Neural-net based control structure with FACTS devices

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Abstract

Load side voltage stability is a main concern in this paper. Neural-network based dynamic load model is incorporated into voltage stability analysis. FACTS (flexible ac transmission systems) devices, such as TCSC (Thyristor Controlled Series Capacitor) and SVC (Static Var Compensator), are applied for power system stability enhancement. The use of dynamic load model and FACTS devices for control may sometimes lead to excitation of generator dynamics, resulting in the whole power system more complex. Conventional methods often neglect either the load dynamics or generator dynamics while the proposed methods deal with both. For the convenience of control design, proper system models are developed. Methods are presented for TCSC and SVC control cases to represent the controlled system through three sets of equations: generator dynamics, load dynamics and control constraints. The control is then synthesized in the form of neural networks, trained by using the pre-specified optimal trajectories. Under some circumstances, simplied neural controllers can be synthesized.

1 Introduction

Many voltage instability incidents have occurred around the world. Some of these incidents even caused partial or complete blackout (voltage collapse) [1, 7]. There are various causes which might lead to these severe system failures. The initial causes may be AC line trip, generator loss, immediate heavy load buildup, special load with unfavorable load dynamic characteristics, etc. It is also observed that very hot or very cold weather has direct influence on the addition of extreme high loads to power systems. In a word, abnormal operations of supply systems, heavy loading patterns and load characteristics are the main causes to voltage instability incidents. The mechanism of load-driven voltage instability has not been very clear. Extensive research has been performed to make predictions for possible voltage instability. This include power flow based static techniques [8, 9, 10], which are still prevailing in many utilities; the quasi-static techniques (e.g. small-disturbance analysis) [11, 12, 13]. To fully address the load-driven voltage stability problem, however, load dynamics, generator dynamics, their interaction, and load modeling must be studied.

On one hand, dynamic load modeling has been an important issue for voltage stability analysis, which was investigated in [2, 3]. Based on the modeling of dynamic load, further dynamic voltage stability analysis then becomes feasible. For control purpose, an aggregate dynamic load model must also be available since it is neither possible nor necessary to model each and every power system load devices. There have been studies on how to model all the downstream loads connected to a specific bus in an aggregate manner using neural networks [3 and therein]. How to incorporate the dynamic load model into control schemes is studied later in this paper.

On the other hand, transient stability and load-driven stability are relatively closely associated with generator angle dynamics and load dynamics, respectively, but are hard to separate. The interaction of generator side transient dynamics and load dynamics can cause serious stability problems, even voltage collapse. The resulting power systems are highly nonlinear and dynamic with uncertainties. The design of controllers must consider these facts.

This paper deals with the very dynamic voltage stability problem by developing appropriate system models and proper control schemes suitable for use with TCSC and SVC. The proposed control schemes consider both load dynamics and generator dynamics with load dynamics being modeled by a recurrent neural network. The resulting system is a nonlinear mixed system, including time-continuous dynamics and time-discrete dynamics. The neural-net based control is synthesized using off-line computed optimal temporal trajectories.

Notation: the expression $x([k,k+n])$ or $x^{[k,k+n]}$ designates a sequence of $x(k)$,$x(k+1)$,$\cdots$, $x(k+n)$; and the expression $\{x_i\}$ represents a set which has element x_i with i in some default (not necessary to specify in the context) set.

2 Control-oriented model for power systems

As is known, the control issue of interconnected power systems has been studied at the generating subsystem level and at the transmission level. For the former level, devices that have been extensively used for control include power system stabilizers (PSS), automatic voltage regulators (AVR) in conjunction with turbine-governor speed regulators. For the latter level, FACTS devices, to cite a few, the thyristor-controlled series capacitors (TCSC), static var compensators (SVC), thyristor-controlled braking resistors (TCBR), have been used for the purpose of control. Though the main concern in the paper is the voltage stability on the load side, yet changes in load may sometimes have some unneglectible impacts on the generation voltage stability. Therefore, for voltage stability study, both load side and generation side dynamics will be considered in this context.

