Artificial Neural Network based Approach to Analyze Transient Overvoltages during Capacitor Banks Switching

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ABSTRACT
The quality of electric power has been a constant topic of study, mainly because inherent problems to it can lead to great economic losses, especially in industrial processes. Among the various factors that affect power quality, those related to transients originating from capacitor bank (CB) switching in the primary distribution systems must be highlighted. This paper presents an Artificial Neural Network (ANN)-based approach to estimate the transient overvoltages due to capacitor energization. In proposed methodology, Levenberg-Marquardt second order method is used to train the multilayer perceptron. ANN training is based on equivalent parameters of the network. Therefore, trained ANN is applicable to every studied system. The developed ANN is trained with the extensive simulated results, and tested for typical cases. Then the new algorithms are presented and demonstrated for a partial of 39-bus New England test system. The simulated results show that the proposed technique can estimate the peak values of switching overvoltages with good accuracy.

Keywords
Artificial neural networks; capacitor banks switching; switching overvoltages.

1. INTRODUCTION
Electric power systems have predominantly inductive loads, so that the systems themselves must supply the reactive power consumed. The most practical and efficient way for the utility to supply the reactive power demanded is through the installation of capacitor bank (CBs) in the system. The installation of shunt CB brings benefits concerning the reduction of system charging and electrical losses, system capacity release, and also improvements in the power factor [1, 2].

Although various factors influence power quality, the work presented here focuses on transients originating from shunt capacitor bank switching in power systems.

The magnitude and shape of the switching overvoltages vary with the system parameters and network configuration. Even with the same system parameters and network configuration, the switching overvoltages are highly dependent on the characteristics of the circuit breaker operation and the point-on-wave where the switching operation takes place [3].

In this paper power system blockset (PSB), a MATLAB/Simulink-based simulation tool [4] is used for computation of both switching and temporary overvoltages. This paper presents the artificial neural network (ANN) application for estimation of overvoltage peaks under switching transients during capacitor energization. A tool such as proposed in this paper that can give the maximum switching overvoltage will be helpful to the operator. It can be used as training tool for the operators. The proposed ANN is expected to learn many scenarios of operation. To give the maximum peak overvoltages 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 transient overvoltages such as voltage at capacitor bus before switching, equivalent resistance, equivalent inductance, equivalent capacitance, line length, switching angle, and capacitor capacity. This information will help the operator to select the proper condition of capacitor switching with transients appearing safe within the limits. Results of the studies are presented for a partial of 39-bus New England test system to illustrate the proposed approach.

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

2.2 Generator model
In [5] 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 [6] which cover the frequency range of harmonic overvoltages phenomena.

2.4 Load and Shunt Devices Model
All of the loads and shunt devices, such as capacitors and reactors, are modeled as constant impedances.

3. TRANSIENT OVERVOLTAGES DURING CAPACITOR ENERGIZATION

One of the major concerns in power system restoration is the occurrence of overvoltages as a result of switching procedures. These can be classified as transient overvoltages, sustained overvoltages, harmonic resonance overvoltages, and overvoltages resulting from ferro-resonance. Steady-state overvoltages occur at the receiving end of lightly loaded transmission lines as a consequence of line-charging currents (reactive power balance). Excessive sustained overvoltages may lead to damage of transformers and other power system equipment. Transient overvoltages are a consequence of switching operations on long transmission lines, or the switching of capacitive devices, and may result in arrester failures. Ferro-resonance is a nonharmonic resonance characterized by overvoltages whose waveforms are highly distorted and can cause catastrophic equipment damages [7-10].

This paper concentrates on the estimation of switching overvoltages during capacitor energization. The CB switching provokes transient overvoltages that theoretically can reach peak phase-to-earth values in the order of 2-3 p.u.

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. In the system studies 400 kV line-to-line base voltage and 100 MVA as a base power is considered. Fig. 2 shows the switching transient at bus 2 when capacitor is energized.

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 capacitor bus before switching
- Equivalent resistance of the network
- Equivalent inductance of the network

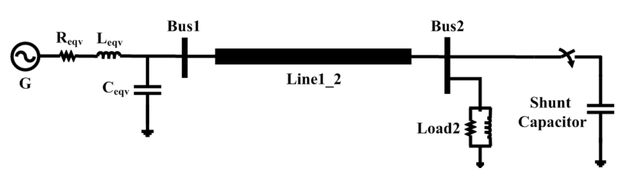

Fig 1: Sample system for capacitor energization study. G: generator, Reqv: equivalent resistance, Leqv: equivalent inductance, and Ceqv: equivalent capacitance.

