Delta-Bar-Delta and Directed Random Search Algorithms Application to Reduce Transformer Switching Overvoltages

Iman Sadeghkhani[1], Abbas Ketabi[2], and Rene Feuillet[3]

[1]Department of Electrical Engineering, Najafabad Branch, Islamic Azad University, Najafabad 85141-43131, Iran
[2]Department of Electrical Engineering, University of Kashan, Kashan 87317-51167, Iran
[3]Grenoble Electrical Engineering Lab (G2ELab), Grenoble INP, France

Abstract: This paper proposed an artificial neural network (ANN)-based approach to mitigate harmonic overvoltages during transformer energization. Uncontrolled energization of large power transformers may result in magnetizing inrush current of high amplitude and switching overvoltages. The most effective method for the limitation of the switching overvoltages is controlled switching since the magnitudes of the produced transients are strongly dependent on the closing instants of the switch. We introduce a harmonic index that it's minimum value is corresponding to the best case switching time. Also, in this paper three learning algorithms, delta-bar-delta (DBD), extended delta-bar-delta (EDBD) and directed random search (DRS) were used to train ANNs to estimate the optimum switching instants for real time applications. ANNs training is performed based on equivalent circuit parameters of the network. Thus, trained ANN is applicable to every studied system. To verify the effectiveness of the proposed index and accuracy of the ANN-based approach, two case studies are presented and demonstrated.

Keywords: Artificial neural networks, delta-bar-delta, directed random search algorithm, harmonic index, switching overvoltages, transformer energization.

1. Introduction

A major process of power system restoration following a blackout would be energization of primary restorative transmission lines in most countries [1-4]. The energizing process begins by starting black-start generators such as hydro generators or gas turbines, and then charging some pre-defined transmission lines to supply cranking power for large generation plants [5,6]. Then the energization of unloaded transformers would be followed by switching action, and that is an inevitable process of bottom-up restoration strategy. During transformer energization, unexpected over-voltage may happen due to nonlinear interaction between the unloaded transformer and the transmission system [1,2]. When a lightly loaded transformer is energized, the initial magnetizing current is generally much larger than the steady-state magnetizing current and often much larger than the rated current of the transformer [7-8]. Controlled switching has been recommended as a reliable method to reduce switching overvoltage during energization of capacitor banks, transformers, and transmission lines [9]. This technique is the most effective method for the limitation of the switching transients since the magnitudes of the created transients are strongly dependent on the closing instants of the switch [10].

The fundamental requirement for all controlled switching applications is the precise definition of the optimum switching instants [10]. This paper presents a novel method for controlled energization of transformers in order to minimize temporary overvoltages. We introduce a harmonic index to determine the best case switching time. Using numerical algorithm we can find the time that the harmonic index is minimum, i.e., harmonic overvoltages is minimum. Also, for real time applications, this paper presents an Artificial

Received: May 3rd, 2012. Accepted: March 8th, 2013

Neural Network (ANN)-based approach to estimate optimum switching angle during transformer energization. Three learning algorithms, delta-bar-delta (DBD), extended delta-bar-delta (EDBD) and directed random search (DRS) were used to train ANNs. The proposed ANN is expected to learn many scenarios of operation to give the optimum switching angle 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 inrush currents such as voltage at transformer bus before switching, equivalent resistance, equivalent inductance, equivalent capacitance, line length, line capacitance, switching angle, and remanent flux. This information will help the operator to select the proper best-case switching condition of transformer to be energized safely with transients appearing safe within the limits.

2. Harmonic Overvoltages Study during Transformer Energization

One of the major concerns in power system restoration is the occurrence of overvoltages as a result of switching procedures [2]. The major cause of harmonic resonance overvoltages problems is the switching of lightly loaded transformers at the end of transmission lines. After transformer energization, inrush currents with significant harmonic content up to frequencies around ten times of system frequency are produced. 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 [11]. This leads to a higher level of saturation resulting in higher harmonic components of the inrush current which again results in increased voltages. They may lead to long lasting overvoltages resulting in arrester failures and system faults and prolong system restoration [2]. 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 [1,7,12].

