The Comparison of the Improving Effects of ULTC and SVC on Dynamical Voltage Stability Using Neural Networks

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Abstract— ***In this paper voltage stability is evaluated by both dynamic P-V curves and time-domain simulations, considering the dynamic control effects of a static var compensator (SVC) and under load tap changing (ULTC) transformer. The proposal in this paper is to use ANN to prediction the ULTC tap ration and SVC susseptance of the voltage stabilty of power system. The objective of this paper is the determination of the critical loading points with bifurcation analysis using a neural network and the comparasion of the ULTC and SVC on the dynamical voltage stabilization. The simulation results and prediction values were obtained using the MATLAB/SIMULINK and NeuroXL prediction simulator respectively.***
Keywords-Voltage Stabilty, SVC, ULTC, ANN.

I. Introduction

In general, voltage magnitude of a substation is controlled by an under load tap changing (ULTC) transformer and several capacitor banks; the transformer changes its tap position to control the lower side voltage magnitude directly, whereas the capacitor banks affect the higher side voltage magnitude indirectly by changing the amount of reactive power demand at the bus. These devices have two major problems; one is the discontinuity caused by their stepwise controls and the other is the limitation to the amount of switchings, which is the reason why dead-band and time-delay are needed in their control [1]. Recently, with the development of power electronics technologies, several flexible ac transmission system (FACTS) devices make it possible to control power flows as well as bus voltages rapidly and accurately [2]–[3]. Among the FACTS devices, static var compensator (SVC) an excellent reactive power source and load as well is an adequate device to control the voltage magnitude in a specific bus.

Voltage control is one of the important control schemes at a distribution substation which conventionally involves regulation of voltage at the distribution feeders. The objectives of distribution voltage control equipment is either increasing the susceptance value or to reduce the operation frequency of tap changers to improve the characteristics of voltage by decreasing the error between the sending end voltage and the sending end reference voltage.

To cope with this problem, some researchers used Artificial Intelligence (AI) techniques to control the ULTC. Takahasi et al. [4] discussed tap changing time in a substation by obtaining control sensitivities using mean voltage errors and time scheduled fuzzy rules. They made fuzzy rules by dividing a day into five periods. However, as each substation has different load characteristics and the load pattern shows a seasonal variation, it is difficult to classify appropriate periods. Kojima et al. [6] controlled transformer taps and shunt capacitors simultaneously using Artificial Neural Networks (ANN). This method needs many data for the training of ANNs, and it is difficult to obtain enough input data for the optimal output. Abdul-Rahman and Daneshdoot [5] proposed a control method of voltage and reactive power in a large system using the central fuzzy expert system. However, it is difficult to implement this method in real power systems, since there is a limitation in the exact control of local voltage in a large system. Mesut E. Baran and Ming-Yung Hsu [7] proposed a supervisory control method for transformer taps and shunt capacitors simultaneously to minimize the operation of transformer taps and shunt capacitors.

Recently, (SVCs) have been widely used in power systems. They can provide rapid control of the susceptance and in turn the reactive power supply at the midpoints of long- distance transmission lines, keeping voltages at or near a constant level and enhancing the power transfer capability [8]. The rapid response feature of SVC also provides many other oppottunities for improving power system performance.

Some conventional method have been used in previous research for control of SVC, hopf bifurcation control[9], nonlinear H∞ control [10], adaptive control[11], PID control[12],etc.

Artificial neural networks (ANN) is considered as an important technique of artificial intelligence and it is being used succesfully in many areas of power systems,such as power system control, prediction etc.[13-14-15]. In Ref [16] are disscussed interesting applications of ANN to power systems in, for example, load forecasting, dynamicsecurity assesment, fault diagnosis, etc. ANNs can identify and learn correlated patterns between input data sets and corresponding target data [16].

The paper is structured as follows: ANN prediction structure is described in Section II. In section III, static and dynamic voltage stability analyses were performed. Performance of ANN predictive is tested briefly the traditional power system models used of a typical test system, ULTC and SVC static analysis together with interesting simulation curves are presented in Section III . Conclusions are presented in Section IV.