2.1 System model for TCSC-based control

To proceed with voltage stability study, a power system can be fully characterized by three equations, i.e., one for each of generator dynamics, network composition, and load dynamics.

Generator dynamics can be characterized, with x_1 being the state vector, by

$$\dot{x_1} = f_1(x_1, u_1) \tag{1}$$

Load dynamics can be characterized, with x_2 being the state vector, by

$$\dot{x_2} = f_2(x_2, u_2) \tag{2}$$

where u_1 and u_2 are vectors composed of input variables, intermediate variables, and control variables, etc.

Network equation can be given by

$$I = YE \tag{3}$$

where I is the current injection vector, E the voltage vector, and Y the network admittance matrix.

Based on the above three equations, system models will be derived for power systems equipped with FACTS device, TCSC, and serving dynamic load.

For simplicity but without loss of generality, some assumptions are made as follows: (1) On load side, only the dynamics of one load is of main concern whereas the dynamics of all other loads is neglected (i.e., they are treated as either constant impedance or constant power devices) (2) Only one FACTS control device is considered, which is the TCSC in charge of series compensation.

The results suitable for the simplified case should be readily generalized to the more complex cases by removing the assumptions one by one.

One simple simulation model, shown in Fig. 1, studied for generation side postfault voltage stabilization [6], will also be used to demonstrate the development of the power system model. Specifically, for the simulation model, with Machine #1 as reference (which is assumed stable, and further, does not participate in the dynamics in the control design studies), the generator dynamics and load dynamics (e.g., at bus #8) are taken into account.

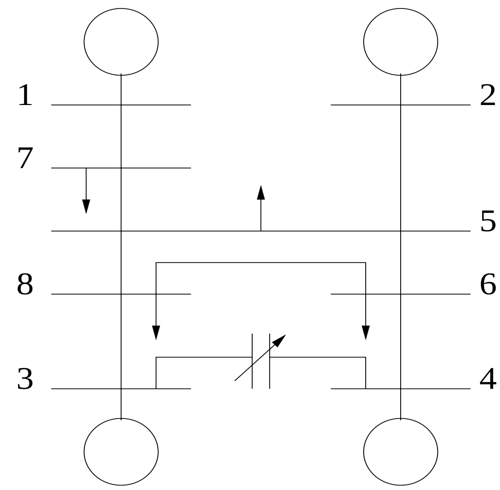

Figure 1: Four-machine system model

$$\frac{2H_i}{\omega_R}\frac{d\omega_i}{dt} + D_i\omega_i = P_{mi} - P_{ei} \tag{4}$$

$$\frac{d\delta_i}{dt} = \omega_i - \omega_R \tag{5}$$

where $i = 2, 3, 4$, and

$P_{ei} = \sum_{j=1}^{8} E_i E_j Y_{ij} cos(\theta_{ij} - \delta_i + \delta_j)$.

For buses #5,6,7, we obtain

$$\begin{cases} P_{li} = P_{ei} \\ Q_{li} = Q_{ei} \end{cases} \tag{6}$$

where P_{li} represents the load connected to bus #l.

For bus #8, assume that the load connected possesses some dynamics identified by a neural network. This neural model, as represented in [6], can be given by

$$P_{l8}(k+1) = f_p(P_{l8}([k-n_p+1,k]); E_8([k-m_p+1,k])) \tag{7}$$

and

$$Q_{l8}(k+1) = f_q(Q_{l8}([k-n_q+1,k]); E_8([k-m_q+1,k])) \quad (8)$$

Consider more general power systems with the following assumptions:
(1) The generators are numbered from 1 to N_g. (2) The buses numbered N_g+2 and N_g+3 correspond to those buses to which the TCSC is connected. (3) The load bus which assumes load dynamics is numbered N_g+1. (4) All other load buses are assumed to be passive.

The network equations can be given by

$$\begin{bmatrix} I \\ 0 \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} E \\ V \end{bmatrix}. \quad (9)$$

where admittance matrix Y is split so that Y_1 corresponds to the generators, TCSC, and dynamic load. This serves to preserve the system structure partially for the purpose of control design, which will be seen more clearly next.