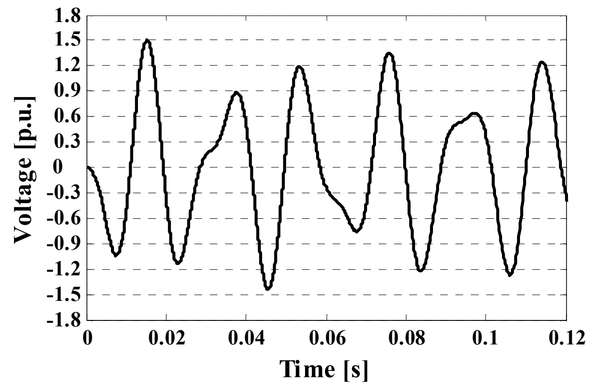

Fig 2: Voltage at bus 2 after switching of capacitor.

- Equivalent capacitance of the network
- Line length
- Closing time of the circuit breaker poles
- Capacitor bank capacity

In proposed method, equivalent parameters of the network as well as other parameters are used as ANN inputs. Thus, ANN is trained just once for simple system of Fig. 1 and developed ANN is applicable to every studied system. For using developed ANN, just studied system must convert to Fig. 1. Section 5 has more details about proposed method.

Source voltage affects the overvoltage strongly. Fig. 3 shows the effect of source voltage on overvoltage at different equivalent resistance. Fig. 4 shows the effect of line length on overvoltages at different source voltage. Controlled switching of high-voltage ac circuit breakers has become a commonly accepted means of controlling switching transients in power systems [11]. Fig. 5 shows effect of switching angle on overvoltages at different equivalent capacitance. Fig. 6 shows the effect of shunt capacitor capacity on overvoltages at different equivalent inductance.

As discussed above for an existing system the main factors which affect the peak values of switching overvoltage are capacitor bus voltage, equivalent resistance, equivalent inductance, equivalent capacitance, line length, switching angle, and capacitor capacity. Here it should be mentioned that a single parameter often cannot be regarded independently from the other important influencing factors. The magnitude of the overvoltages normally does not depend directly on any single isolated parameter and a variation of one parameter can often alter the influence of another parameter, in other words there exists an interaction between the various system and breaker parameters. This forbids the derivation of precise generalized rule of simple formulae applicable to all cases [12]. So an ANN can help to estimate the peak values of switching overvoltages generated during reactor energization. An ANN is programmed by presenting it with training set of input/output patterns from which it then learns the relationship between the inputs and

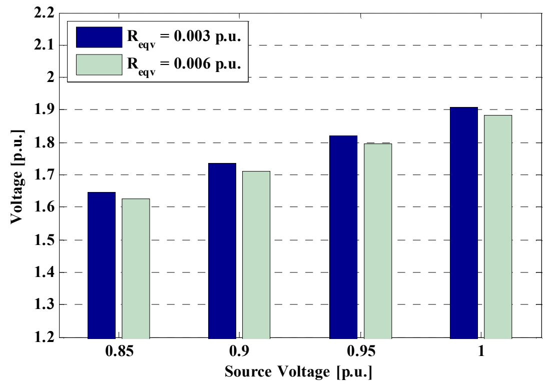

Fig 3: Overvoltage peak at bus 2 as source voltage while equivalent inductance 0.025 p.u., equivalent capacitor 1.2825 p.u., line length 200 km, switching angle 20°, and shunt capacitor capacity 30 MVAR. R_{eqv} is equivalent resistance.

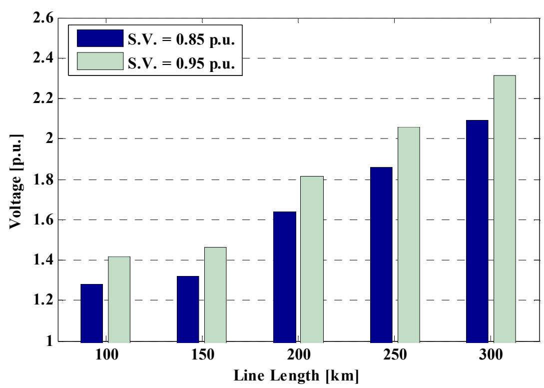

Fig 4: Overvoltage peak at bus 2 as line length while equivalent resistance 0.004 p.u., equivalent inductance 0.025 p.u., equivalent capacitance 1.2825 p.u., switching angle 20°, and capacitor capacity 30 MVAR. S.V. is source voltage.

outputs. In next section an ANN-based approach is described which can give a acceptable solution of switching transients by the help of which an operator can take a quick decision at the time of operation.

