ARTIFICIAL NEURAL NETWORKS FOR ASSESSMENT POWER SYSTEM TRANSIENT STABILITY WITH TCVR

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Abstract*. This paper shows the modeling and the effectiveness of Thyristor Controlled Voltage Regulator (TCVR) for power systems transient stability improvement. Two applications of transient stability assessment are presented in this article: The first uses a Runge-Kutta method; the second application shows the effectiveness of artificial neural networks (ANNs) to calculate the CCT. Critical Clearing Time (CCT) is used as an index for evaluated transient stability. The effectiveness of the proposed methodology is tested in the WSCC3 nine-bus system in the case of three-phase short circuit fault on one transmission line. A simulation and comparison are presented in this document.*

Key words: *Artificial neural networks, Critical clearing time, TCVR, transient stability.*

1. Introduction.

Modern power systems have been larger and more complex for interconnections of the countries or electric companies. Several advances have been made to improve the performance, efficiency, reliability, and security of power systems. In power system analysis, the transient stability study is of paramount importance, it is considered when the power system is confronted with large disturbance. These disturbances can be faults such as: a short circuit on a transmission line, loss of a generator, loss of a load, gain of load or loss of a portion of transmission network …etc. The transient stability of an electric power system is referred as the ability to regain an equilibrium state after being subjected to a physical disturbance.

Transient stability in the face of severe disturbances is a very important characteristic, which should be considered in every power system. Studies over more than two decades have proved that this technique can improve system stability in an effective. These are the methods of numerical integration [1,4]. Direct methods (methods of energy) [1,5], probabilistic methods [6,7], methods based on pattern recognition and nonlinear adaptive methods [3,8-9]. However, some of these methods are time consuming and in many cases cannot be applied for on-line assessment. The uncertainty of predicting future operating conditions has created a need for on-line Transient stability assessment. This complex technique constitutes a challenge to provide comprehensive analysis with the required accuracy, speed and robustness [8]. Recent applications of ANN have shown that they have considerable potential in overcoming the difficult tasks of data processing and interpretation. Four major steps are necessary in ANNs application: selection of input features, selection of ANNs architecture and training the ANNs and testing.

Several methods of analysis of transient stability using neural networks have been developed, they are classified according to the release of ANNs into three categories: prediction of Critical Clearing Time (CCT) [3,9-10]. Calculating the margin of energy in order to maintain stability [11,12], predicting the stability by boolean output [13,14].

Various methods have been taken to improve the transient stability of power systems. One of the solutions is the application of Flexible AC Transmission Systems (FACTS), which depend on power electronics technologies [15-17]. FACTS technology opens up new opportunities for controlling power and enhancing usable capacity of the existing lines. The FACTS systems modify the characteristic of electrical components in order to increase their thermic capacity and remedy the problems of power system. In recent years, a large number of FACTS controller schemes based on various control techniques have been proposed to improve the transient and dynamic stability of power systems [18-20].

In this paper controller are considered namely Thyristor Controlled Voltage Regulator (TCVR), the effectiveness is evaluated by carrying out a transient stability analysis with and without considering these controllers embedded in the system. The TCVR is member of the family of combined FACTS, the TCVR inserts a voltage in series which is in phase with the bus voltage where the TCVR is connected, so as to increase or decrease its magnitude [15-19].

This paper presents an application of ANNs for Transient stability assessment and calculating CCT, which the effectiveness of the TCVR for transient stability of WSCC3 nine-bus system has been carried out. The nonlinear mapping relation between the TCVR margin and CCT at any instant for different operating conditions was established using a multilayered backpropagation ANNs. The proposed approach has been tested on WSCC3 nine-bus power system.