It follows from elimination of V that

$$I = (Y_1 - Y_2 Y_4^{-1} Y_3)E \quad (10)$$

where $I = [I_g^\tau \quad I_l^\tau \quad 0^\tau]^\tau$, $E = [V_g^\tau \quad V_l^\tau \quad V_{tcsc}]^\tau$. The admittances concerning the TCSC are all included in Y_1, and $Y_1 - Y_2 Y_4^{-1} Y_3$ is the reduced admittance matrix, thereby preserving the structure for control.

Denote the above reduced admittance matrix by

$$\begin{bmatrix} \overline{Y}_{11} & \overline{Y}_{12} & \overline{Y}_{13} \\ \overline{Y}_{21} & \overline{Y}_{22} & \overline{Y}_{23} \\ \overline{Y}_{31} & \overline{Y}_{32} & \overline{Y}_{33} \end{bmatrix}.$$

Then

$$\begin{bmatrix} I_g \\ I_l \\ 0 \end{bmatrix} = \begin{bmatrix} \overline{Y}_{11} & \overline{Y}_{12} & \overline{Y}_{13} \\ \overline{Y}_{21} & \overline{Y}_{22} & \overline{Y}_{23} \\ \overline{Y}_{31} & \overline{Y}_{32} & \overline{Y}_{33} \end{bmatrix} \begin{bmatrix} V_g \\ V_l \\ V_{tcsc} \end{bmatrix} \quad (11)$$

Therefore,

- Generator's dynamical equation for the ith machine is given by

  $$\begin{cases} \frac{d\delta_i}{dt} = \omega_i - \omega_1 \\ \frac{d\omega_i}{dt} = \frac{1}{M_i}[P_{mi} - P_{ei} - D_i(\omega_i - \omega_1)] \end{cases} \quad (12)$$

  where $P_{ei} = Re\{V_g I_g^*\}$

- Dynamic load model and associated constraint are given by

  $$\begin{aligned} P_l(k+1) &= f_p(P_l([k-n_p+1,k]); V_l([k-m_p+1,k])) \\ Q_l(k+1) &= f_q(Q_l([k-n_q+1,k]); V_l([k-m_q+1,k])) \end{aligned} \quad (13)$$

  where $S_l = P_l + jQ_l = V_l I_l^* = \overline{Y}_{21}^* V_g^* V_l + \overline{Y}_{22}^* |V_l|^2 + \overline{Y}_{23}^* V_{tcsc}^* V_l$.

- TCSC constraint is given by

  $$0 = \overline{Y}_{31} V_g + \overline{Y}_{32} V_l + \overline{Y}_{33} V_{tcsc} \quad (14)$$

  Or, after the substitution of $\overline{Y}_{33}(u) = \overline{Y}_{33}(0) + juF_{33}$,

  $$0 = \overline{Y}_{31} V_g + \overline{Y}_{32} V_l + (\overline{Y}_{33}(0) + juF_{33}) V_{tcsc} \quad (15)$$

The above model can be reformulated as follows:

$$\begin{cases} \dot{x} = f(x, y_1, y_2) \\ r(k+1) = h(r(k), |y_2|) \\ y(k) = s(r(k)) \\ g(x, y_1, y_2, u) = 0 \\ t(y(k), y_1, y_2)) = 0 \end{cases} \quad (16)$$

where x represents the state vector composed of the relative rotor angles and rotor speeds; y_1 represents the voltage vector composed of the voltage magnitudes of generators and voltages for those buses to which TCSCs are connected; y_2 represents the voltage of the load side bus. $r(k)$ represents the discrete time state of the neural network model for the dynamic load; and $y(k)$ represents the real/reactive power of the dynamic load. It is observed that this system model is a combination of a continuous time model (i.e., generator swing equation) and a discrete time model (neural-net-based load model, described in state-space form) and equality constraints for the TCSC control and also load side real/reactive power. It is noted that such a formulation can also be done for power systems with multiple TCSC devices and multiple dynamical loads.