II. ARTIFICIAL NEURAL NETWORK(ANN)

The neural network predictive controller that is implemented in the artifical neural network software uses a neural network model of a nonlinear plant to predict future plant performance. The first step in model predictive control is to determine the neural network plant model (system identification). Next, the plant model is used by the controller to predict future performance. The process is represented by the showning in Figure 1 [17].

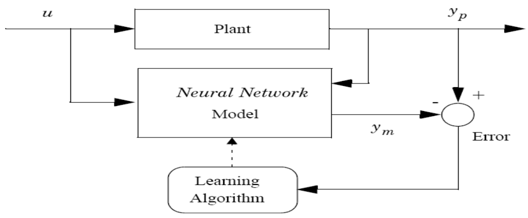


Figure 1 The predictive control scheme based on the neural model [17]

The back-propagation feed-forward ANN is a universal function approximator that typically yields better results than traditional approximation methods in practical applications[19].

ANN can deal with continuous and random nonlinear problems with a refined modeling agility in complex nonlinear systems and excellent ability for fitting data[20].

A. *Designing Artificial Neural Network*

The artificial neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output.

The components of the input pattern consisted of the control variables of the machining operation (power and voltage), whereas the output pattern components represented the measured factors (suseptance or tap ration). The nodes in the hidden layer were necessary to implement the nonlinear mapping between the input and output patterns. In the present work, 2-input, 4-hidden layers, 1 output layer back propagation neural network has been used.

These ANN models were varied to investigate the influence of variations in the number and the selection of training data.

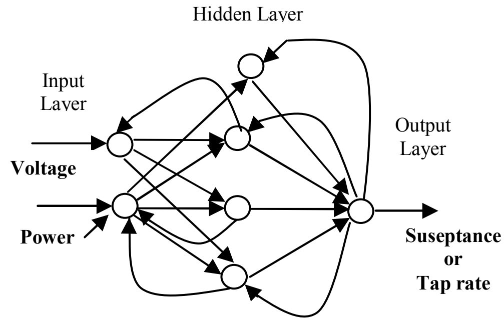


Figure 2. BPN network used for modeling

III. VOLTAGE STABILITY

In recent years voltage stability and voltage collapse phenomena have become more and more important issues in power system analysis and control. Researchers have suggested techniques for voltage stability analysis considering both static and dynamic aspects.

A. *Static voltage stability analyses*

The *P-V* Curve, *Q*-V Curve, have been widely used to analyze power system behaviors under varying loading conditions. Voltage stability analysis and loadability analysis are examples of the application of these curves in power system analysis. We consider the simple system of Fig 3.a, which consist of one load fed by an generator bus through a transmission line. The transmission line is represented by its series resistance *R* and reactance *X*, as given by the classical pi-equivalent in Fig 3(b)

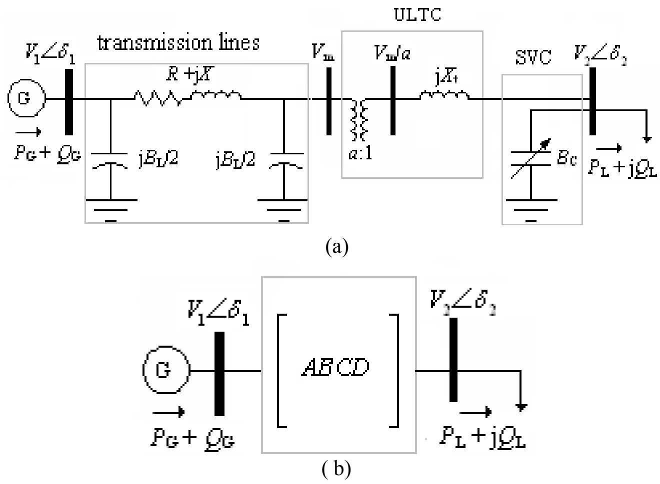


Figure 3.The simple system a) A simple two bus example system b)Pi-equivalent of reciprocal two-ports

Where, the parameters of pi equivalent circuit having the 2-bus are; $A = a\zeta(1 - B_C X_t) - \frac{XB_C}{a}$, $B = j(a\zeta X_t + \frac{X}{a})$, $C = j(a\xi B_L + \frac{\zeta}{a} B_C - a\xi B_L B_C X_t)$ and $D = \frac{\zeta}{a} - a\xi B_L B_C X_t$ respectively.