4. THE ARTIFICIAL NEURAL NETWORK

The proposal in this work considers the adoption of feed forward Multilayer Perceptron (MLP) architecture. A MLP trained with the back-propagation algorithm may be viewed as a practical vehicle for performing a nonlinear input–output mapping of a general nature [3, 13]. Function approximation by feed forward MLP network is proven to be very efficient, considering various learning strategies like simple back propagation or the robust Levenberg–Marquardt. Its ability to perform well is affected by the chosen training data as well as training scheme. The schematic diagram of the proposed MLP neural networks architecture is shown in Fig. 7. The

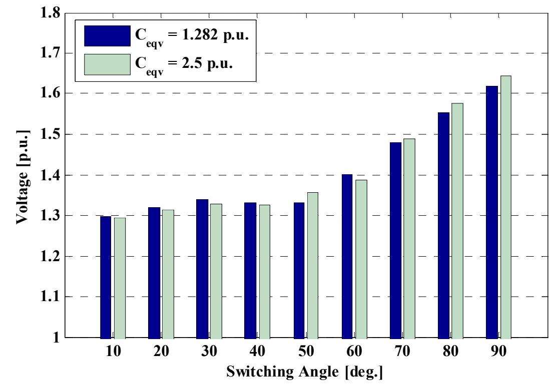

Fig 5: Overvoltage peak at bus 2 as switching angle while source voltage 0.9 p.u., equivalent resistance 0.003 p.u., equivalent inductance 0.03 p.u., line length 150 km, and capacitor capacity 20 MVAR. Ceqv is equivalent capacitance.

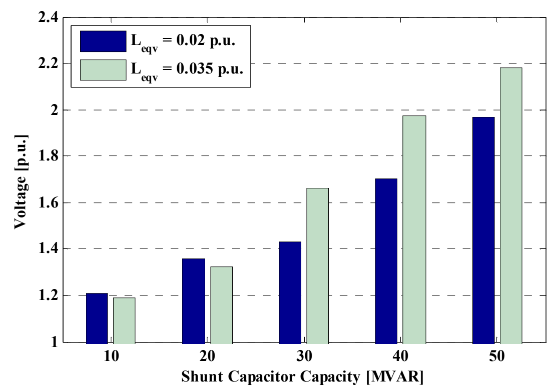

Fig 6: Overvoltage peak at bus 2 as shunt capacitor capacity while source voltage 0.9 p.u., equivalent resistance 0.003 p.u., equivalent capacitance 1.8912 p.u., line length 150 km, and switching angle 30°. Leqv is equivalent inductance.

composition of the input variables for the proposed neural networks has been carefully selected.

Supervised training of ANN is a usual training paradigm for MLP architecture. Fig. 8 shows the supervised learning of ANN for which input is given to PSB to get the peak values of transient overvoltages and the same data is used to train the ANN. Error is calculated by the difference of PSB output and ANN output. This error is used to adjust the weight of connection. Since the switching transient demands a solution with high precision, the neural network has to be trained considering a very small stopping criterion. Output values of the trained neural networks must be capable of computing the voltages with very good precision. Gradient-based training algorithms, like back propagation, are most commonly used for training procedures. They are not efficient due to the fact that the gradient vanishes at the solution. Hessian-based algorithms allow the network to learn more subtle features of a complicated mapping. The training process converges quickly as the solution