2.2 System model for SVC-based control

As is known, the TCSC can provide series compensation by adjusting the line impedance. Similarly, the SVC can provide shunt compensation by injecting or absorbing reactive power to or from the power system. As shown for the TCSC-based control case, the system model suitable for SVC control can also be derived.

Likewise, some assumptions are made as follows: (1) On load side, only the dynamics of one load is of main concern whereas the dynamics of all other loads is neglectible; (2) Only one control device — SVC is considered, and it is located in a specific load bus to which a dynamic load is connected.

Consider a power system with following assumptions: (1) The generators are numbered from 1 to N_g; (2) The load bus which assumes dynamics is numbered N_g+1, to which a SVC is connected; (3) All other load buses are assumed to be passive.

The network equation can then be given by

$$\begin{bmatrix} I \\ 0 \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} E \\ V \end{bmatrix}. \quad (17)$$

where Y admittance matrix is split so that Y_1 corresponds to the generators and dynamical load, which serves to preserve the system structure partially for the purpose of control design.

It follows from elimination of V that

$$I = (Y_1 - Y_2 Y_4^{-1} Y_3)E \quad (18)$$

where $I = [I_g^\tau \;\; I_l^\tau]^\tau$, $E = [V_g^\tau \;\; V_l^\tau]^\tau$. The admittance concerning the SVC is included in Y_1, and $Y_1 - Y_2 Y_4^{-1} Y_3$ is the reduced admittance matrix, thereby preserving the structure for control.

Denote the above reduced admittance matrix by

$$\begin{bmatrix} \overline{Y}_{11} & \overline{Y}_{12} \\ \overline{Y}_{21} & \overline{Y}_{22} \end{bmatrix}.$$

Then

$$\begin{bmatrix} I_g \\ I_l \end{bmatrix} = \begin{bmatrix} \overline{Y}_{11} & \overline{Y}_{12} \\ \overline{Y}_{21} & \overline{Y}_{22} \end{bmatrix} \begin{bmatrix} V_g \\ V_l \end{bmatrix} \quad (19)$$

Therefore,

- Generator's dynamical equation for the ith machine is given by

$$\begin{cases} \frac{d\delta_i}{dt} = \omega_i - \omega_1 \\ \frac{d\omega_i}{dt} = \frac{1}{M_i}[P_{mi} - P_{ei} - D_i(\omega_i - \omega_1)] \end{cases} \quad (20)$$

  where $P_{ei} = Re\{V_g I_g^*\}$

- Dynamic load model and associated constraint are given by

$$\begin{aligned} P_l(k+1) &= f_p(P_l([k-n_p+1,k]); V_l([k- \\ &\quad m_p+1,k])) \\ Q_l(k+1) &= f_q(Q_l([k-n_q+1,k]); V_l([k- \\ &\quad m_q+1,k])) \end{aligned} \quad (21)$$

  where $S_l = P_l + jQ_l = V_l I_l^* = \overline{Y}_{21}^* V_g^* V_l + \overline{Y}_{22}^* |V_l|^2$
  It is noted that the SVC control is included in $\overline{Y}_{22}$. Let $\overline{Y}_{22}(u) = \overline{Y}_{22}(0) + juF_{22}$. From this expression, it is observed that the control u is directly related to the SVC capacitive admittance and that if u is zero then the SVC is actually disconnected to the load bus.

Further, a somewhat more general model can be derived, following the same procedures detailed in the above, as follows:

$$\begin{cases} \dot{x} = f(x, y_1, y_2) \\ r(k+1) = h(r(k), |y_2|) \\ y(k) = s(r(k)) \\ g(x, y_1, y_2, u, y(k)) = 0 \end{cases} \quad (22)$$

where x represents the state vector composed of the relative rotor angles and rotor speeds; y_1 represents the voltage vector composed of the voltage magnitudes of generators; y_2 represents the voltage of the load side bus. $r(k)$ represents the discrete time state of the neural network model for the dynamic load; and $y(k)$ represents the real/reactive power of the dynamic load. It is observed that this system model is also a combination of a continuous time model (i.e., generator swing equation) and a discrete time model (neural-net-based load model, described in state-space form) and an equality constraint for the SVC control and also load side real/reactive power.