2. Power System Modelling

2.1 Generator Modelling

The dynamics of the machine can be represented by the following differential equations [1]:

$$\frac{d\delta}{dt} = \omega - 2.\pi.f \tag{1}$$

$$\frac{d\omega}{dt} = \frac{d^2\delta}{dt^2} = \frac{\pi.f}{H}(P_m - P_e) \tag{2}$$

$$\frac{dE_q^{'}}{dt} = \frac{1}{T_{do}^{'}}\left[E_{ex} - E_q^{'} + \left(X_d - X_d^{'}\right)I_d\right] \tag{3}$$

$$\frac{dE_d^{'}}{dt} = \frac{1}{T_{qo}^{'}}\left[-E_d^{'} - \left(X_q - X_q^{'}\right)I_q\right] \tag{4}$$

Where H_i, D_i, ω_i, δ_i, P_{mi}, P_{ei} are respectively the inertia constant, the damping constant, the rotor angular velocity, the rotor angle, the mechanical input power; the electrical power of the i-th generator; T'_{d0i}, T'_{q0i}, are the d-axis and q-axis transient time constants; E'_{di}, E'_{qi} are d-axis and q-axis transient emf; x'_{di}, x'_{qi} are generator d-axis and q-axis transient reactances; I'_{d0i}, I'_{q0i} are the d-axis and q-axis of the generator currents, V_{ex} is the field voltage controlled by a voltage regulator.

2.2 Voltage Regulator Modelling

The terminal generator voltage V_t is controlled via an AVR (Automatic Voltage Regulator) represented by the block diagram of Figure 1.

It is modeled with three variables: the exciter output voltage V_{ex}, the regulator voltage V_1 and the stabilizer state V_2 related by the following equations:

$$\frac{dV_1}{dt} = \frac{1}{T_r}\left(V_{ref} - V_t - V_1\right) \tag{5}$$

$$\frac{dV_R}{dt} = \frac{1}{T_A}\left[K_A\left(V_1 + \frac{V_{oR}}{K_A} - V_2\right) - V_R\right] \tag{6}$$

$$\frac{dE_{ex}}{dt} = \frac{1}{T_E}\left[V_R - \left(S_E + K_E\right)E_{ex}\right] \tag{7}$$

$$\frac{dV_2}{dt} = \frac{1}{T_F}\left(K_F\frac{dE_{ex}}{dt} - V_2\right) \tag{8}$$

Where:

K_A, K_E, K_F : are the gains, T_A, T_E, T_F : are system time constants; V_1, V_2, E_{ex}, V_R: are the AVR state variables and V_{ref} is the terminal voltage reference setting.

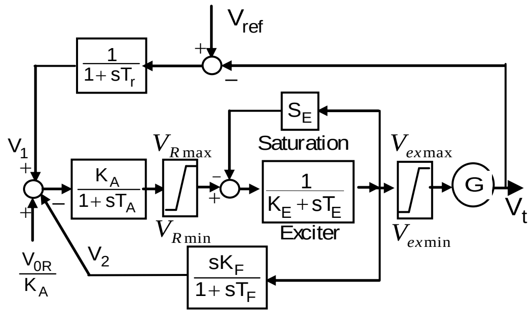

Fig. 1 Block diagram of AVR model

2.3 Speed Regulator Modelling

The speed governor for hydroelectric generators used in this work is illustrated in the block diagram of

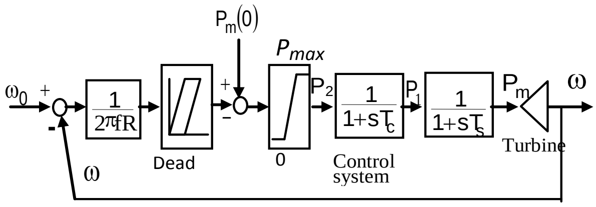

Fig. 2 Block diagram of governor turbine for hydro - generator

The state variables of the regulator are related by the following equations:

$$\frac{dP_m}{dt} = \frac{1}{T_S}(P_1 - P_m) \tag{9}$$

$$\frac{dP_1}{dt} = \frac{1}{T_C}(P_2 - P_1) \tag{10}$$

$$P_2 = P_m(0) - \frac{1}{R}\left[\frac{\omega_b - \omega}{2\pi f} \pm DBt\right] \tag{11}$$

Where:

R is the speed regulation; T_c, T_s are time constants; P_m is the mechanical power; $P_m(0)$ is the initial mechanical power; P_1, P_2 are the intermediate state variables; *DBt* is the dead band travel.