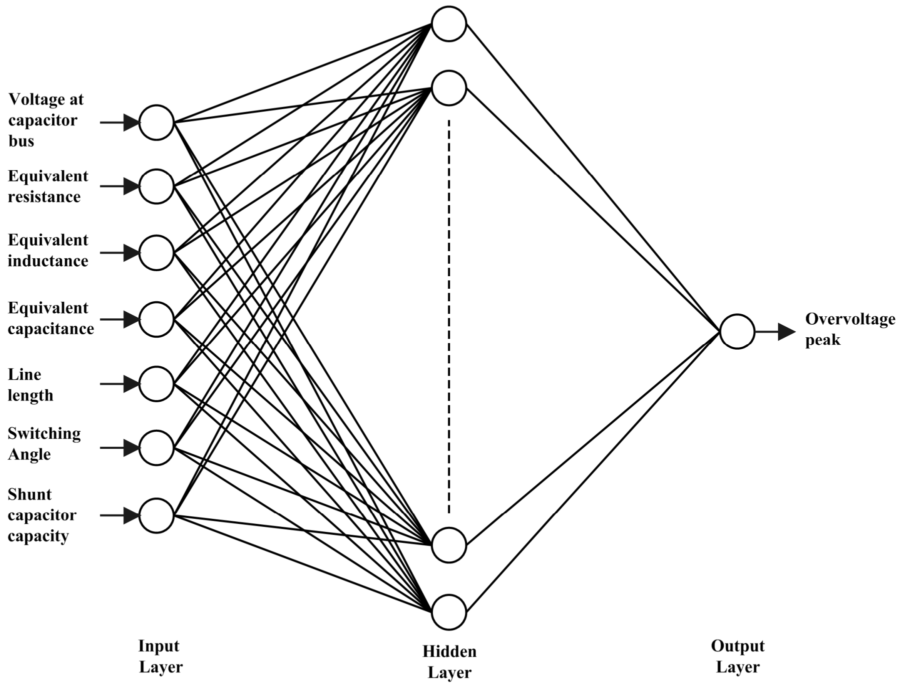

Fig 7: Proposed MLP-based ANN architecture.

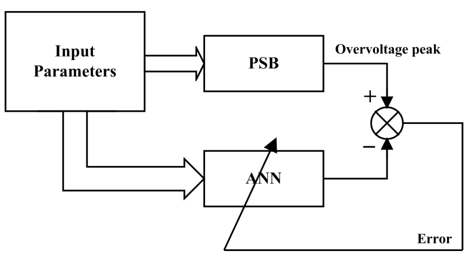

Fig 8: Supervised learning of ANN.

is approached, because the Hessian does not vanish at the solution. To benefit from the advantages of Hessian based training, we focused on the Levenberg–Marquardt (LM) algorithm reported in [14].

4.1 Levenberg-Marquardt (LM) Algorithm

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

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

where $e_i(x)$ is the error for ith input. Then the Marquardt–Levenberg modification to the Gauss–Newton method is

$$\Delta\,\mathbf{x} = \left[\mathbf{J}^{\mathrm{T}}(\mathbf{x})\mathbf{J}(\mathbf{x}) + \mu\mathbf{I}\right]^{-1}\mathbf{J}^{\mathrm{T}}(\mathbf{x})\mathbf{e}(\mathbf{x}) \tag{2}$$

where $\mathbf{J}(x)$ is the jacobian matrix. The parameter μ is multiplied by some factor β whenever a step would result in an increased $\xi(\mathbf{x})$. When a step reduces $\xi(\mathbf{x})$, μ is divided by β. Notice that when μ is large the algorithm becomes steepest descent; while for small μ the algorithm becomes Gauss–Newton. The LM algorithm is very efficient when training networks have up to few hundred weights. Although the computational requirements are much higher for the each iteration of the LM algorithm, this is more than made up for by the increased efficiency. This is especially true when high precision is required.

4.2 Training Artificial Neural Network

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:

$$\text{error}(\%) = \frac{|\text{ANN} - \text{PSB}|}{\text{PSB}} \times 100 \tag{3}$$

Neural network is trained with the goal of mean square error (MSE) 1e-3. Fig. 9 shows the training of neural network. Results for a sample test data are presented in Table 1 and Figs. 10-11. Table 1 contains the some sample result of test data. Values in column V_{PSB} are the absolute values of peak voltage at bus 2 calculated by PSB program in p.u. where the V_{ANN} values are the values simulated by trained network. Also, Fig.10 shows overvoltage peak at bus 2 against the line length and Fig.11 shows overvoltage peak at bus 2 against the shunt capacitor capacity.

