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Neural Network Control of the StatCom in Multimachine Power Systems

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Abstract: - This paper presents the application of neural networks for controlling the static synchronous compensator (StatCom) device. The primary duty of the StatCom is the regulation of the AC bus bar voltage where the device is connected. Additionally, a secondary task may be added to such device for obtaining a positive interaction with other controllers in order to mitigate low frequency oscillations. For this task, a neural network is proposed due to its simple structure, adaptability, robustness, considering the power grid nonlinearities. The applicability of the proposition is studied by digital simulation exhibiting satisfactory performance. Results of simulation for different disturbances and operating conditions demonstrate the effectiveness of the feedback variables selected in the control scheme.

Key-Words: - Controllers, damping, flexible AC transmission systems, neural networks.

1 Introduction

The modern power systems represent a huge operational challenge. They exhibit highly complex topology and varied structural components. Usually, decentralized control devices are employed, which provides local control to different power grid equipment such as power system stabilizers (PSSs), automatic voltage regulators (AVRs), flexible ac transmission systems (FACTS) devices, etc. These control agents have helped to alleviate voltage, frequency, angular problems, and to mitigate inter-area oscillations. However, the new control elements connected to the system must be able to positively interact with the previously installed controllers. Thus, they must be coordinated to obtain a satisfactory performance.

In this paper a B-Spline Neural Network (B-SNN) is employed for the voltage control of a static synchronous compensator (StatCom) connected to the grid, taking care of a key feature: the proposed controller must be able to enhance the power systems stabilizer's performance for damping purposes.

The use of artificial neural networks (ANNs) offers an attractive alternative for the StatCom's control. The ANNs are able to model on-line nonlinear, MIMO (multiple inputs-multiple outputs), and non-stationary systems. The ANNs' nature makes them robust, adaptive, optimum, and hybrid control techniques, with attractive features to power system control [2].

2 Modeling

In this paper, data of a power system available in open literature - 16-machines, 68-buses - is employed in order to exemplify the proposition, Fig. 1.

The development of systematic methodologies for the location of control devices is a problem that requires special attention. In [11] the problem of static compensators' location (SVC) using nodal participation factors derived from the modal analysis of the power flow equations is solved. The obtained results show that the best location to install one SVC is the critical area center, determined by the participation factors' study. Also, strategies of FACTS devices location based on singular values analysis of a power system equivalent model have been proposed [12].

In order to show the applicability of the present proposition, one StatCom is located at two different buses – first at bus 21, and then at bus 35 - with the aim of controlling such voltage magnitudes within some reference value, while helping to mitigate low frequency oscillation problems. Such buses are elected due to their relative low short circuit ratio and their singular value sensitivities. Furthermore, a FACTS device electrically close to a generating unit could be inefficient for voltage purposes. Ultimately, the main purpose for trying two locations is to illustrate that the proposed control strategy does not depend on the FACTS location. That is, such one can be practically arbitrary.