2.4 TCVR Modelling

The schematic diagram of TCVR is presented in figure.3 :

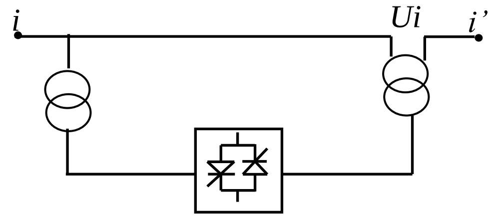

Fig. 3 Schematic diagram of TCVR

The π equivalent circuit of the transmission line with TCVR is presented in fig. 4 [16]:

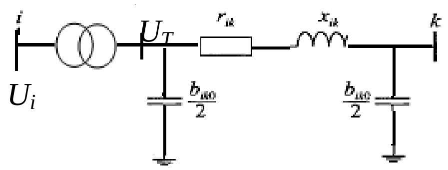

Fig. 4 The π equivalent circuit of the transmission line with TCVR

Were r_{ik}, x_{ik} and b_{ik} are resistance, reactance line and capacitance line respectively.

The TCVR inserts a voltage in series which is in phase with the bus voltage where the TCVR is connected, so as to increase or decrease its magnitude. This series voltage is made variable with a variety of power electronics topologies.

The tension U_T is defined by:

$$U_T = k_T U_i \tag{12}$$

Where k_T is the control variable that can take a discrete number of values in the range [16]:

$$-0.15 < k_T < 0.15 \tag{13}$$

With the transformation ratio is:

$$\mu_T = \frac{1}{1+k_T} \tag{14}$$

3. Control Strategy

The proposed control improves the dynamic stability of the power system by suitably modulated of voltage bus. The control strategy used in this paper is based to reduce the acceleration of the machines after a fault. The rapid controllability of FACTS devices can be used to significantly enhance the power system stability. The electric power is modulated by changing the magnitude of the bus voltage where the TCVR is connected. The detail of such a control strategy is given in the following [18,20]:

$$U_T = \begin{bmatrix} (k_T+1)U_i(where: \omega > \omega_{\max}, k_T = k_{\max}, \textit{first}\ \text{swing} \\ (k_T+1)U_i(where: k_T = f(\omega), k_{T\min} \le k_T \le k_{T\max}(afterwards) \\ \text{until the machine reaches the equilibrium} \end{bmatrix} \tag{15}$$

4. System Study and Result Analysis

The main objective of this study is to analyze the effectiveness of TCVR controller to improve transient stability of power system. In all cases, it is considered for the TCVR (k_{max}=-k_{min}).

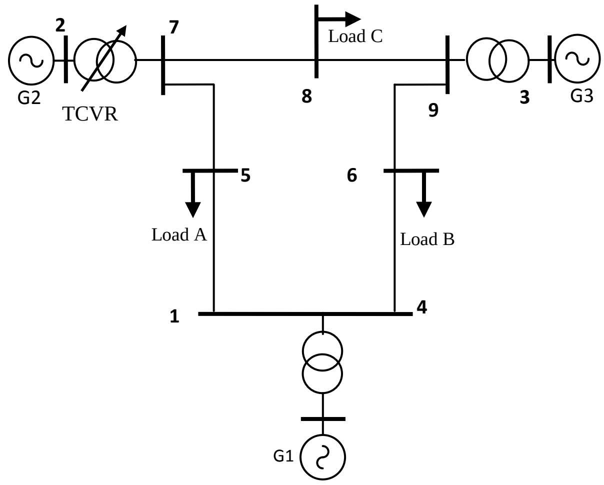

Fig. 5 A Three machine power system

The modified WSCC 3-machine system is used as our test system in the case of three-phase short circuit fault in the transmission line. The system configuration is shown in figure 5. Load flow data, machine and exciter data can be found in reference [20]. In study purpose, the criterion of relative rotor angles using Runge-Kutta method is used.