The root cause of this phenomenon is the unfavorable combination of the source impedance, the shunt capacitance of the energized circuits, the non-linear magnetizing characteristics of the energized transformer, inadequate damping of the system and the source voltage phase angle at the moment the transformer is energized. Key factors for the harmonic overvoltages analysis can be listed as follows:

- The resonance frequency of the network;
- The system damping including the network losses, and the load connected to the network;
- The voltage level at the end of the EHV lines;
- The saturation characteristic of the transformers;
- The remanent fluxes in the core of the transformer;
- The closing time of the circuit breaker pole;

3. Study System Modeling

Simulations presented in this paper are performed using the PSB [13]. This program has been compared with other popular simulation packages (EMTP and Pspice) in [14]. In [15] generators have been modeled by generalized Park's model that both electrical and mechanical part are thoroughly modeled, but it has been shown that a simple static generator model containing an ideal voltage source behind the sub-transient inductance in series with the armature winding resistance can be as accurate as the Park model. Thus in this work, generators are represented by the static generator model. Phases of voltage sources are determined by the load flow results. Transmission lines are described by the distributed line model. This model is accurate enough for frequency dependent parameters, because the positive sequence resistance and inductance are fairly constant up to approximately 1 KHz [16] which cover the frequency range of harmonic overvoltages phenomena. The transformer 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 [7]. For the target transformer, hysteresis is added, in order to take into account the remanent fluxes in the iron core. The remanent fluxes in the transformer core can be obtained via the integration of the voltages measured on the transformer windings during its disconnection. The correct estimation of the residual flux is extremely important for the success of the controlled switching strategy. All of the loads and shunt devices, such as capacitors and reactors, are modeled as constant impedances.

4. Evaluation of Optimum Switching Condition

The main part of a controlled switching arrangement is a controller, which is the "brain" of the system. It receives the signals from the measuring devices, determines the appropriate reference phase angles and sends the switching commands to each pole of the switching device so that closing operation occurs at the optimum instant.

Normally for harmonic overvoltages analysis, the best 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. Using the best switching condition, the harmonic overvoltages peak and duration can be reduced significantly.

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

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

This index can be a definition for the best-case switching condition. Using a numerical algorithm, one can find the switching time for which W is minimal (i.e., harmonic overvoltages is minimal).

The sample system considered for explanation of the proposed methodology is a 400 kV EHV network shown in Figure 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. Also, 100 MVA is considered as a base power.

In this paper equivalent circuit parameters are used as ANN inputs together other parameters to achieve good generalization capability for trained ANN. In fact, in this approach ANN is trained just once for sample system of Figure 1. Since ANN training is based on equivalent circuit parameters, developed ANN is applicable to every studied system. This issue is better understood in section 6 that trained ANN is tested for a 39-bus New England test system.

Figure 2 shows the result of the frequency analysis at bus 2. The magnitude of the Thevenin impedance, seen from bus 2, Z_{bus2} shows a parallel resonance peak at 230 Hz. Figure 3 shows changes of harmonic currents and W index with respect to the switching angle, where k is harmonic number. Figure 4 shows the harmonic overvoltages after the transformer energization for the best-case condition (i.e., 56°). Table 1 summarizes the results of overvoltages simulation for five different switching conditions that verify the effectiveness of W index.

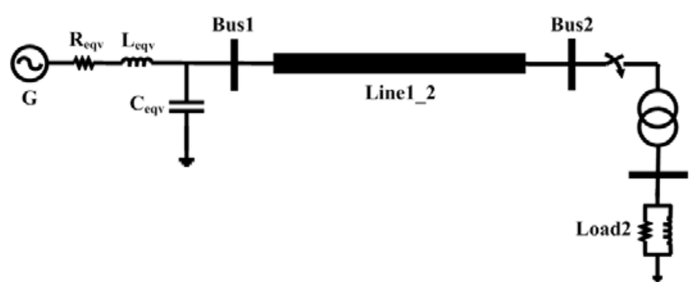

Figure 1. Sample system for transformer energization study. G: generator, R_{eqv}: equivalent resistance, L_{eqv}: equivalent inductance, and C_{eqv}: equivalent capacitance.