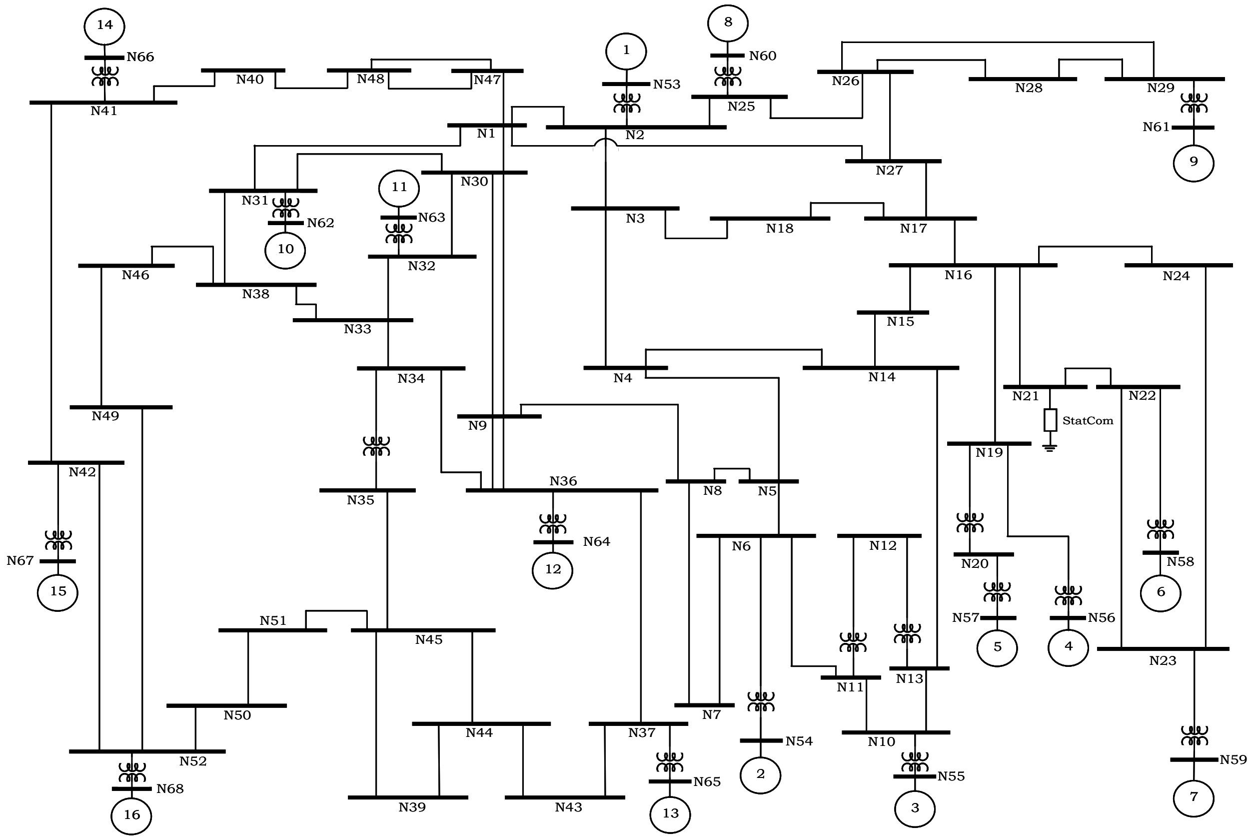

Fig. 1. 16-machines, 68-buses power system.

The proposed control scheme allows achieving a satisfactory coordination among the StatCom and eight PSSs installed in the following generators: (*a*) *StatCom at bus 21* – PSS's at 5, 7, 8, 9, 12, 14 and 15; (*b*) *StatCom at bus 35* – PSS's at 1, 2, 3, 7, 9, 10, 12, and 16. Similarly to the FACTS location, the main aim is to show that the proposed neurocontroller does not depend on the PSSs location and tuning, but it is able to enhance the electro-mechanical behavior after a disturbance, when it is appropriately designed.

The fourth order dynamic model is employed for generators including a static excitation system [1]. The reference generator is that in bus 65 (generator 13). For each generator, the elected state variables are: δ (rad) and ω (rad/s) represent the rotor angular position and angular velocity; E'_d (pu) and E'_q (pu) are the internal transient voltages of the synchronous generator; E_{fd} (pu) is the excitation voltage.
The fundamental structure of the StatCom is based on a Voltage Source Converter (VSC), and a coupling transformer that it is used as a link with the electric power system, Fig. 2; $\mathbf{E}_{ST}$ represents the StatCom's complex bus voltage, and $\mathbf{E}_k$ the power system complex bus voltage; all angles are measured respect to the general reference, in this case bus 65.

The model is represented as a voltage variable source $\mathbf{E}_{ST}$, whose magnitude and phase angle can be adjusted with the purpose of regulating the *k-th* voltage magnitude. The magnitude V_{ST}, it is conditioned by a maximum and a minimum limit, depending on the VSC's capacitor rating. In the carried out simulations, the interval of the magnitude, V_{ST}, is settled down within [0.9, 1.1] p.u.; the phase angle, δ_{ST}, may vary within [0, 2π] rad.

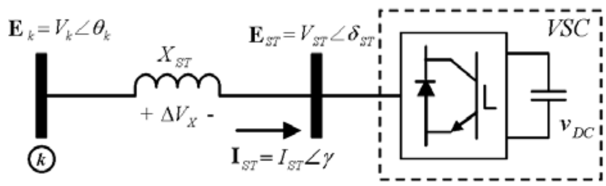

Fig. 2. StatCom's schematic representation.

A simplified dynamic model of StatCom is employed and represented by the capacitor voltage equation [15, 16],

$$\frac{dv_{DC}}{dt} = \frac{mk}{C_{DC}}\left(I_{STd}\cos\psi + I_{STq}\sin\psi\right) \qquad (1)$$

$$V_{ST} = mkv_{dc} \tag{2}$$

$$\delta_{ST} = \psi \tag{3}$$

where $\mathbf{I}_{ST} = I_{STd} + jI_{STq}$, represent the d and q StatCom's current components, respectively; v_{DC} is the DC StatCom voltage; C_{DC} is the capacitance; m is the modulation ratio defined by the PWM; ψ is the phase angle defined by the PWM, and it determines the phase δ_{ST}; k is the ratio between the ac and dc voltage depending on the inverter structure. Thus, signals V_{ST} and δ_{ST} will be controlled by the proposed B-SNN controller.

