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Mitigation of Shunt Reactor Overvoltages Using Delta-Bar-Delta and Directed Random Search Algorithms

***Abstract**. This paper introduces an intelligent-based method using artificial neural network (ANN) to reduce shunt reactor switching overvoltages. In power systems, an overvoltage could be caused by core saturation on the energization of a shunt reactor with residual flux. 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. In addition, in this paper three learning algorithms, delta-bar-delta (DBD), extended delta-bar-delta (EDBD) and directed random search (DRS), were used to train the ANNs to estimate the optimum switching instants for real time applications. ANN is trained with equivalent circuit parameters of the network, so that developed 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.*

***Streszczenie.** W artykule przedstawiono metodę redukcji możliwych przepięć łączeniowych, występujących w reaktancji bocznikowej, przy wykorzystaniu algorytmu inteligentnego, opartego na sieciach neuronowych. Wyznaczono wskaźnik określający najlepsze momenty przełączeń, w zależności od pojawiających się stanów nieustalonych. Do trenowania sieci neuronowej wykorzystano trzy algorytmy uczące się. Przedstawiono dwa przykłady potwierdzające skuteczność działania. (**Redukcja przepięć w reaktancji bocznikowej – algorytmy DBD oraz DRS**).*

Keywords: Artificial neural networks, harmonic index, transient overvoltages, shunt reactor switching.
Słowa kluczowe: sztuczne sieci neuronowe, indeks harmonicznych, przepięcia, przełączanie reaktancji bocznikowej.

1. Introduction

Long EHV transmission lines are generally compensated by means of shunt reactor sets [1]. Reactor failures have directed attention to the transient overvoltages generated by reactor switching. Shunt reactors are applied to regulate the reactive power balance of a system by means of compensating for the surplus reactive power generation of transmission lines. Reactors are normally disconnected at heavy load and are connected to the lines at periods of low load. Consequently, frequent switching is a significant characteristic of shunt reactors in order that they can react to the changing system load condition [1,2].

As is well known, if a sinusoidal current of an inductive element is interrupted before the natural current zero, high overvoltage of an oscillating nature can arise. The bigger the current chopped, the higher the overvoltage peak. If the circuit breaker cannot withstand the oscillating recovery voltage stress, a restrike occurs. In this case the voltage across the open contacts becomes a surge input to the network, leading to transient overvoltages [1].

The fundamental requirement for all controlled switching applications is the precise definition of the optimum switching instants [3]. This paper presents a novel method for controlled energization of shunt reactors in order to minimize transient 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 Neural Network (ANN)-based approach to estimate optimum switching angle during shunt reactor energization. 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 shunt reactor 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 shunt reactor to be energized safely with transients appearing safe within the limits.

2. Modelling Issues

2.1. PSB

Simulations presented in this paper are performed using the PSB [4]. 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 [5]. The user friendly graphical interfaces of PSB enable faster development for power system transient analysis.

2.2. Generator Model

In [6] 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.

2.3. Transmission-Line Model

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 [7] which cover the frequency range of harmonic overvoltages phenomena.

2.4. Shunt Reactor Model

The model takes into account the leakage inductance 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 [8].

2.5. Load Model

All of the loads are modeled as constant impedances.

3. Study of Shunt Reactor Overvoltages

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 [8,9]. 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 [10-13].

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 [11,14,15].

4. Optimum Switching Condition Determination for Overvoltages Simulation

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, shunt reactor 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

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

where: t_0 – switching time, ϕ_r – remanent flux, k – harmonic order.

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 Fig. 1. The normal peak value of any phase voltage is 400√2/√3 kV and this value is taken as base for voltage p.u. In the system studies 400 kV line-to-line base voltage and 100 MVA as a base power is considered.

Fig. 2 shows the 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 200 Hz. Fig. 3 shows changes of harmonic currents and *W* index with respect to the switching angle, where *k* is harmonic number. Fig. 4 shows the harmonic overvoltages after the shunt reactor energization for the best-case condition (i.e., 64°). For temporary overvoltages, the overvoltage duration has to be taken into account in addition to the amplitude [16]. Table 1 summarizes the results of overvoltages simulation for five different switching conditions that verify the effectiveness of *W* index.

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

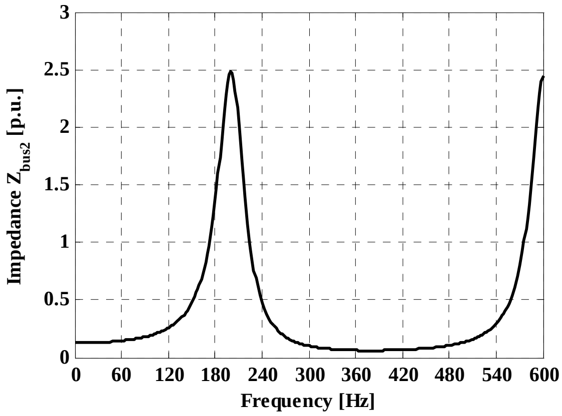

Fig. 2. Impedance at bus 2.