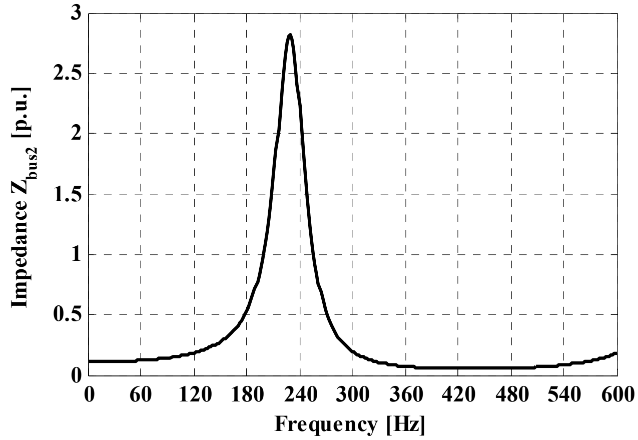

Figure 2. Impedance at bus 2.

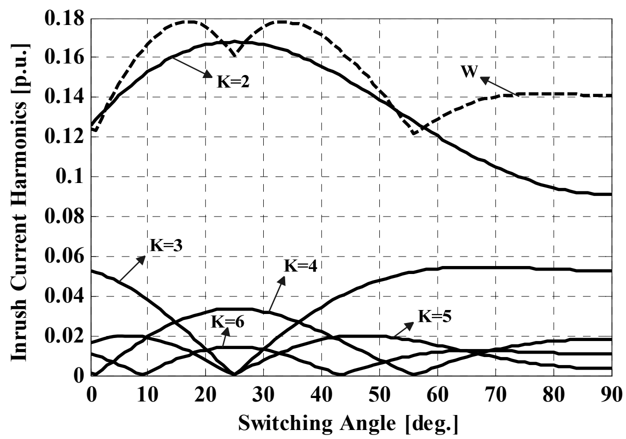

Figure 3. Changes of harmonic currents and *W* index with respect to the switching angle.

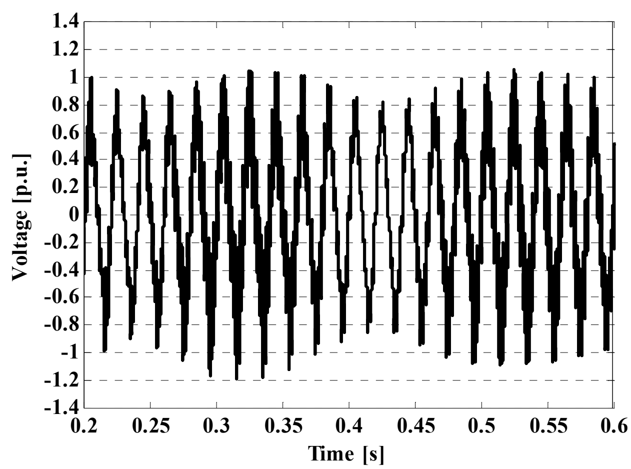

Figure 4. Voltage at bus 2 after switching of transformer for best switching condition.

Table 1. Effect of Switching Angle on the Minimum of Overvoltages 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]
56	1.1857	0
45	1.5104	0.3752
33	1.6527	0.4253
70	1.3892	0.1442
10	1.5861	0.3248

5. The Artificial Neural Network

Te The basic structure of the Artificial Neural Network (ANN) is shown in Figure 5. The ANN 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 [17-20]. 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 ANN [21]. 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*. Error is calculated by the difference of PSB output and ANN output:

$$\text{Error}(\%) = \frac{|\text{ANN} - \text{PSB}|}{\text{PSB}} \times 100 \qquad (2)$$

In the next section, these learning algorithms have been explained briefly.

