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Radial Basis Function based Approach to reduce Shunt Reactor Switching Overvolatges

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Abstract – This paper presents an approach for switching overvoltages reduction during shunt reactor energization. Radial Basis Function Neural Network (RBFNN) has been used to evaluate optimum switching condition. The most effective method for the limitation of the switching overvoltages is controlled switching since the magnitudes of the produced transients are heavily dependent on the closing instants of the switch. This work presents a harmonic index whose minimum value corresponds to the best case switching time. Artificial Neural Network (ANN) is trained with equivalent circuit parameters of the network, so that developed ANN can be applied to every studied system. In order to ascertain the effectiveness of the proposed index and accuracy of the ANN-based approach, two case studies are disussed.

Keywords – Switching overvoltages, radial basis function, shunt reactor energization.

1. Introduction

What compensates for Long EHV transmission lines is shunt reactor sets. Reactor failures have drawn attention to the transient overvoltages generated by reactor switching. Shunt reactors are used 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. As a result, frequent switching is a significant property of shunt reactors because they can react to the changing system load condition [1], [2].

As is well known, the interruption of a sinusoidal current of an inductive element before the natural current zero can result in the high overvoltage of an oscillating nature. The bigger the current is chopped, the higher the overvoltage will peak. If the circuit breaker cannot withstand the oscillating recovery voltage stress, a restrike happens, in which case the voltage across the open contacts changes into a surge input to the network, which will lead to transient overvoltages [1].

What is basically required for all controlled switching applications is the precise definition of the optimum switching instants [3-5]. This paper presents a new method for controlled energization of shunt reactors so that transient overvoltages will be minimised. A harmonic index introduced will determine the best case switching time. Numerical algorithm can be employed to find the time that the harmonic index is minimum, i.e., harmonic overvoltages is minimum. Also, for real time applications, this paper proposes 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 required during online operation of power systems. In the proposed ANN the crucial aspects have been taken into account, which impact 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 that appear to be safe within the limits.

2. Shunt Reactor Switching Overvoltages

This paper deals with the estimation of harmonic overvoltages, which 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., which may lead to long lasting overvoltages that lead to arrester failures and system faults [6-8].

The electrical components of the network are modeled with the MATLAB/Simulink environment [9], [10]. These models ought to be adapted for the desired frequency range (here the frequencies up to $f = 10f_0$ are considered to be sufficient). The generator is represented by an ideal voltage source behind the sub-transient inductance in series with the armature winding resistance which can be as accurate as the Park model [11]. Phase of voltage source is decided by the load flow results. Transmission lines are described by distributed line models. The circuit breaker is represented by an ideal switch. The shunt reactor model considers 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. All of the loads are modeled as constant impedances.

3. Proposed Method for Optimum Condition Determination

3.1. Worst Switching Condition Determination for Overvoltages Simulation

As usual, for harmonic overvoltages analysis, the most efficient factors as function of switching time, shunt reactor characteristics and its initial flux condition, and impedance characteristics of the switching bus are concerned and must be optimized for switching condition. Using the best switching condition, the harmonic overvoltages peak and duration can be reduced significantly.

In order to conclude the best-case switching time, the applied index is defined as:

$$W = \sum_{h=2}^{10} Z_{jj}(h) \cdot I_j(h, t_0, \phi_0) \qquad (1)$$

where t_0 is the switching time and ϕ_0 is initial reactor flux. This index can be a definition for the best-case switching condition. Using a numerical algorithm, switching time that results by minimizing W, can be calculated (i.e., harmonic overvoltages is minimal).

For clarification of the suggested methodology, consider a 400 kV EHV network shown in Fig. 1 as a sample system. The normal peak value of each phase voltage is 400√2/√3 kV and this value is taken as base for voltage p.u. where 100 MVA as a base power is considered.

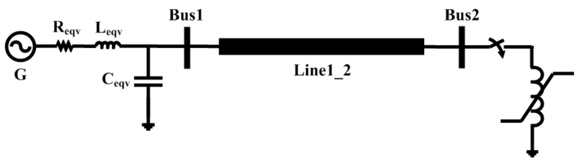

Figure 1. Sample system for shunt reactor energization study. G: generator, R_{eqv}: equivalent resistance, L_{eqv}: equivalent inductance, and C_{eqv}: equivalent capacitance.