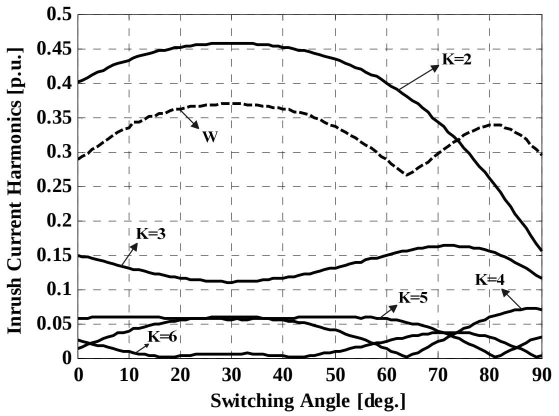

Fig. 3. Changes of harmonic currents and *W* index with respect to the switching angle.

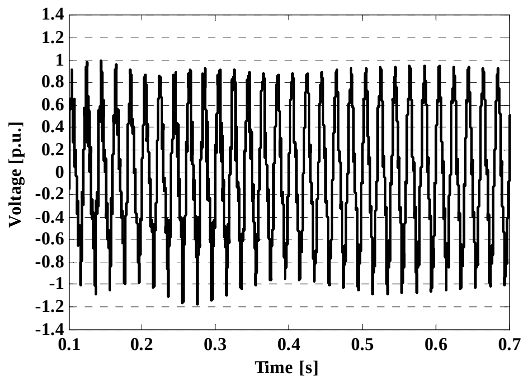

Fig. 4. Voltage at bus 2 after switching of shunt reactor for best switching condition.

Table 1. Effect of Switching Time 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]
64	1.1762	0
32	1.6215	0.4362
10	1.4935	0.3008
69	1.3284	0.0873
40	1.5509	0.3127

5. The Artificial Neural Network

The basic structure of the Artificial Neural Network (ANN) is shown in Fig. 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 [17,18]. 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 [19]. 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:

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

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

5.1. Delta-bar-delta (DBD) algorithm

The DBD algorithm is a heuristic approach to improve the convergence speed of the weights in ANNs [20]. The weights are updated by

$$w(k+1) = w(k) + \alpha(k)\delta(k) \tag{3}$$

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

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

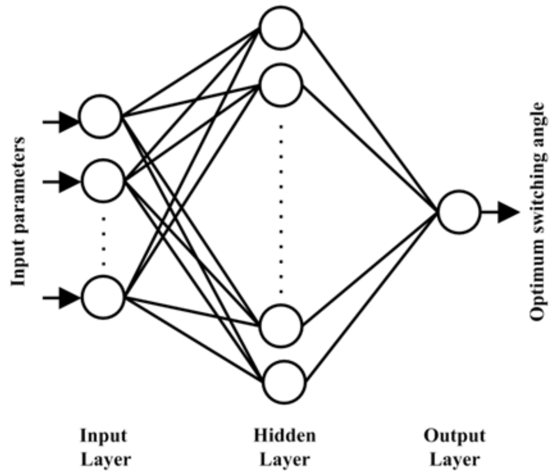

Fig. 5. The structure of artificial neural network.

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.

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

The EDBD algorithm is an extension of the DBD and based on decreasing the training time for ANNs [21]. 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

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

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

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

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 [21].

5.3. 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 [22]. 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

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

In [22], a directed procedure has been added to the random step to further improve with reversals. The new weights are obtained from:

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

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 shunt reactor 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. Steps of Optimum Switching Angle Estimation

The steps for optimum switching angle evaluation and estimation are listed below:

1) Determine the characteristics of shunt reactor that must be energized.
2) Calculate the $Z_{ii}(h)$ at the shunt reactor bus for $h = 2f_0,\ldots,10f_0$.
3) Calculate the best switching condition.
4) Repeat the above steps with various system parameters to learn artificial neural network
5) Test of artificial neural network with different system parameters

7. 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 [23]. The simulations are undertaken on a single phase representation.

7.1. Case 1

Fig. 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. In order to reduce the steady state overvoltage of no load transmission line, a shunt reactor is connected at bus 19. When the reactor is energized, harmonic overvoltages can be produced because of its nonlinear magnetization characteristics.

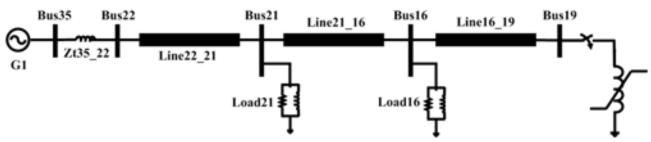

Fig. 6. Studied system for case 1.