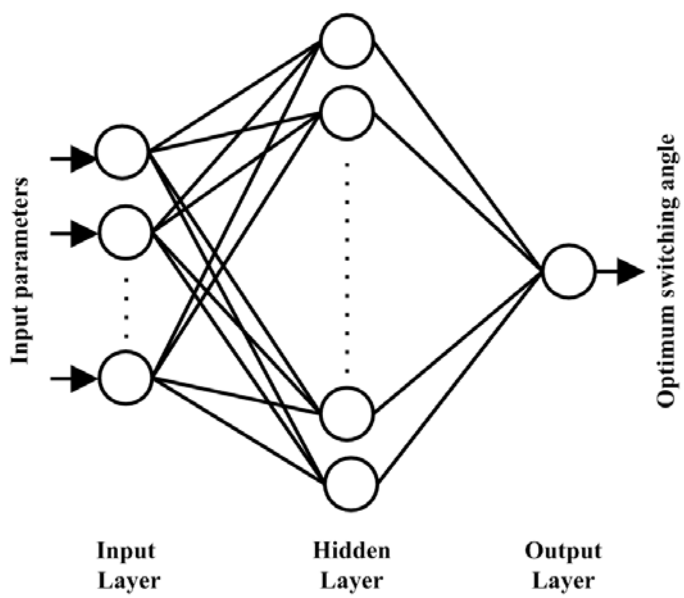

Figure 5. The structure of artificial neural network.

A. Delta-bar-delta (DBD) algorithm

The DBD algorithm is a heuristic approach to improve the convergence speed of the weights in ANNs [22]. The weights are updated by

$$w(k+1) = w(k) + \alpha(k)\delta(k) \qquad (3)$$

where $\alpha(k)$ is the learning coefficient and assigned to each connection, $\delta(k)$ is the gradient component of the weight change. $\delta(k)$ is employed to implement the heuristic for incrementing and decrementing the learning coefficients for each connection. The weighted average $\bar{\delta}(k)$ is formed as

$$\bar{\delta}(k) = (1-\theta)\delta(k) + \theta\delta(k-1) \tag{4}$$

where θ is the convex weighting factor. The learning coefficient change is given as

$$\Delta\alpha(k) = \begin{cases} \kappa & \bar{\delta}(k-1)\delta(k) > 0 \\ -\varphi\alpha(k) & \bar{\delta}(k-1)\delta(k) < 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where κ is the constant learning coefficient increment factor, and φ is the constant learning coefficient decrement factor.

B. Extended delta-bar-delta (EDBD) algorithm

The EDBD algorithm is an extension of the DBD and based on decreasing the training time for ANNs [23]. In this algorithm, the changes in weights are calculated from:

$$\Delta w(k+1) = \alpha(k)\delta(k) + \mu(k)\Delta w(k) \tag{6}$$

and the weights are then found as

$$w(k+1) = w(k) + \Delta w(k) \tag{7}$$

In Eq. (6), $\alpha(k)$ and $\mu(k)$ are the learning and momentum coefficients, respectively. The learning coefficient change is given as

$$\Delta\alpha(k) = \begin{cases} \kappa_\alpha \exp(-\gamma_\alpha \left|\bar{\delta}(k)\right| & \text{if} \quad \bar{\delta}(k-1)\delta(k) > 0 \\ -\varphi_\alpha\alpha(k) & \text{if} \quad \bar{\delta}(k-1)\delta(k) < 0 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where κ_α is the constant learning coefficient scale factor, *exp* is the exponential function, φ_α is the constant learning coefficient decrement factor, and γ_α is the constant learning coefficient exponential factor. The momentum coefficient change is also written as

$$\Delta\mu(k) = \begin{cases} \kappa_\mu \exp(-\gamma_\mu \left|\bar{\delta}(k)\right| & \text{if} \quad \bar{\delta}(k-1)\delta(k) > 0 \\ -\varphi_\mu\mu(k) & \text{if} \quad \bar{\delta}(k-1)\delta(k) < 0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where κ_μ is the constant momentum coefficient scale factor, φ_μ is the constant momentum coefficient decrement factor, and γ_μ is the constant momentum coefficient exponential factor.

In order to take a step further to prevent wild jumps and oscillations in the weight space, ceilings are placed on the individual connection learning and momentum coefficients [23].

C. Directed random search (DRS)

The directed random search is a reinforcement learning approach and used to calculate the weights of ANNs. This algorithm also tries to minimize the overall error [24]. Random steps are taken in the weights and a directed component is added to the random step to enable an impetus to pursue previously search directions. The DRS is based on four procedures as random step, reversal step, directed procedure and self-tuning variance. In the random step, a random value is added to each weight of network and the error is then evaluated for all training sets as

$$w(k+1) = w_{best} + dw(k) \tag{10}$$

where w_{best} is the best weight vector previous to iteration k and $dw(k)$ is the delta weight vector at iteration k. Depending on the error evaluation, the weights are replaced with the new weights. If there is no improvement at the error in the random step, some random value is subtracted from the weight value during the reversal step, that is

$$w(k+1) = w_{best} - dw(k) \tag{11}$$

In [24], a directed procedure has been added to the random step to further improve with reversals. The new weights are obtained from:

$$w(k+1) = w_{best} - dw(k) + dp(k) \tag{12}$$

where $dp(k)$ is the directed procedure and based on the history of success or failure of the random steps.