The result of the frequency analysis at bus 2 is shown in Fig. 2. A parallel resonance peak at 200 Hz can be distinguished from the magnitude of the Thevenin impedance, seen from bus 2, Z_{bus2}. Changes of harmonic currents and W index considering the switching angle is shown in Fig. 3, where h is harmonic number. Fig. 4 shows the harmonic overvoltages after the shunt reactor energization that is achieved in the best-case condition (i.e., 64°). In addition to the amplitude, the overvoltage duration has to be taken into consideration for temporary overvoltages [12]. Table 1 gives the outline of results of overvoltages simulation for five different switching conditions that is the confirmation of the W index effeciency.

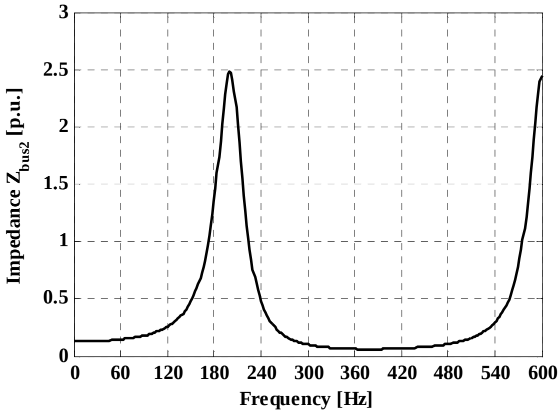

Figure 2. Impedance at bus 2.

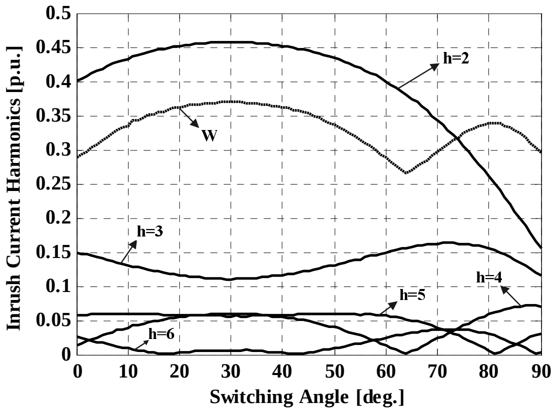

Figure 3. Changes of harmonic currents and W index with respect to the switching angle.

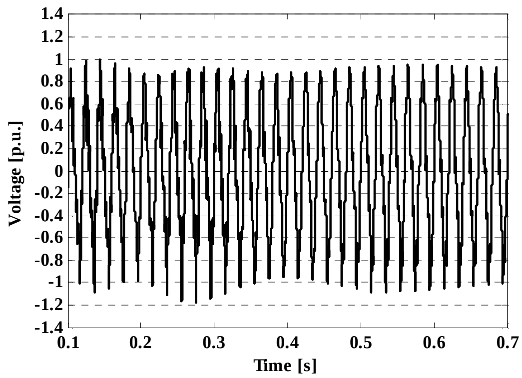

Figure 4. Voltage at bus 2 after switching of shunt reactor for best switching condition.

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

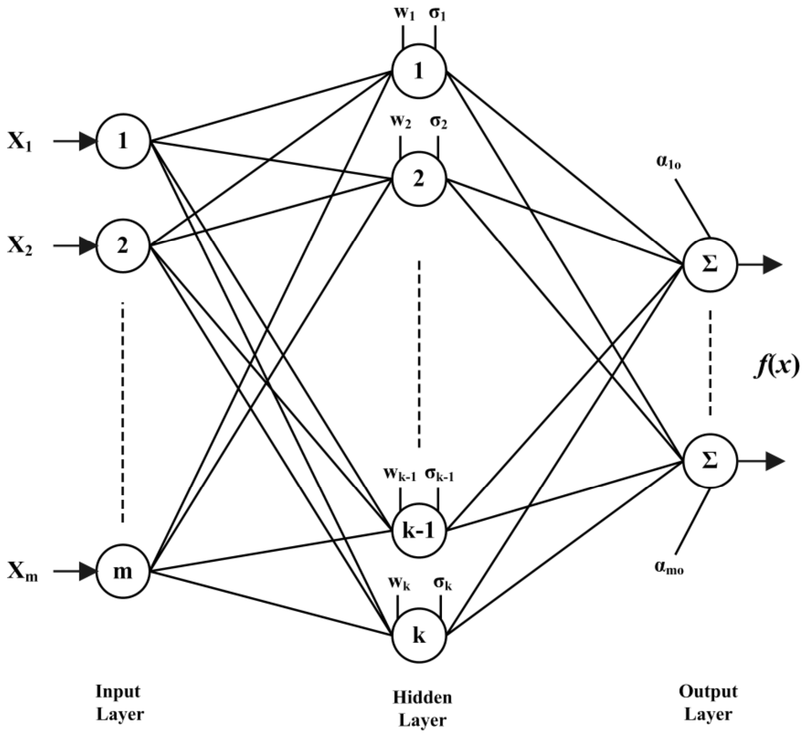

Figure 5. The structure of RBF neural network.