The simulation is done in three steps. The pre-fault is considered for a stable system. Then, a symmetrical fault is applied at one transmission line. Simulation of the fault condition continues till the fault is cleared. Then, the post-fault system is simulated for a longer time to observe the nature of the transient stability.

The optimal value of the CCT is determined by trial and error. For this, several values of the fault duration (Td) are preselected and tested consecutively until the system becomes unstable. This time corresponds to the CCT [18-20].

4.1 Simulation Results without FACTS

To study the efficiency of TCVR on transient stability, a three phase fault on line is considered and it is cleared by opening the line at both ends.

Fig.6 and Fig.7 demonstrates the rotor angles and frequency for three phase fault on the line 6-4 near the bus number 4 for fault cleared at Td=0.448s. It can be said that the system is stable.

Fig.8 and Fig.9 demonstrates the rotor angles and frequency for three phase fault on the line 6-4 near the bus number 4 for fault cleared at Td=0.449s. It may be seen that (δ_{12}, δ_{13}) increase indefinitely and we can be observed that the system becomes unstable. The loss of the stability is also shown in the Fig. 9 in which the frequencies of machines are asynchronous and the system was not able to take back the synchronous; so the system is unstable. In this case of fault, if the time delay exceeds 0.448s, the system becomes unstable. As conclusion, the critical clearing time CCT equals to 0.448s.

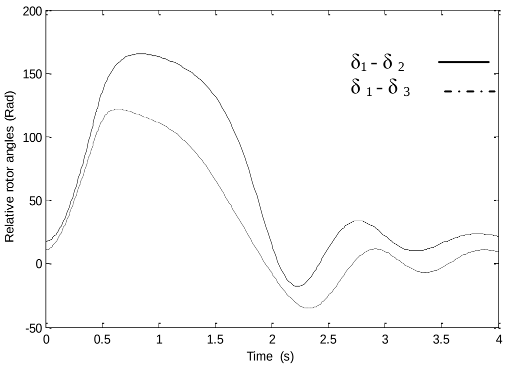

Fig. 6 Relative rotor angles without FACTS

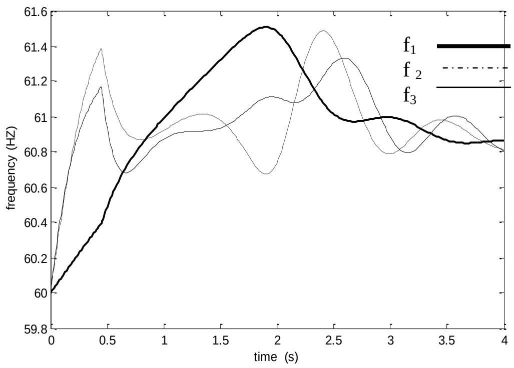

Fig. 7 Frequency without FACTS (Td=0.448s)

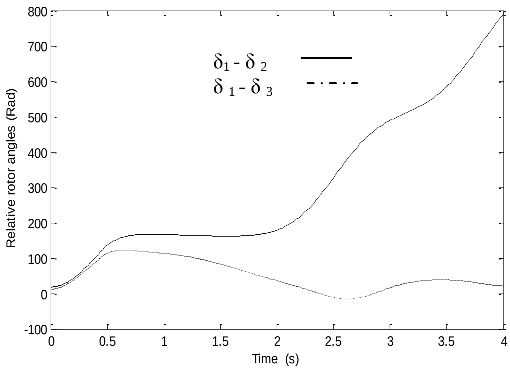

Fig. 8 Relative rotor angles without FACTS (Td=0.449s)