Following parameters have been used as ANN inputs:

- Voltage at transformer bus before switching
- Equivalent resistance of the network
- Equivalent inductance of the network
- Equivalent capacitance of the network
- Line length
- Line capacitance
- Remanent flux

6. 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, which its parameters are listed in [25].

A. Case 1

Figure 6 shows a one-line diagram of a portion of 39-bus New England test system which is in restorative state. The generator at bus 35 is a black-start unit. The load 19 shows cranking power of the later generator that must be restored by the transformer of bus 19. When the transformer is energized, harmonic overvoltages can be produced because the transformer is lightly loaded.

As mentioned in section 4, first, equivalent circuit of this system, seen behind bus 16, is determined and values of equivalent resistance, equivalent inductance, and equivalent capacitance are calculated, in other words, this system is converted to equivalent system of

Figure 1. In this case, values of equivalent resistance, equivalent inductance and equivalent capacitance are 0.00291 p.u., 0.02427, and 2.474 p.u., respectively. For testing trained ANN, values of voltage at transformer bus (bus 19), line length, and remanent flux are varied and in each step, optimum switching angle values are calculated from trained ANN and proposed method. Table 2 contains the some sample result of test data of case 1.

Table 2. Case 1 some sample testing data and output

Delta-bar-delta algorithm:

V [p.u.]	L.L. [km]	Φ_r [p.u.]	B.S.A.$_{HI}$ [deg.]	B.S.A.$_{DBD}$ [deg.]	Error [%]
0.9243	100	0.2	80.6	79.0	2.0150
0.9541	150	0.3	37.5	37.9	1.0054
1.0195	200	0.4	18.3	18.9	3.1244
1.0481	230	0.4	44.8	44.7	0.3241
1.0977	250	0.5	62.1	62.7	1.0237
1.0977	250	0.6	89.7	87.1	2.8766
1.1505	270	0.7	67.7	70.1	3.4791
1.1776	290	0.8	32.6	32.7	0.2374

Extended delta-bar-delta algorithm:

V [p.u.]	L.L. [km]	Φ_r [p.u.]	B.S.A.$_{HI}$ [deg.]	B.S.A.$_{EDBD}$ [deg.]	Error [%]
0.9243	100	0.2	80.6	81.4	0.9450
0.9541	150	0.3	37.5	37.9	1.0209
1.0195	200	0.4	18.3	18.8	2.8778
1.0481	230	0.4	44.8	44.2	1.4402
1.0977	250	0.5	62.1	63.2	1.8443
1.0977	250	0.6	89.7	86.8	3.2207
1.1505	270	0.7	67.7	68.6	1.3270
1.1776	290	0.8	32.6	33.3	2.2361

Directed random search algorithm:

V [p.u.]	L.L. [km]	Φ_r [p.u.]	B.S.A.$_{HI}$ [deg.]	B.S.A.$_{DRS}$ [deg.]	Error [%]
0.9243	100	0.2	80.6	78.3	2.8808
0.9541	150	0.3	37.5	36.8	1.8974
1.0195	200	0.4	18.3	18.2	0.3234
1.0481	230	0.4	44.8	45.3	1.0335
1.0977	250	0.5	62.1	60.8	2.1078
1.0977	250	0.6	89.7	89.1	0.6399
1.1505	270	0.7	67.7	66.0	2.5661
1.1776	290	0.8	32.6	33.2	1.9211

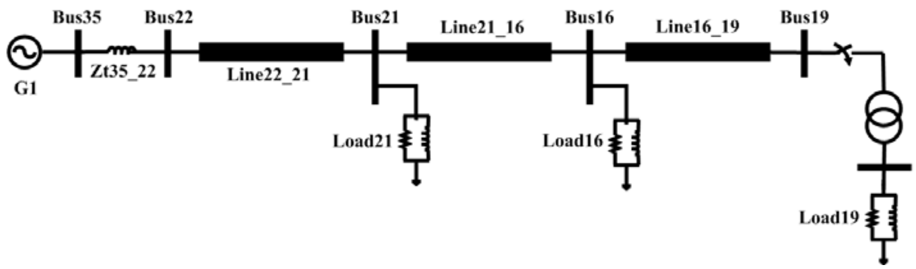

Figure 6. Studied system for case 1.

