ESTIMATION OF CAPACITOR BANK SWITCHING OVERVOLTAGES USING ARTIFICIAL NEURAL NETWORK

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Abstract: *According to power quality concerns, the insertion of capacitor banks into the electrical power system is interested in the case of power factor compensation and voltage support. Due to capacitor bank switching process, a transient overvoltage appears on the system and represents hazard on equipment insulations. In this paper the capacitor bank switching overvoltage dependent parameters are studied and the artificial neural network (ANN) is used to estimate this overvoltage. ANN is trained according to the factors that affect the overvoltage. ANN training data is provided by MATLAB/Simulink environment. The simulated results show that the proposed technique can estimate the peak values and durations of capacitor bank switching overvoltages with good accuracy*.

Keywords: *Capacitor bank energization, switching overvoltages, power factor correction, artificial neural network.*

1. Introduction

Capacitor bank energizing transients are becoming increasingly more important with the growing number of capacitor bank installations in power systems. This is because capacitor bank switching is one of the most frequent utility operations, potentially occurring multiple times per day and hundreds of time per year throughout the system, depending on the need for system voltage and reactive power support from the banks. During the switching of shunt capacitor banks, high magnitude and high frequency transients can occur. The transient is characterized by a surge of current having a high magnitude and a frequency as high as several hundred Hertz. There is also a transient overvoltage on the bus, caused by the surge of inrush current coming from the system source [1].

Excessive overvoltages may lead to damage of power system equipment so; capacitor bank energizing transients should be studied to achieve power quality concerns. 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 [2],[3].

This paper presents how to estimate the switching overvoltages caused due to the entering of capacitor bank into the service by using MATLAB/Simulink. Artificial neural network (ANN) will be used also, as a real time application method to determine the overvoltages due to this power factor compensation process. ANN will be trained by a large pattern of data that the capacitor bank switching overvoltage depends on it to achieve a high level of accuracy as well as the results that be obtained from the usage of any electrical power system simulation program as MATLAB/Simulink.

This paper presents the following sections: in section 2 a brief description of switching overvoltages during capacitor energization is presented. Section 3 presents power system modelling. Section 4 studies the effect of the variation of capacitor bank switching overvoltage dependent factors. In section 5 the ANN-based approach to estimate the overvoltage during capacitor energization is illustrated. Section 6 provides the conclusion about this paper.

2. Capacitor energization

When the capacitor in Fig. 1 is energized by closing of the circuit breaker the voltage and current in this capacitor considering a discharged capacitor are given by equations 1 and 2 respectively [4], [5].

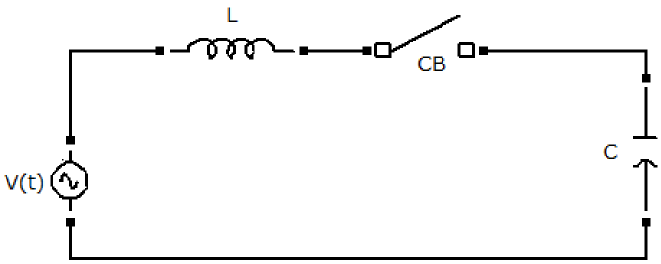


Fig. 1. Capacitor energization.

$$v_c(t) = v - v \sin \omega t \quad (1)$$

$$i_c(t) = \frac{v}{z_o} \sin \omega t \quad (2)$$

Where:

υ is circuit breaker voltage at closing instant.

ω is natural frequency = $1/\sqrt{LC}$.

z_o is surge impedance = $\sqrt{L/C}$.

At the instant of capacitor bank insertion, a capacitor is a sudden short circuit, because the voltage across the capacitor cannot change suddenly. The voltage of the bus to which the capacitor is connected will dip severely. This voltage dip and the transient step change is a function of the source impedance behind the bus. The voltage will then recover through a high frequency oscillation. In the initial oscillation the transient voltage can approach 2 per unit of the bus voltage as shown in Fig. 2 [1], [6].