$\zeta = 1 - \frac{XB_L}{2}, \xi = 1 - \frac{XB_L}{4}$ are the parametric line constants of the sample system of Figure 3(a) and X=0.5 p.u and B_L=0 p.u are reactance and shunt capacitance of transmission line, respectively. The line shunt capacitance and resistance are neglected for simplicity.

The load power demand is $P_d + jQ_d$. a and X_t are tap rate and leakage reactance of ULTC, respectively. B_C susceptance of shunt compensator.

Fig.4 shows a situation where as load power increases, more shunt compensation has to be added or ULTC tap ratio decreases in order to keep the voltage within the limits.

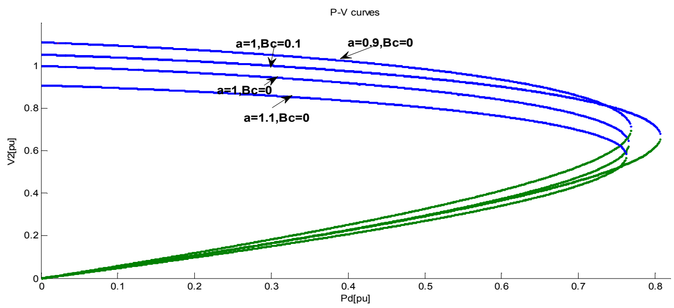


Figure 4. PV curves for various compensation levels and tap ration

B. *Dynamic Voltage Stability Analysis*

Voltage stability is a dynamic phenomenon and analysis based on static modeling is not sufficient and usually leads to erroneous results. A common situation that is often encountered is that the system can collapse after a disturbance even if a post disturbance equilibrium point exists. In such cases, detailed dynamic models need to be used to analyze system stability.

The simple two bus system is shown in figure 3.a whose dynamic equations for machine and load are given by:

$$\dot{\omega} = \frac{1}{M}(P_M - P_G - D_G\omega) \tag{1}$$

$$\delta = \omega \tag{2}$$

$$\dot{V}_2 = \frac{1}{\tau}(Q_L - Q_D) \tag{3}$$

where the generator inertia and damping constants are represented by M and D_G, and τ stand for the dynamic load voltage time constants respectively [18].

1) *SVC Application*

In this paper, SVC has been represented by model [21]

$$\dot{B}_{SVC} = \frac{1}{T_B}(-V_2 + V_{ref}) \tag{4}$$

where T_B ve V_{ref} are time constant and reference voltage values of load bus taken as 50 s and 1.0 pu, respectively.

For the simple system is shown in figure 3.(a) Active and reactive power are given equations

$$P_G = V_1^2 G - V_1 V_2 (G\cos\delta - B\sin\delta) \tag{5}$$

$$P_L = -V_2^2 G + V_1 V_2 (G\cos\delta + B\sin\delta) \tag{6}$$

$$Q_G = V_1^2 B - V_1 V_2 (G\sin\delta + B\cos\delta) \tag{7}$$

$$Q_L = -V_2^2 (B - B_{SVC}) - V_1 V_2 (G\sin\delta - B\cos\delta) \tag{8}$$

where $\delta = \delta_1 - \delta_2$, $G = \frac{R}{R^2 + X^2}$, $B = \frac{X}{R^2 + X^2}$.

The steady state load demand is modeled through the parameter Pd, under the assumption that reactive power load demand is directly proportional to the active power demand, i.e, Qd=k.Pd ; this parameter is used here to carry out he voltage collapse studies. SVC operated capacitive mode figures out compensation effect for power system stability. To simplify the stability analysis, the resistance and line susceptance are neglected (R=0, BL=0), Pm=Pd. The initial loading condition, as considered or not, as discussed below. The p.u time constants are assumed to be M =1, DG =0.1, τ =8; the load power factor is assumed to be 0.97 lagging, i,e., k =0.25, and reactance of transmission line X= 0.5 pu. The value belonging to limit point of system is $P_d^{\max} = 0.78078$ pu.