V = voltage at transformer bus before switching, L.L. = line length, Φ_r = remanent flux, $B.S.A_{HI}$ = the best switching angle obtained by the harmonic index, $B.S.A_{DBD}$ = the best switching angle obtained by the DBD, $B.S.A_{EDBD}$ = the best switching angle obtained by the EDBD, $B.S.A_{DRS}$ = the best switching angle obtained by the DRS, and Error = switching angle error.

B. Case 2

As another example, the system in Figure 7 is examined. In the next step of the restoration, unit at bus 6 must be restarted. In order to provide cranking power for this unit, the transformer at bus 6 should be energized. In this condition, harmonic overvoltages can be produced because the load of the transformer is small. After converting this system to equivalent circuit of Figure 1, various cases of transformer energization are taken into account and corresponding optimum switching angles are computed from proposed method 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. Summery of few result are presented in Table 3. It can be seen from the results that the ANNs are able to learn the pattern and give results to acceptable accuracy.

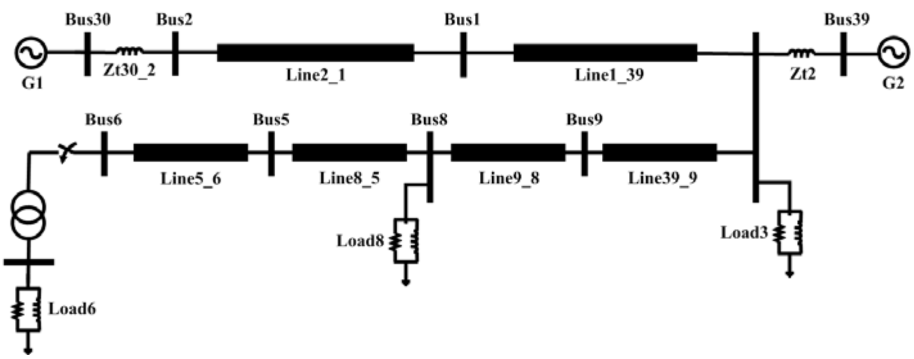

Figure 7. Studied system for case 2.

Conclusion

This paper presents an ANN application to evaluate optimum switching condition during transformer energization for real time application. The proposed method is based on the harmonic index which integrates the key parameters of overvoltages generation. The minimum value of this index is corresponding to the best switching time for the transformer energization. The delta-bar-delta, extended delta-bar-delta and directed random search has been adopted to train ANN. Training ANN is based on equivalent circuit parameters to achieve good generalization capability for trained ANN. Simulation results confirm the effectiveness and accuracy of the proposed harmonic index and ANNs scheme.

Table 3. Case 2 some sample testing data and output

Delta-bar-delta algorithm:

V [p.u.]	L.L. [km]	Φ_r [p.u.]	B.S.A.$_{HI}$ [deg.]	B.S.A.$_{DBD}$ [deg.]	Error [%]
0.9335	125	0.8	75.4	74.6	1.0268
0.9512	155	0.7	42.9	42.8	0.2798
0.9906	175	0.6	56.1	54.3	3.2491
0.9906	175	0.5	90	89.5	0.5837
1.0502	215	0.4	82.3	83.4	1.3537
1.0595	225	0.3	29.4	28.9	1.7010
1.1025	240	0.2	45.6	44.3	2.8381
1.1293	265	0.2	51.2	50.5	1.4200

Extended delta-bar-delta algorithm:

V [p.u.]	L.L. [km]	Φ_r [p.u.]	B.S.A.$_{HI}$ [deg.]	B.S.A.$_{EDBD}$ [deg.]	Error [%]
0.9335	125	0.8	75.4	72.9	3.2789
0.9512	155	0.7	42.9	42.1	1.7887
0.9906	175	0.6	56.1	55.7	0.7395
0.9906	175	0.5	90	88.7	1.4739
1.0502	215	0.4	82.3	84.7	2.9034
1.0595	225	0.3	29.4	29.5	0.4986
1.1025	240	0.2	45.6	46.1	1.1257
1.1293	265	0.2	51.2	52.7	2.8627