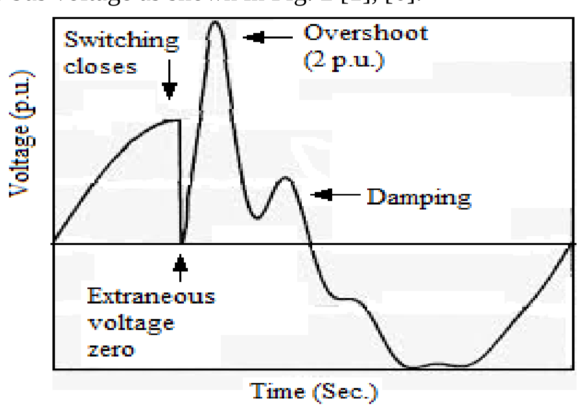


Fig. 2. Overvoltage transient across the switched capacitor.

3. Network modelling

The sample system considered for explanation of the proposed methodology is shown in Fig. 3. The normal peak value of any phase voltage at bus n is $22 \times \sqrt{2}/\sqrt{3}$ kV and this value is taken as base for voltage p.u. Fig. 4 shows the switching transient at bus n when capacitor is energized.

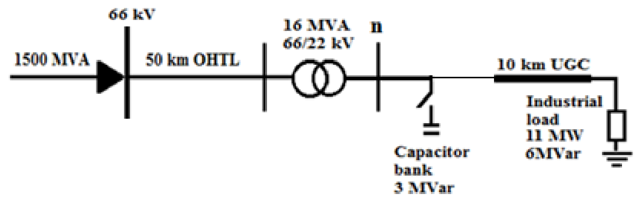


Fig. 3. Single line diagram of the studied system before the insertion of the capacitor bank.

The user friendly graphical interfaces of MATLAB/Simulink enable faster development for power system transient analysis. The modelling of studied power system is detailed as below:

3.1. 66 kV supply network

The system equivalent can be modeled by a three phase voltage source with amplitude equals to $66 \times \sqrt{2}/\sqrt{3}$ kV and internal impedance (R=0.466 Ω, L= 9.25 mH) calculated from the value of 1500 MVA [1].

3.2. Transmission line model

Transmission line (OHTL or UGC) is described by PI cell, where the R, L and C parameters being derived from lumped-line models. This model is also accurate enough for frequency dependent parameters, because the positive sequence resistance and inductance are fairly constant up to approximately 1 kHz which covers the frequency range of phenomena that this paper deals with [7].

3.3. Transformer model

The substation transformer 66/22 kV is modeled by 3-phase, Δ-Y, with ground Y transformer where this 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 piecewise linear characteristic [8].

3.4. Circuit breaker model

Circuit breaker can be modeled by a resistance R_{on} when the breaker is closed and an infinite resistance when the breaker is open, where the opening and closing times can be controlled by external control signal [9].

3.5. Load and capacitor bank model

The load is modeled as three phase Y connected constant impedances specified by active and reactive power [10]. The capacitor bank is presented as three phase Δ connected reactive power generation units specified by the required reactive power for the system.

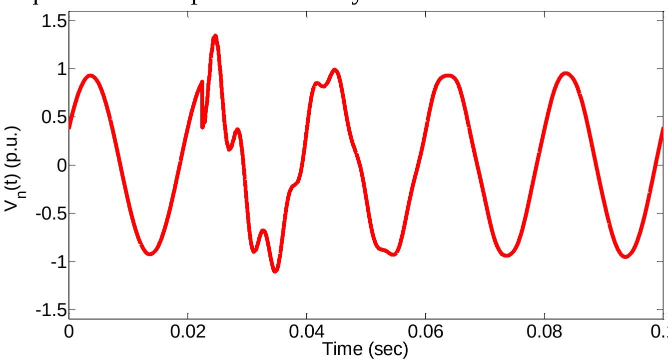


Fig. 4. Voltage response at bus n when capacitor is energized.