3 Control schemes with FACTS devices

Observations for equations (16) and (22) indicate that the control u is governed by constraints with other variables, which in turn affect the generator dynamics and loading dynamics. It is also interesting to see that the functions describing constraints are linear in the control u, from which the control design will benefit.

3.1 TCSC-based control scheme

The control objective to the TCSC control-oriented system model (16) is to find u such that x and y_2 will be stabilized within the prespecified region (i.e., $x \in \Omega_x$, $y_2 \in \Omega_v$).

The measurements that are assumed to be available are generators' relative rotor angles $\{\delta_i\}$.

Since generator's dynamics is much faster that load's, it is common knowledge that generator's dynamics is often considered while load dynamics is neglected, and vice versa. However, this may not be true since any change of TCSC control will have influence both on generators and loads. It might be possible that under some circumstances some changes of TCSC control may stabilize the generators while they have much less (or even neglectible) influence on load side, and vice versa. Therefore, the control u can be split into two parts u_1 and u_2 while u_1 is designed, based on the measurements of relative rotor angles, for generator control and u_2 is designed, based on $y_2(k)$ (load voltage magnitude) and its previous values, for load bus voltage stabilization.

The total control u can be expressed as

- linear sum of 2 control signals

$$u = \lambda_1 u_1 + \lambda_2 u_2 \quad (23)$$

  where $[\lambda_1 \;\; \lambda_2]^\tau = NN_\lambda(\{\delta_i\}, \{y_2[k-i]\})$. This indicates that the coefficients can be trained using measurements and some calculated values.

- nonlinear weighted sum of 2 control signals

$$u = NN_u(u_1, u_2) \tag{24}$$

Such a control methodology can be illustrated in Fig. 2.

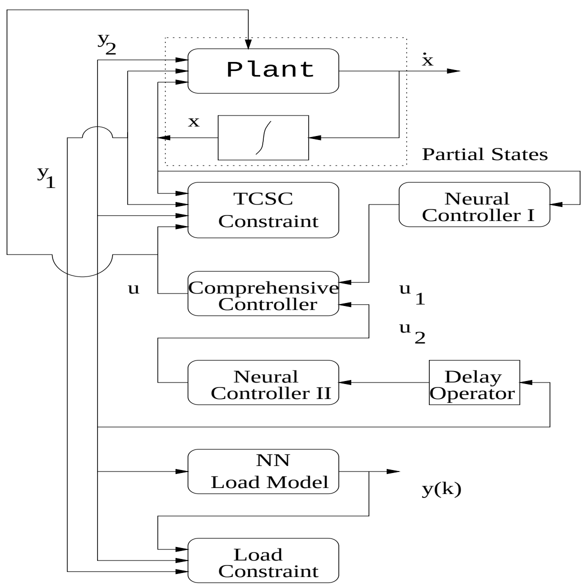

Figure 2: System model and Control scheme

From equations (23) and (24), it is observed that

Case I: If generator dynamics can be neglected, then u_1 is not needed, and hence the control structure may be simplified.

Case II: If on the load side, constant load is assumed, thereby no load dynamics being under consideration, u_2 is not needed. The control structure can also be simplified.

Case III: Both generator dynamics and load dynamics should be considered. A control scheme, shown in Fig. 2, may be employed.

A more general TCSC control should take a more general form of recurrent neural network model such that

$$u_{tcsc}^{n+1} = NN(u_{tcsc}^{[n-n_u,n]}, y_2^{[n-n_y+1,n]}, \{\delta_i\}^{[n-n_\delta+1,n]}) \tag{25}$$

It is observed that the above function is actually also a function of the neural net weights which are omitted for simplicity. This neural network can be trained either on-line or off-line. The off-line training can be achieved by using the nominal optimal trajectories obtained to minimize/maximize some pre-specified performance index, as is usually done for optimal control design.

Let an nominal optimal trajectory ϕ^j be denoted by $\phi = \{(k, \phi_k) : 1 \leq k \leq N_j\}$ where N_j is the total points and ϕ_k is a vector that has a component of u_{tcsc}, y_2 and δ. Let a collection of M nominal optimal trajectories be denoted by $\Phi = \{\phi^j : 1 \leq j \leq M\}$.