Directed random search algorithm:

V [p.u.]	L.L. [km]	Φ_r [p.u.]	B.S.A.$_{HI}$ [deg.]	B.S.A.$_{DRS}$ [deg.]	Error [%]
0.9335	125	0.8	75.4	76.1	0.9575
0.9512	155	0.7	42.9	44.3	3.2421
0.9906	175	0.6	56.1	56.6	0.8216
0.9906	175	0.5	90	89.6	0.4479
1.0502	215	0.4	82.3	81.1	1.4442
1.0595	225	0.3	29.4	28.7	2.2215
1.1025	240	0.2	45.6	45.3	0.6354
1.1293	265	0.2	51.2	51.9	1.4113

V = voltage at transformer bus before switching, L.L. = line length, Φ_r = remanent flux, B.S.A$_{HI}$ = the best switching angle obtained by the harmonic index, B.S.A$_{DBD}$ = the best switching angle obtained by the DBD, B.S.A$_{EDBD}$ = the best switching angle obtained by the EDBD, B.S.A$_{DRS}$ = the best switching angle obtained by the DRS, and Error = switching angle error.

References

[1] M.M. Adibi and R.J. Kafka, "Power System Restoration Issues," IEEE Computer Application in power, vol. 4, no. 2, pp. 19-24, Apr. 1991.

[2] M. M. Adibi, R.W. Alexander, and B. Avramovic, “Overvoltage control during restoration,” IEEE Trans. Power Syst., vol. 7, no. 4, pp. 1464–1470, Nov. 1992.

[3] A. Ketabi, A.M. Ranjbar, and R. Feuillet, “Analysis and Control of Temporary Overvoltages for Automated Restoration Planning,” IEEE Trans. Power Delivery, vol. 17, no. 4, pp. 1121–1127, 2002.

[4] S.A. Taher and I. Sadeghkhani, Estimation of Magnitude and Time Duration of Temporary Overvoltages using ANN in Transmission Lines during Power System Restoration, Simulation Modelling Practice and Theory, vol. 18, no. 6, pp. 787-805, Jun. 2010.

[5] G. Morin, “Service restoration following a major failure on the hydroquebec power system,” IEEE Trans. Power Delivery, vol. 2, pp. 454–463, Apr. 1987.

[6] O. Bourgault, G. Morin, “Analysis of harmonic overvoltage due to transformer saturation following load shedding on hydro-quebec-NYPA 765 kV interconnection,” IEEE Trans. Power Delivery, vol. 5, no. 1, pp. 397–405, Jan. 1990.

[7] G. Sybille, M. M. Gavrilovic, J. Belanger, and V. Q. Do, “Transformer saturation effects on EHV system overvoltages,” IEEE Trans. Power App. Syst., vol. PAS-104, no. 3, pp. 671–680, Mar. 1985.

[8] A. Ketabi, I. Sadeghkhani, and R. Feuillet, Using Artificial Neural Network to Analyze Harmonic Overvoltages during Power System Restoration, European Transactions on Electrical Power, vol. 21, no. 7, pp. 1941-1953, Oct. 2011.

[9] J.H. Brunke, K.J. Fröhlich, “Elimination of Transformer Inrush Currents by Controlled Switching–Part I: Theoretical Considerations,” IEEE Trans. on Power Delivery, vol. 16, no. 2, pp. 276 – 280, April 2001

[10] K. Dantas, D. Fernandes, L.A. Neves, B.A. Souza, L. Fonseca ,“Mitigation of switching overvoltages in transmission lines via controlled switching,” Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE, pp. 1-8, Jul. 2008.

[11] T. Hayashi et al., “Modeling and simulation of black start and restoration of an electric power system. Results of a questionnaire,” Electra, no. 131, pp. 157–169, July 1990.

[12] L.H. Fink, K.L. Liou, C.C. Liu, “From generic restoration actions to specific restoration strategies,” IEEE Trans. Power Syst., vol. 10, no. 2, pp. 745–752, May 1995.