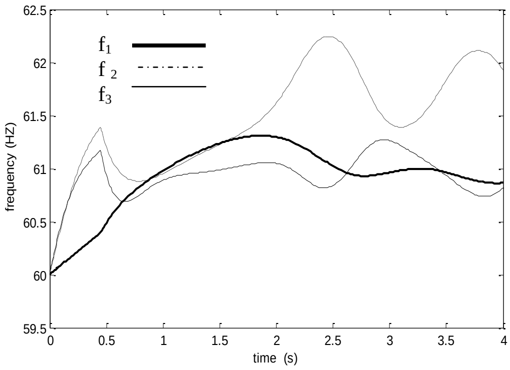

Fig. 9. Frequency without FACTS (Td=0.449s)

4.2 Simulation Results with TCVR

The proposed method of evaluating the additional damping provided by a TCVR controller is tested in multi-machine system as shown in Figure.5. For the purposes of this work, the TCVR controller margins are defined by Eq.(13):

Fig. 10 and Fig. 11 illustrate relative rotor angles and frequency respectively in the case of three-phase short circuit on the line 4-6 near the bus number 4 for fault cleared at 0.449s with TCVR connected at bus number 2, where we can see that the system become stable with TCVR.

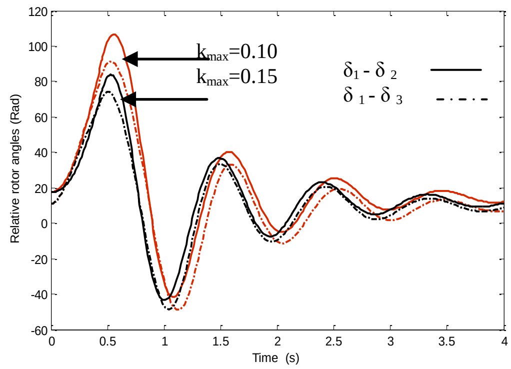

Fig. 10 Relative rotor angles with TCVR (Td=0.449s, k_{max}=0.15, 0.10)

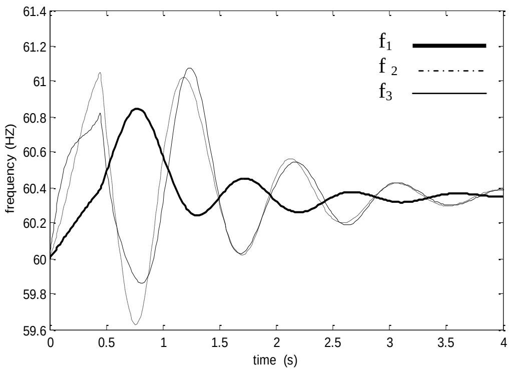

Fig . 11 Frequency with TCVR (Td=0.449s)

The results of CCT after three phase fault on the line 4-6 near the bus 4 with TCVR are given in table 1.

Table 1 CCT for various ratings of TCVR

k_{max} TCVR	Transformer ratio	CCT(s) with compensator
0	1	0.448
0.05	1.05	0.512
0.07	1.07	0.542
0.10	1.10	0.602
0.12	1.12	0.701
0.15	1.15	0.751

5. Assessment Transient Stability By Neural Networks

Neural networks have been used for a wide variety of application. Especially for transient stability assessment, application of ANNs can be summarized in four steps [14].

5.1 Selection of Input Variables

Selection of input variables is the most important factor in the successful use of ANNs and therefore needs a special attention. Especially to choice suitable independent variables which affect the ANNs output [7,14].

5.2 Data Generation

In this step, we develop a model which covers the possible operating conditions, so all inputs can be provided off-line using traditional methods [7,14].

5.3 Selection of ANN Architecture

In this step, we determine the number of neurons in each layer, and the number of hidden layers, the optimum number of neurons in the hidden layer, and the number of hidden layers, is determined on a heuristic basis, mostly a Multilayered backpropagation ANNs is used for function approximation and classification [14].