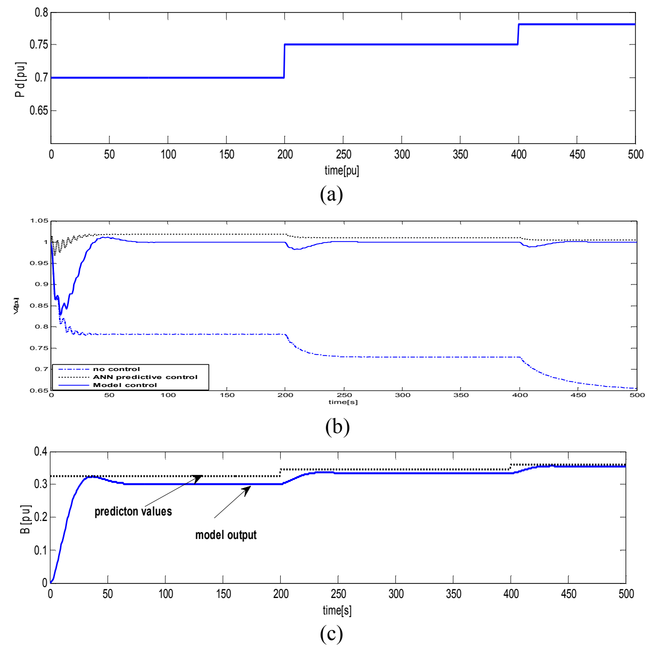


Figure 5. SVC system's a) demand power [P_d] b) voltage c) susceptance values

Fig. 5 shows the active power, voltage and susceptance of SVC against time of the sample system. Augmentation scenarios are considered as load disturbance. Saddle Node Bifurcation(SNB) (or critical point) is obtained by bifurcation analysis. Critical values and the SVC susceptance values estimated by ANN are given in Table I. Fig. 5(c) also shows voltage instability of power system without any control method.

TABLE I. VALUES MAKING THE VOLTAGE TO 1.0 PU AT DIFFERENT POWER

P_d	Suseptance values	
	Model output	*ANN prediction*
0.7	0.3015	0.324766
0.75	0.3335	0.345127
0.78078(SNB)	0.3539	0.359025

2) ULTC Application

The continuous ULTC model is based on the assumption of a continuously changing tap $a(t)$, which can take all real values between amin and amax. Usually the effect of the dead band is neglected in a continuous ULTC model, so that the following differential equation results [22],

$$\dot{a} = \frac{1}{T_c}(V_2 - V_2^0) \qquad a^{\min} \le a \le a^{\max} \tag{9}$$

Where V_2^0 is the reference voltage, and T_C is the time constant and taken 50 s as simulation time. The ULTC is modeled as an integral controller using (9).

For the simple system is shown in figure 3(a) active and reactive power values fed from buses using load flow equations are given (10-12)

$$P_G = \frac{B_l \xi X + \zeta^2}{a^2 X_t \zeta + X} a V_1 V_2 \sin\delta \tag{10}$$

$$P_L = \frac{1}{a^2 X_t \zeta + X} a V_1 V_2 \sin\delta \tag{11}$$

$$Q_L = \frac{a V_1 V_2 \cos\delta - V_2^2 a^2 \zeta}{a^2 X_t \zeta + X} \tag{12}$$

Where a and X_t =0.01 p.u are tap rate and leakage reactance of ULTC, respectively.

TABLE II. VALUES MAKING THE VOLTAGE TO 1.0 PU AT DIFFERENT POWER

P_d	Tap change values	
	Model output	*ANN prediction*
0.7	0.7753	0.779208
0.75	0.7167	0.716688
0.76547(SNB)	0.6841*	0.703781

* ULTC can not avoid instability due to slow down at this point.

Fig. 6 shows the active power, voltage and tap change ration of ULTC against time of the sample system. Augmentation scenarios are considered as load disturbance. Saddle Node Bifurcation(SNB) (or critical point) is obtained by bifurcation analysis. Critical values and the ULTC tap change ration values estimated by ANN are given in Table II. Fig. 6(c) also shows voltage instability of power system without any control method.