Then the weights are adapted such that the errors between the output trajectories Ψ (with the same explanation as Φ) from the trained neural network and the nominal optimal trajectories are minimized. That is, $E = \sum_{j=1}^{M} \sum_{k=1}^{N_j} |\psi_k^j - \phi_k^j|^2$. Various kinds of training methods can be used for training neural networks.

Since this neural controller for TCSC and the neural identifier for the dynamic load are discrete in time, and they are used with continuous time generator model and network model, a careful manipulation should be done. That is, for any period of time $t \in [k, k+1)\delta T$ (δT is the sampling period), the control $u(t) = u_{tcsc}^k$; and similarly $P(t) = P^k$, $Q(t) = Q^k$ for $t \in [k, k+1)\delta T$.

3.2 SVC-based control scheme

In case of fault or big build-up, the flow of reactive power will be not balanced to some degree, which creates a situation that the reactive power demand may not be met in time. This may lead to the further instability problem. In this regard, the SVC is used to provide sufficient reactive power promptly. Proper control of the SVC can ensure more real power to flow to the load side from the generator side while still keeping synchronism and load side voltage stability.

Assume the relative rotor angles can be measured. Then the SVC control then can be synthesized as a function of the measurements $\{\delta_i\}$ and the dynamic load side voltage magnitude y_2 as well. Since the whole power system is nonlinear, the proper control may be a complex nonlinear function in terms of $\{\delta_i\}$ and y_2. A recurrent neural network can be trained such that

$$u_{svc}^{n+1} = NN(u_{svc}^{[n-n_u,n]}, y_2^{[n-n_y+1,n]}, \{\delta_i\}^{[n-n_\delta+1,n]}) \tag{26}$$

It is observed that the same situation is encountered for SVC control as for TCSC control. Therefore, the training of an appropriate neural network can be achieved by using some pre-specified optimal trajectories. The same procedures for designing TCSC neural controller can then be followed for SVC control design.

4 Case Study

It is worthwhile to identify a few simplified cases that confirm that the proposed control methodology is useful. Even the simplified cases are not trivial problems at all. As a matter of fact, they are typical problems that have been a subject of extensive study.

If the power system does not experience significant generator dynamics, but operates in critical modes in which it is likely to experience significant voltage drop, the neural-network based dynamic load model can be used to perform dynamic voltage stability analysis. This kind of study was performed in [3]. From the proposed control schemes, the control can be synthesized to mainly stabilize the load side voltage [5].

If the power system does not experience significant load dynamics, but significant generator dynamics, the neural-network based control can be synthesized based on optimal performance index, for instance, time-optimal control, to stabilize the power system in a timely manner. This kind of study was performed in [14].

If the power system experience significant generator dynamics as well as load dynamics, the neural-network based control can be synthesized to stabilize the generator side dynamics to keep synchronism while stabilize the load side dynamics to keep good voltage profile. Simulations in a similar setup for a three-machine system were performed in [5], where both generator dynamics and load dynamics, and their interaction are present, while there also exists uncertainty in exogenous power demand. But the control scheme proposed in this paper is more complicated than the one in [5].

5 Conclusions

This paper is devoted to controller design for load side voltage instability or voltage collapse. Load dynamics as well as generator dynamics is taken into account for this purpose. Neural-network based dynamic load model is incorporated into voltage stabilization scheme. Conventional methods often neglect either the load dynamics or generator dynamics while the methods proposed in this paper deal with both generator dynamics and load dynamics. For control design, this paper presents the methods for TCSC and SVC control cases to represent the whole system through three sets of equations: generator dynamics, load dynamics and control constraints. The control is then synthesized in the form of neural networks which may be trained by using the pre-specified (or off-line computed) optimal trajectories.

Future research includes extensive simulations with the proposed control structure and methods for TCSC and SVC control which can be used to stabilize postfault power systems or power systems which are operating on critical mode or unstable modes. The reader is referred to [4] for further discussions.

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