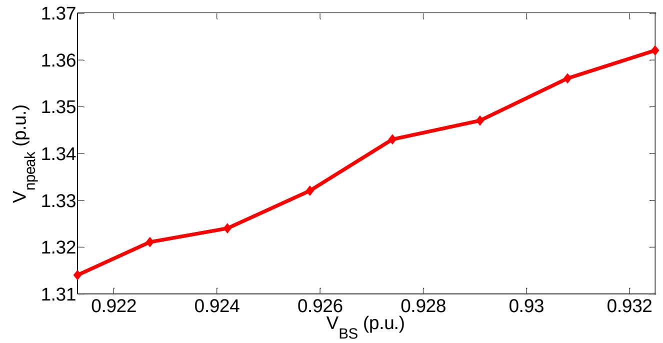
4. Capacitor bank switching overvoltage dependent factors

The magnitude and frequency of the transient overvoltages resulting from capacitor bank insertion is a function of [2], [7]:

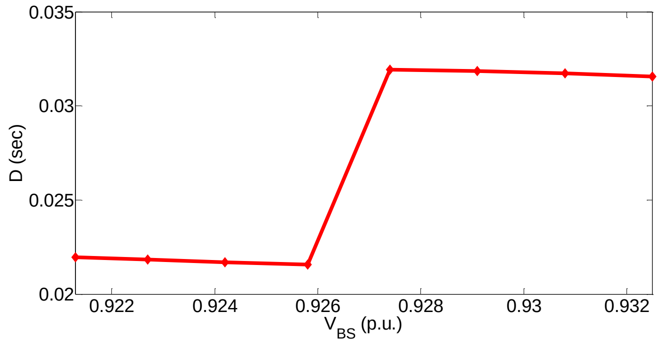
- Voltage at capacitor bank bus before switching (V_{BS})
- Capacitor bank capacity (Q_c)
- Switching angle of the circuit breaker poles (α)
- Charge on the capacitor bank at closing instant

This section presents the effects of these factors on the switching transients due to capacitor bank insertion. Electrical power system in Fig. 3 is simulated and run to record the overvoltage peak (V_{npeak}) and duration (D) at different values of the factors that affecting on it. The inserted capacitor in this network has not any pre-switching charge due to the connection of the earthing switch to ground before the insertion process so; this factor is not considered in this work.

Fig. 5 shows the effect of voltage at capacitor bank bus before switching on overvoltage. Fig. 6 shows the effect of capacitor bank capacity on overvoltages. Controlled switching of high voltage ac circuit breakers has become a commonly accepted means of controlling switching transients in power systems [11]. Fig. 7 shows effect of switching angle of the circuit breaker on overvoltages.

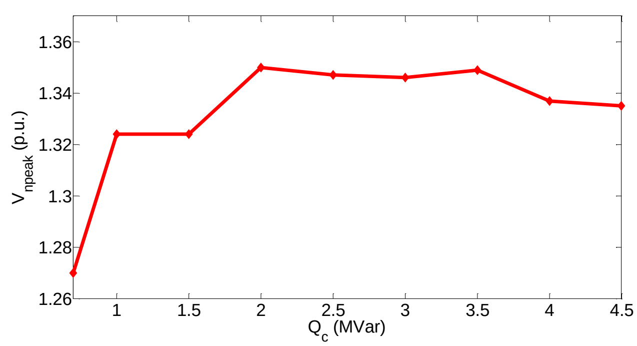


(a)

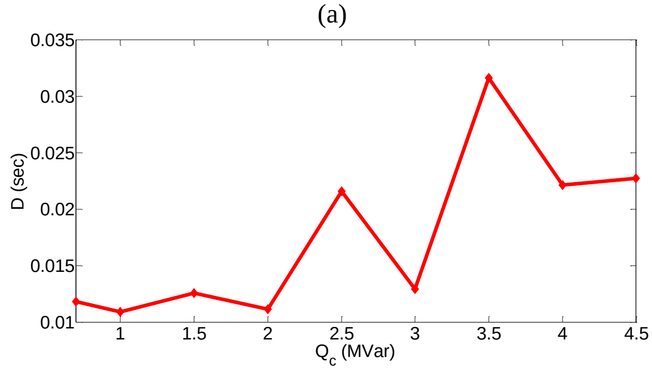


(b)

Fig. 5. The effect of voltage at capacitor bank bus before switching on overvoltage (a) peak and (b) duration.



(a)



(b)

Fig. 6. The effect of capacitor bank capacity on overvoltage (a) peak and (b) duration.