3 PSS's Tuning

The PSSs interaction may increase or reduce the damping in any rotor oscillation mode. To enhance their performance, a satisfactory coordination between power system control devices should exist, guaranteeing robustness under diverse scenarios. For this task, several algorithms to achieve an optimal design have been developed [3-4]. For instance, simulated annealing (SA) and genetic algorithms (GA) have been used for designing and tuning PSSs and FACTS device stabilizers (FDSs) [3-4]. Besides, recently there have been increased use of ANNs in power grid control, operation and planning, allowing the diversification of control alternatives [5-8].

The conventional PSS structure connected at the i-th generator consists of a washout block, filters, and a limiter, Fig. 3. In this paper, the difference between the angular velocity, ω_i, and the synchronous velocity, ω_0, is elected as the input to the PSS.

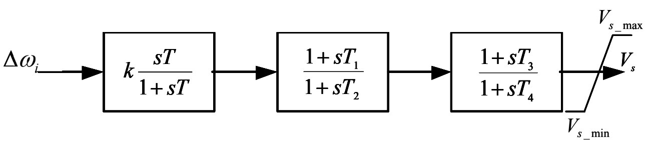

Fig. 3. Block diagram of the PSS.

The eigenvalue sensitivity analysis has been used for power system dynamic studies and the controller's design. It has been found that the trajectories of the dominant eigenvalues under system parameter changes are nonlinear, and the first-order estimates are not enough accurate [3]. In this paper, it is assumed that the decision to include PSSs has been taken, and the corresponding parameters of each one have been estimated.

Related to the StatCom's controller, it does not exhibit the conventional PSS structure. Therefore, it is incorporated as specified in the following section.

4. Neuro-controller modeling

The major advantages of the ANNs are the controller's design simplicity, and their compromise between the complexity of a conventional nonlinear controller and its performance. The B-SNNs are a particular case of neural networks that allow to control and model systems adaptively, with the option of carrying out such tasks on-line, and taking into account the power grid non-linearities.

A B-spline function is a piecewise polynomial mapping, which is formed from a linear combination of basis functions, and the multivariate basis functions are defined on a lattice. The on-line B-spline associative memory network (AMN) adjusts its weights iteratively in an attempt to reproduce a particular function, whereas an off-line or batch B-spline algorithm typically generates the coefficients by matrix inversion or using conjugate gradient. B-spline AMNs adjust their (linear) weight vector, generally using instantaneous least mean square (LMS)-type algorithms, in order to realize a particular mapping, modifying the strength with which a particular basis function contributes to the network output.

Through B-SNN there is the possibility to bound the input space by the basis functions definition. Generally, only a fixed number of basis functions participate in the network's output; therefore not all the weights have to be calculated each sample time, thus reducing the computational effort and time, [9].

The major task of the StatCom is to maintain the bus voltage magnitude on a reference value, through controlling the signals V_{ST} and δ_{ST}, Fig. 4. Besides, the proposed control scheme should help to enhance the low frequency oscillations. With this purpose, signal e_y is added for controlling δ_{ST}. That is, without such purpose the control of δ_{ST} can be obtained through the error input e_z only. The B-SNN's output can be described by [9],

$$y = \mathbf{a}^T \mathbf{w} \tag{4}$$

$$\mathbf{w} = \left[w_1\ w_2 \dots w_p\right]^T, \qquad \mathbf{a} = \left[a_1\ a_2 \dots a_p\right]^T$$

where w_i and a_i are the i-th weight and the i-th B-SNN basis function output, respectively; p is the number of weights.

The proposed neural controller is composed by two B-SNNs, Fig. 4. The error, e_y, between the reference voltage and the actual *k*-th bus voltage, is the input for controlling V_{ST}. It is assumed that the StatCom should maintain a null active power interchange with the power system. Thus, the error, e_z, between the reference interchanged power (0 pu) and the actual corresponding power, is used as the input for controlling δ_{ST}. Then the networks can be described as follows:

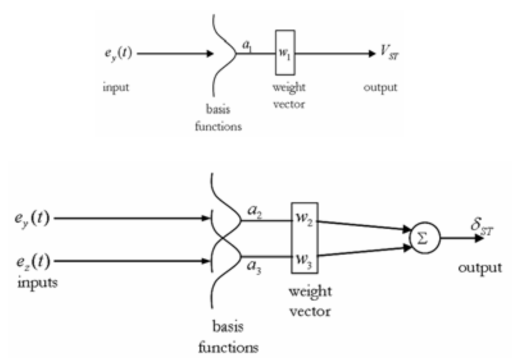

Fig. 4. Proposed B-SNN controller.

$$V_{ST} = NN_1(e_y,\ \mathbf{w}_1) \tag{5}$$

$$\delta_{ST} = NN_2(e_y, e_z,\ \mathbf{w}_2) \tag{6}$$

where NN_i denotes the B-SNN which is used to calculate V_{ST} and δ_{ST}; $\mathbf{w}_1 = w_1$ and $\mathbf{w}_2 = [w_2\ w_3]$.

