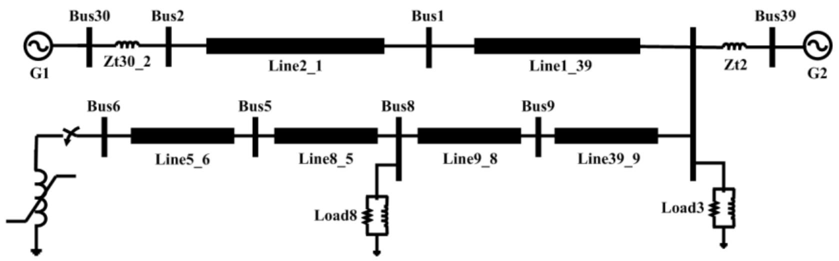


Fig. 11. Studied system for shunt reactor energization.

After converting this system to equivalent circuit of Fig. 1, i.e., after calculating equivalent circuit seen from bus 5, various cases of reactor energization are taken into account and corresponding overvoltages peak and duration are computed from PSB program and trained ANN. In this case, values of equivalent resistance, equivalent inductance and equivalent capacitance are 0.00577 p.u., 0.02069, and 0.99 p.u., respectively. Summary of few result are presented in Table 2. It can be seen from the results that the ANN is able to learn the pattern and give results to acceptable accuracy.

5 Discussion

As can be seen in Table 2, all trained ANNs based on BDB, EDBD, and DRS algorithms can estimate overvoltages peak and duration with proper accuracy. Table 3 presents a comparison between these algorithms based on average of relative and absolute error. Based on Table 3, it can be concluded that EDBD algorithm has better performance (smaller relative and absolute error) and is proper for evaluating of shunt reactor overvoltages in restoration studies.

6 Conclusion

This paper presents an artificial neural network (ANN) to study switching overvoltages during shunt reactor energization. The delta-bar-delta, extended delta-

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bar-delta and directed random search has been adopted to train ANN. Also, a new approach is proposed to reduce time-domain simulations based on worst switching angle and remanent flux determination. In addition, since equivalent circuit parameters of the network are used as ANN inputs, developed ANN is applicable to every studied system.

Table 2. Some sample testing data and output

Delta-bar-delta algorithm:								
V	L.L.	S.R.	V_{PSB}	V_{DBD}	$error_V$	T_{PSB}	T_{DBD}	$error_T$
1.1442	150	70	1.5011	1.4644	2.4451	0.1936	0.1922	0.7166
1.1561	165	45	1.5453	1.5618	1.0689	0.2375	0.2299	3.1937
1.2302	178	30	1.6769	1.7256	2.9026	0.3469	0.3388	2.3294
1.2514	200	30	1.7481	1.8075	3.3971	0.3952	0.3888	1.6181
1.3326	215	23	1.9507	1.9712	1.0504	0.5104	0.5095	0.1692
1.3326	215	17	1.9914	1.9218	3.4932	0.5536	0.5447	1.6115
1.4165	230	17	2.1652	2.1986	1.5426	0.6742	0.6553	2.7998
1.4327	242	10	2.2479	2.2474	0.0218	0.7593	0.7516	1.0130
Extended delta-bar-delta algorithm:								
V	L.L.	S.R.	V_{PSB}	V_{EDBD}	$error_V$	T_{PSB}	T_{EDBD}	$error_T$
1.1442	150	70	1.5011	1.5351	2.2653	0.1936	0.1916	1.0217
1.1561	165	45	1.5453	1.5202	1.6232	0.2375	0.2317	2.4216
1.2302	178	30	1.6769	1.6227	3.2298	0.3469	0.3409	1.7250
1.2514	200	30	1.7481	1.7333	0.8460	0.3952	0.3940	0.2922
1.3326	215	23	1.9507	1.9056	2.3105	0.5104	0.5069	0.6853
1.3326	215	17	1.9914	1.9682	1.1630	0.5536	0.5347	3.4216
1.4165	230	17	2.1652	2.1291	1.6686	0.6742	0.6656	1.2817
1.4327	242	10	2.2479	2.2110	1.6407	0.7593	0.7630	0.4880
Directed random search algorithm:								
V	L.L.	S.R.	V_{PSB}	V_{DRS}	$error_V$	T_{PSB}	T_{DRS}	$error_T$
1.1442	150	70	1.5011	1.5530	3.4598	0.1936	0.1890	2.3990
1.1561	165	45	1.5453	1.5827	2.4205	0.2375	0.2455	3.3850
1.2302	178	30	1.6769	1.6911	0.8458	0.3469	0.3536	1.9262
1.2514	200	30	1.7481	1.6986	2.8343	0.3952	0.3844	2.7202
1.3326	215	23	1.9507	2.0145	3.2708	0.5104	0.5213	2.1362
1.3326	215	17	1.9914	1.9824	0.4508	0.5536	0.5344	3.4601
1.4165	230	17	2.1652	2.1132	2.4039	0.6742	0.6753	0.1689
1.4327	242	10	2.2479	2.2713	1.0404	0.7593	0.7331	3.4489

V = voltage at reactor bus before switching [p.u.], L.L. = line length [km], S.R. = shunt reactor capacity [MVAR], V_{PSB} = overvoltage peak calculated by PSB [p.u.], V_{DBD} = overvoltage peak calculated by BDB [p.u.], V_{EDBD} = overvoltage peak calculated by EBDB [p.u.], V_{DRS} = overvoltage peak calculated by DRS [p.u.], T_{PSB} = overvoltage duration calculated by PSB [s], T_{DBD} = overvoltage duration calculated by BDB [s], T_{EDBD} = overvoltage duration calculated by EBDB [s], T_{DRS} = overvoltage duration calculated by DRS [s], $error_V$ = voltage relative error [%], and $error_T$ = duration time relative error [%].

Table 3. Values of relative and absolute errors for various algorithms

ANN model	Average of relative peak error [%]	Average of absolute peak error [p.u.]	Average of relative duration time error [%]	Average of absolute duration time error [s]
Delta-bar-delta	1.9902	0.0357	1.6814	0.0075
Extended delta-bar-delta	1.8434	0.0337	1.4171	0.0062
Directed random search	2.0908	0.0377	2.4556	0.0109

The proposed ANN approach is tested on a partial 39-bus New England test system. 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. Results show that EDBD algorithm presents best performance. 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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