3.2. Steps of Optimum Switching Condition Evaluation

The steps for optimum switching angle evaluation and estimation are:

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) Compute the best switching condition.
4) Steps above must be repeated with various system parameters to learn artificial neural network.
5) Test of artificial neural network with different system parameters.

4. Radial Basis Function Neural Network

Fig. 5 shows the structure of the RBF neural network, which comprises of three layers. The hidden layer possesses an array of neurons, referred to as the computing units. The number of such units can be varied depending on user's requirement [13], [14]. Different basis functions like spline, multiquadratic, and Gaussian functions have been studied, but the most widely used one is the Gaussian type. In comparison to the other types of neural network used for pattern classification like back propagation feedforward networks, the RBF network requires less computation time for learning and has a more compact topology. The Gaussian RBF is found not only suitable in generalizing a global mapping but also in refining local features without altering the already learned mapping. Each hidden unit in the network has two parameters called a center (ω) and a width (σ) associated with it. The response of one such hidden unit to the network input is expressed as

$$\phi_k(x_n) = \exp\left(-\frac{1}{\sigma_k^2}\|x_n - \omega_k\|^2\right) \qquad (2)$$

where ω_k is the center vector for kth hidden unit, σk is the width of the Gaussian function, and $\|\ \|$ denotes the Euclidean norm. The output layer comprises a number of nodes depending on the number of fault types to be classified which perform simple summation. The response of each hidden unit (1) is scaled by its connecting weights (α's) to the output nodes and then summed to produce the overall network output. The overall network output is expressed as

$$f_m(x_n) = \alpha_{mo} + \sum_{k=1}^{N} \alpha_{mk}\phi_k(x_n) \qquad (3)$$

where k indicates the total number of hidden neurons in the network, α_{mk} is the connecting weight of the kth hidden unit to mth output node, and α_{mo} is the bias term for the corresponding mth output neuron.

The learning process of the RBFNN involves with the allocation of new hidden units and tuning of network parameters. The learning process is terminated when the output error goes under the defined threshold [15].

Table 2. Some sample testing data and output

V	R_{eqv}	L_{eqv}	C_{eqv}	L.L.	C_{Line}	Φ_r [p.u.]	B.S.A.$_{HI}$	B.S.A.$_{RBF}$	Error
1.0078	0.003	0.0375	2.1956	105	1.199e-8	0.8	53.2	54.1	1.6248
1.0558	0.0035	0.0375	2.1956	118	1.199e-8	0.7	82.5	81.4	1.3792
1.1301	0.004	0.035	1.5869	135	1.224e-8	0.6	58.1	55.9	3.7058
1.1954	0.0045	0.0325	1.5869	150	1.224e-8	0.5	34.8	35.4	1.7153
1.1645	0.005	0.03	1.2825	176	1.237e-8	0.4	60.8	62.1	2.1504
1.2372	0.0055	0.0275	1.2825	200	1.237e-8	0.3	90	89.2	0.8715
1.2679	0.006	0.025	0.9781	210	1.249e-8	0.2	29.7	28.6	3.6184
1.3715	0.004	0.025	0.9781	249	1.249e-8	0.1	44.2	44.7	1.0553

V = voltage at shunt reactor bus before switching [p.u.], R_{eqv} = equivalent resistance [p.u.], L_{eqv} = equivalent inductance [p.u.], C_{eqv} = equivalent capacitance [p.u.], L.L. = line length [km], C_{Line} = line capacitance [F/km], Φ_r = remanent flux [p.u.], B.S.A$_{HI}$ = the best switching angle obtained by the harmonic index [°], B.S.A$_{ANN}$ = the best switching angle obtained by the RBF [°], and Error = switching angle error [%].

Following parameters are effective in determination of optimum switching angle during shunt reactor energization and selected as RBFNN 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

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:

$$\text{error}(\%) = \frac{|\text{ANN} - \text{PSB}|}{\text{PSB}} \times 100 \quad (4)$$

Results for a sample test data are presented in Table. 2.

5. Case Study

To illustrate the method performance, the proposed algorithm is demonstrated for two case studies that include a portion of 39-bus New England test system. System's parameters are listed in [16]. The simulations are undertaken on a single phase representation.