[13] A. Ketabi and I. Sadeghkhani, Electric Power Systems Simulation Using MATLAB, 2nd Edition, Morsal Publications, 2012. (in Persian)

[14] G. Sybille, P. Brunelle, L. Hoang, L. A. Dessaint, and K. Al-Haddad, “Theory and applications of power system blockset, a MATLAB/Simulink-based simulation tool for power systems,” in Proc. IEEE Power Eng. Soc. Winter Meeting, pp. 774–779, 2000.

[15] M.M. Duro, “Damping Modelling in Transformer Energization Studies for System Restoration: Some Standard Models Compared to Field Measurements,” in Proc. IEEE Bucharest Power Tech Conference, Bucharest, Romania, Jun. 2009.

[16] P.G. Boliaris, J.M. Prousalidis, N.D. Hatziargyriou, and B. C. Papadias, “Simulation of long transmission lines energization for black start studies,” in Proc. 7th Mediterranean Electrotechn.Conf., pp. 1093–1096, 1994.

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

[18] A. Maren, C. Harston, R. Pap, Handbook of Neural Computing Applications, London Academic Press, 1990.

[19] D.A. Asfani , A.K. Muhammad, Syafaruddin, M.H. Purnomo, T. Hiyama, “Temporary short circuit detection in induction motor winding using combination of wavelet transform and neural network,” Expert Systems with Applications, vol. 39, no. 5, pp. 5367–5375, Apr. 2012.

[20] A. Ebrahimzadeh Shrme, “Hybrid intelligent technique for automatic communication signals recognition using Bees Algorithm and MLP neural networks based on the efficient features,” Expert Systems with Applications, vol. 38, no. 5, pp. 6000-6006, May 2011.
[21] R. Bayindir, S. Sagiroglu, I. Colak, "An intelligent power factor corrector for power system using artificial neural networks," Electric Power Systems Research, vol. 79, no. 1, pp. 152–160, 2009.
[22] R.A. Jacobs, "Increased rate of convergence through learning rate adaptation," Neural Networks, vol. 1, no. 4, pp. 295–307, 1988.
[23] A. Minai and R.D. Williams, "Acceleration of backpropagation through learning rate and momentum adaptation," International Joint Conference on Neural Networks, pp. 676–679, 1990.
[24] J. Matyas, "Random optimization," Automation and Remote Control, vol. 26, no. 2, pp. 246–253, 1965.
[25] S. Wunderlich, M.M. Adibi, R. Fischl, and C.O.D. Nwankpa, “An approach to standing phase angle reduction,” IEEE Trans. Power Syst., vol. 9, no. 1, pp. 470–478, Feb. 1994.

Iman Sadeghkhani received the B.Sc. and M.Sc degrees both with honors in Electrical Engineering, from Department of Electrical Engineering, Najafabad Branch-Islamic Azad University and University of Kashan, Iran, in 2007 and 2009, respectively. Currently, he is working towards the Ph.D. degree in Electrical Engineering at Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan, Iran. His research interests are power system restoration, transient studies, and artificial intelligence application to power systems. He has authored three books and more than 35 papers on power systems. Mr. Sadeghkhani was the recipient of the University of Kashan Award for Distinguished Research in 2010.

Abbas Ketabi received the B.Sc. and M.Sc. degrees in electrical engineering from the Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran, in 1994 and 1996, respectively, and the Ph.D. degree in electrical engineering jointly from Sharif University of Technology and the Institut National Polytechnique de Grenoble, Grenoble, France, in 2001. Since then, he has been with the Department of Electrical Engineering, University of Kashan, Kashan, Iran, where he is currently an Associate Professor. He has published more than 50 technical papers and three books. He is the Manager and an Editor of *Energy Management*. His research interests include the power system restoration, expert systems, and transient studies. Dr. Ketabi was the recipient of the University of Kashan Award for Distinguished Teaching and Research.

Rene Feuillet received his Dr. Eng. Degree in Electrical Engineering from INPG in 1979. In 1991, he received the degree of “Habilitation a Diriger des Recherches” from the same institute. From 1979 to1998, he has been appointed as Assistant Professor at the National Electrical Engineering School of Grenoble (ENSIEG), France, and since 1998 he served as a full professor. His research activities in LEG include modeling of power electronics converters and interference perturbations on power networks and components.