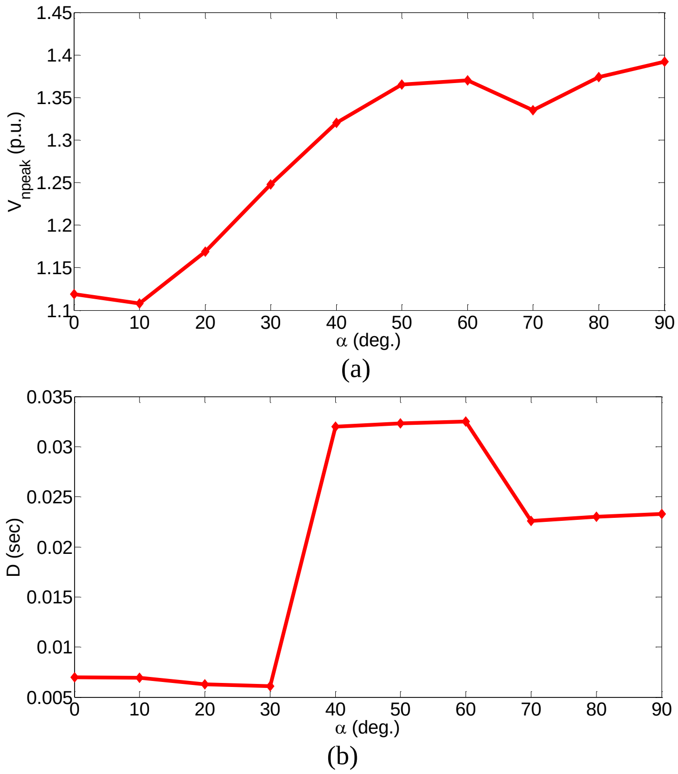


Fig. 7. The effect of switching angle of the circuit breaker on overvoltage (a) peak and (b) duration.

In fact, it is difficult to say that the overvoltage is increased or decreased by seeing to overvoltage peak only but overvoltage duration should be considered also. Where the overvoltage peak may be increased under certain conditions but in the same time the overvoltage duration is decreased. On the contrary, the overvoltage peak may be decreased under certain conditions but in the same time the overvoltage duration is increased such as obtained in Figs. 5, 6 and 7. Now can be said that due to overvoltage dependent factors variation not only overvoltage peak is varied but overvoltage duration is varied also.

In the next section for real time applications an artificial neural network (ANN) based approach to estimate capacitor bank switching overvoltage is presented.

5. Artificial neural network scenario

Fig. 8 shows the structure of the radial basis function neural network (RBFNN), 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 [12], [13]. Different basis functions like spline, multi-quadratic, 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 feed forward 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 [14]. Each hidden unit in the network has two parameters called a center (ω) and a width (q) associated with it [14]. The response of one such hidden unit to the network input is expressed as

$$\phi_d(x_n) = \text{EXP}\left(-\left[\frac{1}{q_d}\|x_n - \omega_d\|\right]^2\right) \quad (3)$$

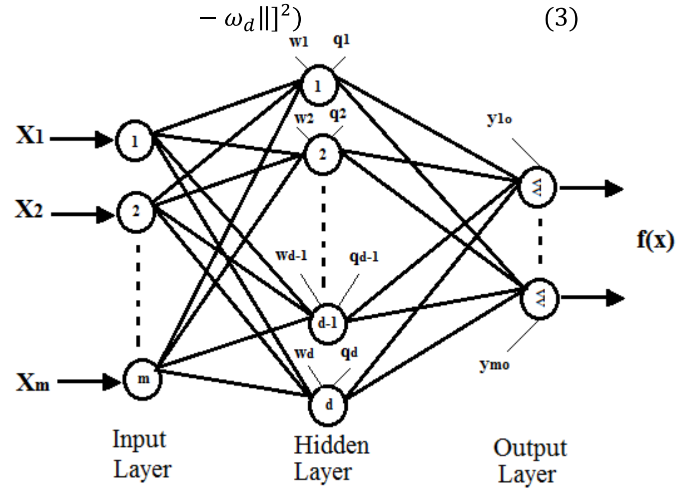


Fig. 8. Structure of RBF neural network.

where ω_d is the center vector for d^{th} hidden unit, q_d is the width of the Gaussian function, and $\| \quad \|$ denotes the Euclidean norm. The output layer comprises a number of nodes depending on the number of input factors to be classified which perform simple summation. The response of each hidden unit (1) is scaled by its connecting weights (y's) to the output nodes and then summed to produce the overall network output [14]. The overall network output is expressed as

$$f_m(x_n) = y_{mo} + \sum_{k=1}^{N} y_{md}\phi_d(x_n) \quad (4)$$

where d indicates the total number of hidden neurons in the network, y_{md} is the connecting weight of the d^{th} hidden unit to m^{th} output node, and y_{mo} is the bias term for the corresponding m^{th} 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].