5.1. Case 1

A one-line diagram of a portion of 39-bus New England test system which is in restorative state is shown in Fig. 6. A black-start unit is applied at the generator at bus 35. A shunt reactor is connected at bus 19 for the purpose of reduction in steady state overvoltage of no load transmission line. Having nonlinear magnetization characteristics in the reactor, by energizing it, harmonic overvoltages can be produced.

Determining equivalent circuit of this system and calculating values of equivalent resistance, equivalent inductance, and equivalent capacitance, 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 3 contains the some sample result of test data of case 1.

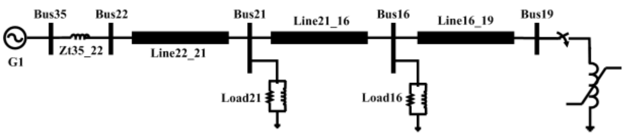

Figure 6. Studied system for case 1.

5.2. Case 2

In order to prove effectiveness of suggested method, the system modeled in Fig. 7 is tested. The next step of the restoration is restarting the unit at bus 29. In order to reduction of steady state overvoltage of no load transmission lines, the shunt reactor at bus 29 should be energized. Harmonic overvoltages can be produced in this condition.

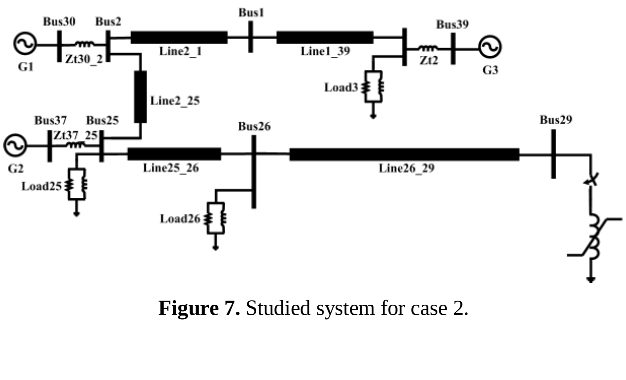

Figure 7. Studied system for case 2.

Table 3. Case 1 some sample testing data and output

V	L.L.	Φ_r [p.u.]	B.S.A.$_{HI}$	B.S.A.$_{RBF}$	Error
1.1153	100	0.8	32.5	33.3	2.4962
1.1318	122	0.7	61.7	62.5	1.2978
1.1804	146	0.6	50.9	48.8	4.1136
1.2593	170	0.5	41.3	40.6	1.7519
1.1249	195	0.4	82.4	80.8	1.9573
1.2779	210	0.3	67.3	69.1	2.7106
1.3425	235	0.2	39.7	40.2	1.1852
1.3641	250	0.1	74.6	73.3	1.7195

V = voltage at shunt reactor bus before switching [p.u.], L.L. = line length [km], Φ_r = remanent flux [p.u.], B.S.A$_{HI}$ = the best switching angle obtained by the harmonic index [°], B.S.A$_{ANN}$ = the best switching angle obtained by the RBF [°], and Error = switching angle error [%].

Table 4. Case 2 some sample testing data and output

V	L.L.	Φ_r [p.u.]	B.S.A.$_{HI}$	B.S.A.$_{RBF}$	Error
1.1344	108	0.8	71.9	72.8	1.2482
1.1462	125	0.7	43.7	43.4	0.6107
1.1907	145	0.6	25.6	26.1	1.8961
1.2175	175	0.5	60.2	61.4	1.9647
1.2693	196	0.4	54.9	55.4	0.9435
1.2907	215	0.3	74.2	71.5	3.6094
1.3497	237	0.2	31.4	31.8	1.3815
1.3871	263	0.2	52.7	51.4	2.4927

V = voltage at shunt reactor bus before switching [p.u.], L.L. = line length [km], Φ_r = remanent flux [p.u.], B.S.A$_{HI}$ = the best switching angle obtained by the harmonic index [°], B.S.A$_{ANN}$ = the best switching angle obtained by the RBF [°], and Error = switching angle error [%].

After calculating equivalent circuit parameters seen from bus 26 and converting this system to equivalent circuit of Fig. 1, various cases are taken into account for energizing the shunt reactor and corresponding optimum switching angles are evaluated 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. Table 4 contains summary of few result achieved in this case. Obtained results confirm that the ANN is able to learn the pattern and gives acceptable accurate results.

6. Conclusion

In this paper a controlled switching approach based on RBFNN has been suggested and implemented to the energization of shunt reactors. The minimum value of used harmonic index is corresponding to the best switching time for energizing the shunt reactor. Using equivalent circuit parameters for developed ANN makes it applicable for any other system. Effectiveness and accuracy of the proposed harmonic index and ANN scheme can be demonstrated by simulation results.

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