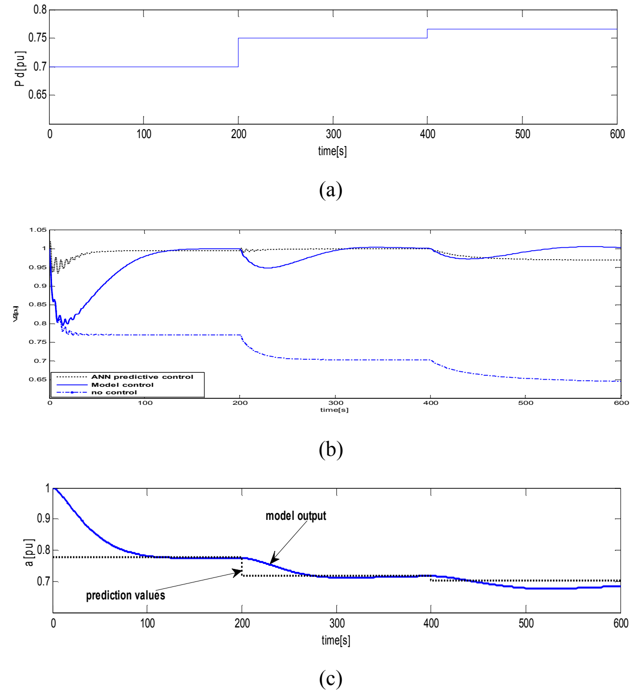


Figure 6. ULTC system's a) demand power [P_d] b) voltage c) tap ration values

a) ANN Prediction results and discussion.

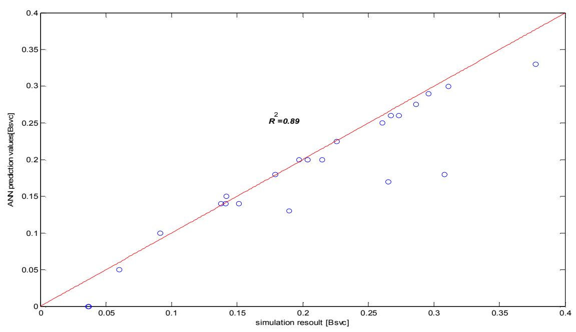
The structure of the proposed neural Networks used for BPN is shown in Fig.2. We trained the neural networks until the error function was less than $1\text{x}10^{-4}$. Using other neural networks parameters, minimum weight delta 0.0001, inital weights 0.3, learning rate 0.6, momentum 0.6 . The used activation function of neural network hyperbolic tangent funtion. ANN having two input and one output neurons were used to model SVC and ULTC.

The input and output parameters are given in Table 3 with correlation coefficient values.

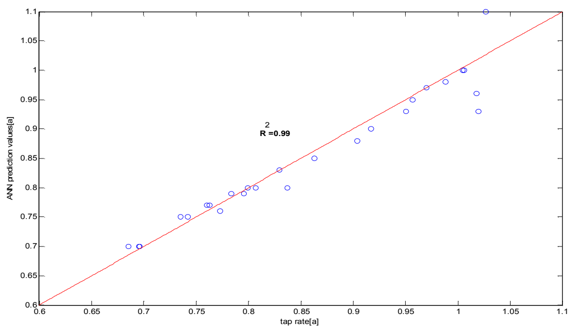
TABLE III. INPUTS AND OUTPUTS FOR TRANING ANN

Devices	ANN parametric values			
	Input (X)	*Output (Y)*	*Data sets*	*Correlation coefficient (R^2)*
SVC	x_1=P_d , x_2=V_2	y_1=B_{SVC}	traning=15 test=23	0.89
ULTC	x_1=P_d , x_2=V_2	y_1=a	traning=20 test=17	0.99

Fig. 7(a) and (b) clearrly show that ANN traning is succesful for both systems



(a)



(b)

Figure 7. Resulting of traning a)of with SVC b)of with ULTC

IV. CONCLUSIONS

In this study *P-V* curves of the sample system are drawn for static voltage stability. The effects of SVC for increasing the stability limit are shown. Critical points of the poewer system are determined by bifurcation analysis.

In this study after a disturbance susceptance values and tap rate values of SVC and ULTC are estimated.

The results estimated at critical points keep power system stable.

Determination of the value of ULTC due to slow down critical points avoid a possible instability.

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