MATLAB/ Simulink simulation tool is used to train the artificial neural network by the capacitor bank switching overvoltage dependent factors as input pattern matrix.

Where these factors are varied and record the each case corresponding result of the capacitor bank switching overvoltage peak and duration obtained from MATLAB/ Simulink simulation tool as output pattern matrix as shown in Fig. 9.

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 by placing the parameter values that are not used in learning, by applying different parameters. A large number of testing data have been used to check the presented solution in the most objective way at practically all possible parameters variation. Results for a sample test data are presented in Table 1, where the percentage error (%E) is calculated as shown in Fig. 10 and in equation (5).

$$\%E = \frac{result_{ANN} - result_{MATLAB}}{result_{ANN}} * 100 \qquad (5)$$

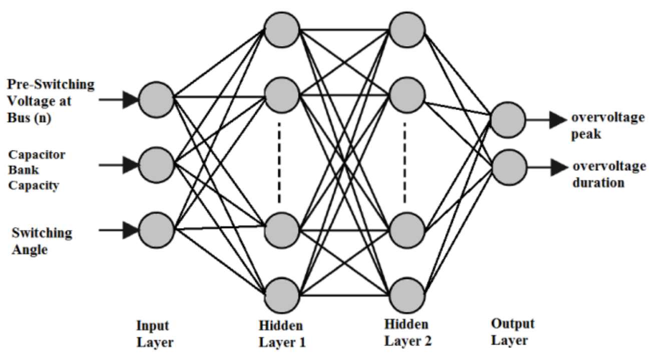


Fig. 9. Structure of neural network for capacitor bank switching overvoltage determination.

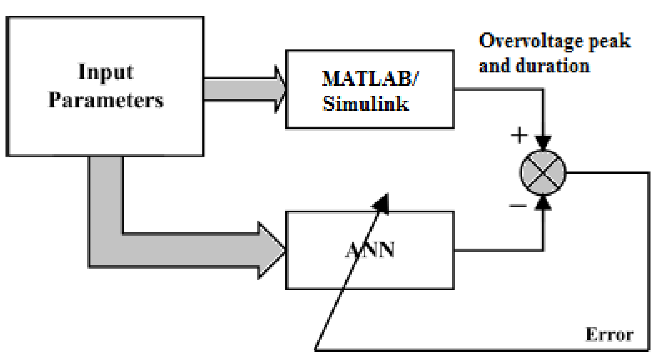


Fig. 10. Supervised learning of ANN [2].

V_{BS}	α	Q_c	V_M	V_{ANN}	$E_v\%$	D_M	D_{ANN}	$E_D\%$
0.9291	45	3.0	1.349	1.378	2.104	0.0129	0.0133	3.008
0.9325	45	3.6	1.362	1.379	1.233	0.0315	0.0320	1.563
0.9370	30	4.0	1.272	1.319	3.563	0.0324	0.0335	3.284
0.9361	65	2.2	1.411	1.450	2.690	0.0310	0.0316	1.899
0.9291	50	3.6	1.365	1.378	0.943	0.0323	0.0327	1.223
0.9308	45	3.6	1.356	1.376	1.453	0.0317	0.0323	1.858
0.9352	90	1.4	1.324	1.348	1.780	0.0289	0.0292	1.027
0.9343	17	2.8	1.123	1.138	1.318	0.0127	0.0130	2.308
0.9281	75	4.1	1.360	1.409	3.478	0.0296	0.0302	1.987
0.9291	45	0.7	1.270	1.290	1.550	0.0117	0.0120	2.500
0.9291	80	3.6	1.374	1.395	1.505	0.0230	0.0234	1.709
0.9274	45	3.6	1.343	1.360	1.250	0.0319	0.0332	3.916
0.9266	15	4.2	1.143	1.152	0.781	0.0232	0.0237	2.110
0.9334	0	3.0	1.096	1.114	1.616	0.0139	0.0140	0.714
0.9235	82	2.6	1.281	1.290	0.698	0.0187	0.0190	1.579
0.9291	45	1.0	1.324	1.329	0.376	0.0109	0.0110	0.909
0.9316	37	4.5	1.311	1.325	1.057	0.0228	0.0229	0.437
0.9299	71	2.3	1.380	1.397	1.217	0.0295	0.0300	1.667
0.9250	71	2.3	1.364	1.372	0.583	0.0302	0.0306	1.307
0.9220	60	1.5	1.359	1.374	1.092	0.0210	0.0212	0.943
0.9205	80	4.0	1.323	1.331	0.601	0.0301	0.0305	1.311
0.9198	50	3.0	1.330	1.373	3.132	0.0200	0.0203	1.478
0.9352	50	3.0	1.381	1.419	2.678	0.0318	0.0323	1.548
0.9291	45	1.5	1.324	1.338	1.046	0.0125	0.0126	0.794
0.9370	50	0.7	1.327	1.328	0.075	0.0210	0.0212	0.943
0.9361	5	3.0	1.083	1.131	4.244	0.0135	0.0136	0.735
0.9352	10	3.2	1.097	1.108	0.993	0.0136	0.0138	1.449
0.9291	45	2.0	1.350	1.357	0.516	0.0111	0.0112	0.893
0.9343	15	1.4	1.024	1.031	0.679	0.0055	0.0056	1.786