Table 1. Some sample testing data and output

V [p.u.]	R_{eqv} [p.u.]	L_{eqv} [p.u.]	C_{eqv} [p.u.]	L.L. [km]	S.A. [deg.]	C [MVAR]	V_{PSB} [p.u.]	V_{ANN} [p.u.]	$error_V$ [%]
0.778	0.0055	0.025	1.2825	125	20	30	1.2589	1.2397	1.5261
0.947	0.0065	0.025	1.2825	325	20	30	2.2192	2.2029	0.7326
1.006	0.0035	0.025	1.2825	325	20	30	2.3791	2.3354	1.8367
0.856	0.0045	0.025	1.2825	175	20	30	1.5191	1.5741	3.6205
0.997	0.0065	0.025	1.2825	275	20	30	2.0904	2.0643	1.2495
0.999	0.0035	0.025	1.2825	275	20	30	2.1173	2.1496	1.5236
0.997	0.0055	0.025	1.2825	225	20	30	1.9829	2.0247	2.1058
0.921	0.0035	0.025	1.2825	125	20	30	1.4702	1.4895	1.3146
0.884	0.003	0.0225	0.3694	150	15	40	1.8591	1.8521	0.3763
0.887	0.003	0.0225	2.1956	150	15	5	1.0916	1.0813	0.9475
0.892	0.003	0.0275	1.5869	150	65	5	1.2704	1.3046	2.6918
0.892	0.003	0.0275	1.5869	150	85	35	2.0641	2.0921	1.3582
0.901	0.003	0.0325	2.8044	150	45	15	1.3656	1.3176	3.5174
0.895	0.003	0.0325	0.9781	150	5	25	1.3541	1.3312	1.6892
0.902	0.003	0.0375	1.5869	150	75	5	1.1871	1.1973	0.8557
0.905	0.003	0.0375	2.8044	150	55	40	2.2417	2.2062	1.5834

V = capacitor bus voltage before switching, R_{eqv} = equivalent resistance, L_{eqv} = equivalent inductance, C_{eqv} = equivalent capacitance, L.L. = line length, S.A. = switching angle, C = shunt capacitor capacity, and $error_V$ = voltage error.

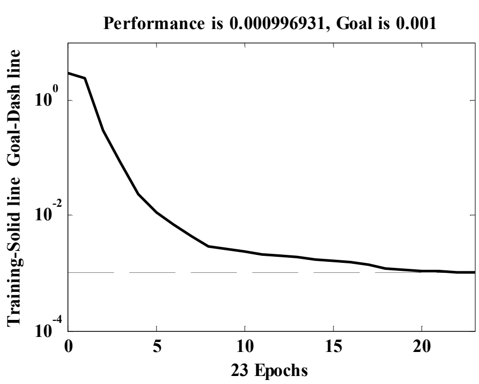

Fig 9: Squared error against epoch curve.

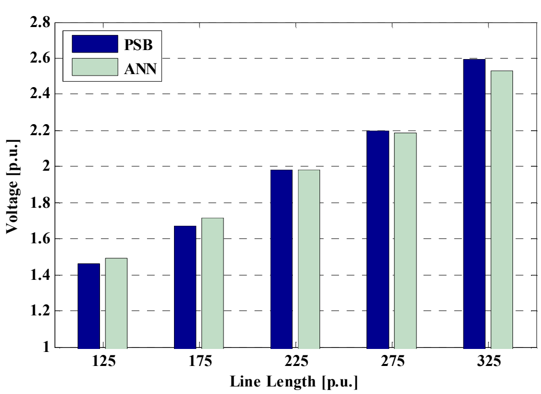

Fig 10: Overvoltage peak vs. line length at bus 2 simulated by ANN and PSB while source voltage 0.9 p.u., equivalent resistance 0.0055 p.u., equivalent inductance 0.025 p.u., equivalent capacitance 1.1285 p.u., switching angle 20°, and capacitor capacity 15 MVAR.

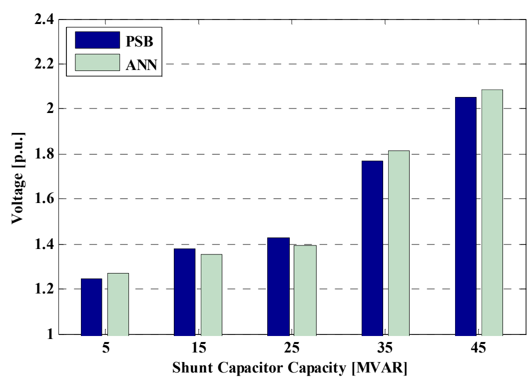

Fig 11: Overvoltage peak vs. shunt capacitor capacity at bus 2 simulated by ANN and PSB while source voltage 0.925 p.u., equivalent resistance 0.003 p.u., equivalent inductance 0.0225 p.u., equivalent capacitance 2.1956 p.u., line length 150 km, and switching angle 45°.