5.4 Training the ANNs and Testing

Training is a function of the development of ANNs in which the connection weights are modified to improve the network's output response performance. For a given ANNs architecture many training algorithms exist and a choice has to be made judiciously to obtain fast and efficient training of the ANNs. The selection of the training items used to form the training facts is of critical importance to the success of operating an ANNs [3,7,14].

5.5Assessment Transient Stability By ANNs

In this work, a feedforward backpropagation ANNs is used with two hidden layers having a log-sigmoid activation function. The first one has eleven neurons and the second has eight neurons. The output layer consists of one output neuron having linear activation function. The structure of the ANNs employed in the proposed classifier is shown in Fig. 12. The optimum number of neurons in hidden layer and the number of hidden layer is determined on a heuristic basis so that the prediction accuracy is acceptable.

The activation function of the neurons in the hidden layers assumes the following form:

$$f(y) = \frac{1}{1+e^{-y}} \tag{16}$$

Where y is the input of the activation function.

The ANNs inputs include prefault variables and during fault variables obtained during data generation step. These are the mechanical powers, the rotor angular velocity and the TCVR control variable of all the generators. Therefore, there are 3*N* input signals which are used for training the ANNs. The output of the ANNs is the CCT, which it represents the maximum time that a particular fault can be allowed to persist on a system before instability will inevitably arise. Three-phase short-circuit faults are simulated at the line 4-6 near the bus 4.

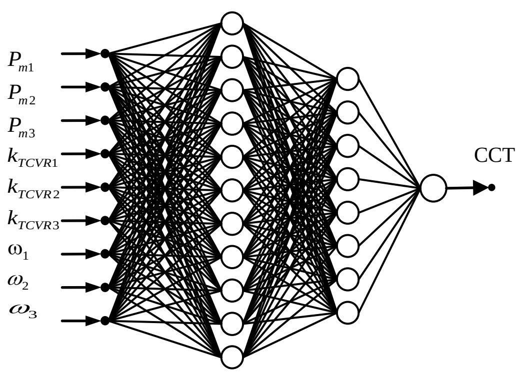

Fig. 12 ANN used for predicting CCT

The results of CCT after three phase fault on the line 4-6 near the bus number 4 with TCVR at bus 2 calculated by ANNs and Runge-Kutta method are given in table 2. The details regarding the values used for ANN training are:

- Number of epochs at the end of training: 748;
- Time elapsed at the end of training (s): 4.25s;
- Error: 0.0098.

Table .2 CCT For various ratings of TCVR Calculated by ANNS and Runge-Kutta methods

k_{max} TCVR	CCT(s) with Runge-Kutta	CCT(s) with ANNs
0	0.448	0.446
0.05	0.512	0.509
0.07	0.542	0.543
0.10	0.602	0.605
0.12	0.701	0.703
0.15	0.751	0.755

It is clear from the results shown in table 1 and table II that the system responses are quite satisfied under three-phase short circuit at transmission line by the TCVR controller.

Table 2 shows the results obtained by ANNs compared with the results calculated by Runge-Kutta. The results obtained by the ANNs are almost identical to those calculated by the numerical method. The proposed method has short response time, which is appropriate for on-line applications of transient stability assessment.

6. Conclusions

In this paper, neural networks and a new control strategy of TCVR have been successfully applied to analyze the state of power system transient stability and the prediction of the CCT. The modeling of various components of power systems is discussed.

Simulations performed on WSCC 3-machine test system indicate that the proposed control strategy of TCVR can improve transient stability. It can be seen from the results that the system responses are quite satisfied for three-phase short circuit at transmission line by the TCVR controllers and feedforward ANNs. The results obtained by the ANNs are almost identical to those calculated by the Runge-Kutta method. The proposed method has short response time, which is appropriate for on-line applications of transient stability assessment. The hard problem that is limiting for ANNs, and the selection and calculation of inputs vectors and the training set which must be determined by another method. However, it has focused attention on the feasibility of using the ANNs as tools for computing the CCT of a power system.

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