Table 1. Some sample testing data and output.

Where V_M and D_M are the overvoltage peak and duration at bus n obtained from MATLAB/ Simulink program respectively. V_{ANN} and D_{ANN} are the overvoltage peak and duration at bus n obtained from ANN respectively. $E_v\%$ is the percentage error between V_{ANN} and V_M. $E_D\%$ is the percentage error between D_{ANN} and D_M.

6. Case study

The trained ANN can be used to predict the switching overvoltage due to capacitor bank energization for any practical system. That is by the knowing of its overvoltage dependent parameters as discussed in section 4. Fig. 11 shows alobour industrial substation. When the capacitor bank of 5.4 MVar is inserted, at pre-switching voltage 0.961 p.u. and zero switching angle, a switching overvoltage occurs. This overvoltage can be predicted by ANN and compared with the field measured data. Table 2 presents the switching overvoltage due to capacitor bank insertion.

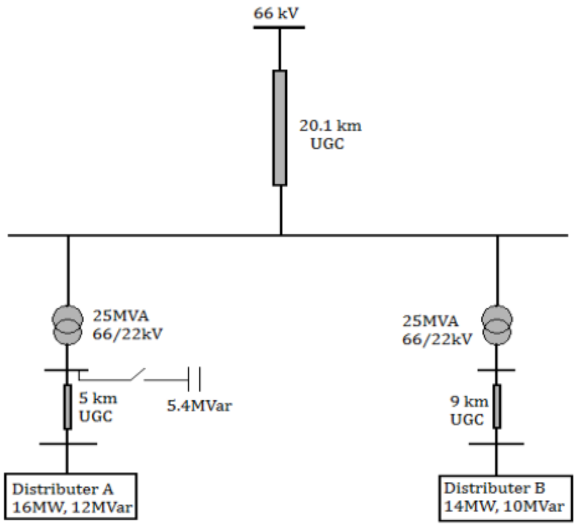


Fig. 11. Alobour industrial substation before the capacitor bank insertion.

Item	*Measured value*	*ANN value*	*Error %*
Overvoltage peak	1.25 p.u.	1.236 p.u.	1.133%
Overvoltage duration	12 msec.	0.0122 sec.	1.64%

Table 2. Switching overvoltage due to capacitor bank insertion at the switched bus.

7. Conclusion

In this paper the capacitor bank switching overvoltage dependent factors are studied and presented. The variation of these factors effect on both overvoltage peak and duration. ANN has been used to estimate the peak and duration of overvoltages due to capacitor bank insertion. Levenberg–Marquardt second order training method has been suggested for obtaining small error without the losing of results accuracy. The results obtained from ANN are close to results obtained from MATLAB/ Simulink simulation tool. The presented ANN can be used to predict the capacitor bank energization overvoltage of other networks with acceptable accuracy. ANN predicts the switching overvoltage due to capacitor bank insertion of alobour industrial substation, where the predicted data is as closely as the field measured data.

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