In the next section, the proposed model tested with portion of 39-bus New England test system. Various cases of capacitor energization are taken into account and corresponding peak values estimated from trained model.

5. CASE STUDY

In this section, the proposed algorithm is demonstrated for two case studies that are a portion of 39-bus New England test system, of which its parameters are listed in [15]. The simulations are undertaken on a single phase representation.

In the proposed method, first, studied system must convert to equivalent circuit of Fig. 1, i.e., values of equivalent resistance, equivalent inductance, and equivalent capacitance are calculated. These values are used in trained artificial neural network to estimate overvoltages peak.

Table 2. Case 1 some sample testing data and output

V [p.u.]	S.A. [deg.]	C [MVAR]	V_{PSB} [p.u.]	V_{ANN} [p.u.]	$error_V$ [%]
0.768	10	17	1.0841	1.0945	0.9562
0.768	50	17	1.2172	1.2248	0.6249
0.831	50	17	1.2915	1.2581	2.5863
0.831	50	35	1.6316	1.6083	1.4275
0.895	45	15	1.2709	1.2478	1.8184
0.895	90	33	1.8497	1.7651	4.5736
0.937	30	12	1.2802	1.3024	1.7351
0.937	75	24	1.5398	1.5801	2.6159

V = capacitor bus voltage before switching, S.A. = switching angle, C = shunt capacitor capacity, and $error_V$ = voltage error.

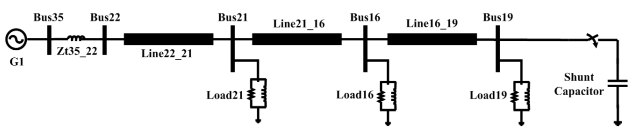

Fig 12: Studied system for case 1.

5.1 Case 1

Fig. 12 shows a one-line diagram of a portion of 39-bus New England test system. 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 Fig. 1. In this case, equivalent parameters are 0.00385 p.u., 0.03129 p.u., and 2.0674 p.u., respectively. For testing trained ANN, values of voltage at capacitor bus (bus 19) before switching, switching angle, and capacitor capacity are varied and in each case, overvoltage peak values are calculated from trained ANN and system of Fig. 12. Table 2 contains the some sample result of test data for case 1.

5.2 Case 2

As another example, the system in Fig. 13 is examined. After converting this system to equivalent circuit of Fig. 1 and calculating equivalent circuit parameters seen from bus 5, various cases of capacitor energization are taken into account and corresponding peak overvoltages are computed from PSB program and trained ANN. In this case, values of equivalent resistance, equivalent inductance, and equivalent capacitance are 0.00731 p.u., 0.02513 p.u., and 1.5724 p.u., respectively. Summery of few result are presented in Table 3. It can be seen from the results that the ANN is able to learn the pattern and give results to acceptable accuracy.

6. CONCLUSION

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

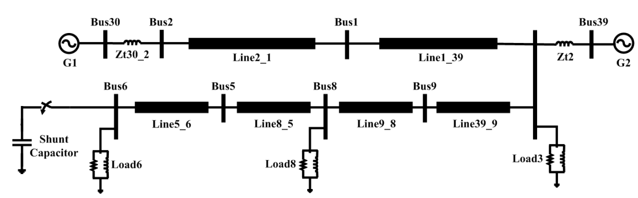

Fig. 13: Studied system for case 2.

Table 3. Case 2 some sample testing data and output

V [p.u.]	S.A. [deg.]	C [MVAR]	V_{PSB} [p.u.]	V_{ANN} [p.u.]	$error_V$ [%]
0.754	70	20	1.3325	1.3584	1.9426
0.754	70	42	2.0094	1.9796	1.4835
0.822	15	42	1.7158	1.7785	3.6539
0.822	55	33	1.5418	1.5084	2.1657
0.879	90	21	1.5788	1.5921	0.8401
0.879	90	14	1.1526	1.1323	1.7592
0.925	30	12	1.2697	1.3103	3.1964
0.925	60	40	1.9712	1.9391	1.6285

V = capacitor bus voltage before switching, S.A. = switching angle, C = shunt capacitor capacity, and $error_V$ = voltage error.

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