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 [%]**
1.1153	100	0.8	32.5	32.4	0.3402
1.1318	122	0.7	61.7	61.1	1.0257
1.1804	146	0.6	50.9	49.7	2.3755
1.2593	170	0.5	41.3	42.7	3.4293
1.1249	195	0.4	82.4	81.2	1.3980
1.2779	210	0.3	67.3	65.4	2.8731
1.3425	235	0.2	39.7	39.5	0.4607
1.3641	250	0.1	74.6	72.4	2.9571
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 [%]**
1.1153	100	0.8	32.5	32.8	0.8145
1.1318	122	0.7	61.7	61.8	0.2350
1.1804	146	0.6	50.9	51.5	1.1601
1.2593	170	0.5	41.3	42.1	2.0133
1.1249	195	0.4	82.4	82.0	0.4789
1.2779	210	0.3	67.3	69.3	3.0373
1.3425	235	0.2	39.7	40.2	1.1524
1.3641	250	0.1	74.6	73.3	1.7080
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 [%]**
1.1153	100	0.8	32.5	32.7	0.5804
1.1318	122	0.7	61.7	59.9	2.8986
1.1804	146	0.6	50.9	52.0	2.2519
1.2593	170	0.5	41.3	41.8	1.1280
1.1249	195	0.4	82.4	82.5	0.0923
1.2779	210	0.3	67.3	68.1	1.2441
1.3425	235	0.2	39.7	40.7	2.6036
1.3641	250	0.1	74.6	73.8	1.0453

V = voltage at shunt reactor 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.

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 [%]**
1.1344	108	0.8	71.9	74.2	3.1451
1.1462	125	0.7	43.7	42.8	2.1630
1.1907	145	0.6	25.6	25.0	2.4497
1.2175	175	0.5	60.2	58.2	3.2868
1.2693	196	0.4	54.9	54.0	1.5823

1.2907	215	0.3	74.2	73.7	0.6184
1.3497	237	0.2	31.4	32.1	2.1587
1.3871	263	0.2	52.7	51.7	1.8143
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 [%]**
1.1344	108	0.8	71.9	71.4	0.6343
1.1462	125	0.7	43.7	43.1	1.4532
1.1907	145	0.6	25.6	26.4	3.0357
1.2175	175	0.5	60.2	58.9	2.1873
1.2693	196	0.4	54.9	54.8	0.1932
1.2907	215	0.3	74.2	73.2	1.4143
1.3497	237	0.2	31.4	31.7	1.0569
1.3871	263	0.2	52.7	52.4	0.5331
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 [%]**
1.1344	108	0.8	71.9	73.5	2.2436
1.1462	125	0.7	43.7	45.2	3.4857
1.1907	145	0.6	25.6	26.0	1.7484
1.2175	175	0.5	60.2	59.3	1.5052
1.2693	196	0.4	54.9	53.3	2.9021
1.2907	215	0.3	74.2	74.5	0.4084
1.3497	237	0.2	31.4	32.1	2.0954
1.3871	263	0.2	52.7	52.3	0.7743

V = voltage at shunt reactor 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.

First, equivalent circuit of this system is determined and values of equivalent resistance, equivalent inductance, and equivalent capacitance are calculated, i.e., this system is converted to system of Fig. 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 shunt reactor bus (bus 19), line length, and remanent flux are varied and in each step, optimum switching angle is calculated from trained ANN and proposed method. Table 2 contains the some sample result of test data of case 1.

7.2. Case 2

As another example, the system in Fig. 7 is examined. In the next step of the restoration, unit at bus 29 must be restarted. In order to reduce the steady state overvoltage of no load transmission lines, the shunt reactor at bus 29 should be energized. In this condition, harmonic overvoltages can be produced.

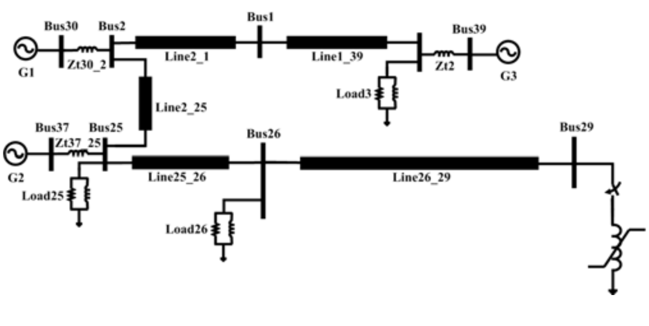

Fig. 7. Studied system for case 2.

After converting this system to equivalent circuit of Fig. 1, i.e., after calculating equivalent circuit seen from bus 26, various cases of shunt reactor 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 0.00792 p.u., 0.0247, and 1.1594 p.u., respectively. Summary of few result are presented in Table 2. It can be seen from the results that the ANNs are able to learn the pattern and give results to acceptable accuracy.

8. Conclusion

This paper presents an ANN-based approach to estimate optimum switching condition during shunt reactor energization. In this approach, a harmonic index has been used which minimum value of this index is corresponding to the best switching time for the shunt reactor energization. The delta-bar-delta, extended delta-bar-delta and directed random search has been adopted to train ANN. To achieve good generalization capability for developed ANN, it has been trained with equivalent circuit parameters. Simulation results confirm the effectiveness and accuracy of the proposed harmonic index and ANNs scheme.

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