The control law is adapted to the operating point modifications or disturbances that can occur. However, it requires the following a-priori information: the bounded values of e_y and e_z, the size, shape and overlap definition of the basis function. Such information allows to bound the B-SNN input and to enhance the convergence and stability of the instantaneous adaptive rule [9]; besides, with this information the B-SNN estimates the optimal weights' value. The neural networks controllers, (5)-(6), are created by univariate basis functions of order 3, considering that both e_y and e_z are bounded within [-1.0, 1.0] pu.

4.1 Learning

Learning in artificial neural networks (ANNs) is usually achieved by minimizing the network's error, which is a measure of its performance, and is defined as the difference between the actual output vector of the network and the desired one.

On-line learning of continuous functions, mostly via gradient based methods on a differentiable error measure is one of the most powerful and commonly used approaches for training large layered networks in general [10], and for nonstationary tasks in particular.

For the voltage magnitude regulation, the controller's quick response is looked for. While conventional adaptive techniques are suitable to represent objects with slowly changing parameters, they can hardly handle complex systems with multiple operating modes. The instantaneous training rules provide an alternative so that the weights are continually updated and reach the convergence to the optimal values. Also, conventional nets sometimes do not converge, or their training takes too much time [9-10, 13-14].

In this paper, the neural controller is trained on-line using the following error correction instantaneous learning rule [9],

$$w_i(t) = w_i(t-1) + \frac{\eta\, e_i(t)}{\|\mathbf{a}(t)\|_2^2} a_i(t) \tag{7}$$

where: η is the learning rate and $e_i(t)$ is the instantaneous output error.

This learning rule has been elected as an alternative to those that use, for instance, Newton's algorithms for updating the weights that require Hessian and Jacobian matrix evaluation. Equation (7) has been obtained through the minimization of the output's mean square error, using descendent gradient rules. That is the reason because it is said that the weights converge to optimal values [9].

Thus, the proposed neurocontroller consists fundamentally on establishing its structure (the definition of basis functions) and the value of the learning rate. Regarding the weights' updating, (7) should be applied for each input-output pair in each sample time; the updating occurs if the error is different from zero. Respect to the learning rate, it takes as initial point one value inside the interval [0, 2] due to stability purposes [9]. This value is adjusted through trial-and-error; with a value close to zero the training becomes slow. However, if such value is large, oscillations can occur; in this application it settles down in 0.55.

Hence, the B-SNN training process is carry out continuously on-line, while the weights' value are updated using only two feedback variables: the bus voltage magnitude and the active power interchange between the StatCom and the power system. The neural network output is calculated by (4).

5 Studied cases

The power system in Fig. 1 is studied in order to exhibit the performance and robustness of the proposed control scheme. To analyze the results, simulations are developed under different scenarios: a) with PSS tuned by GA [3] and StatCom controlled by B-SNN controller (NNC); b) with PSS tuned by GA and StatCom with conventional PI control (CONV); c) with PSS tuned by GA [3], without StatCom (WPSS). Three operating conditions are analyzed.

5.1 Case 1

To validate the neural control performance, different disturbances are simulated. In the first case the system is subjected to a three-phase fault on bus-16, at t = 0.08 s during 120 ms; after the fault is cleared, the system returns to the initial configuration. Fig's. 5-6 display the evolution of some representative signals.

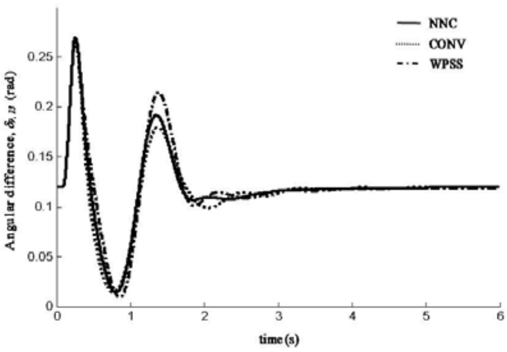

Fig. 5. Angular difference at generator 9, *Case 1*.

The results exhibit an NNC satisfactory performance, showing better characteristics than that of CONV and WPSS control techniques, especially those related with the amplitude of the overshoots and the settling time. Likewise, the bus voltage response exhibits similar features maintaining bus-21 voltage at reference value despite the closeness to the fault, Fig. 6.

For the *Case 1* (base case) notorious differences are not exhibited among the behaviors of the NNC and CONV controllers, since this last one has been tuned under such condition and it is expected to present good performance.

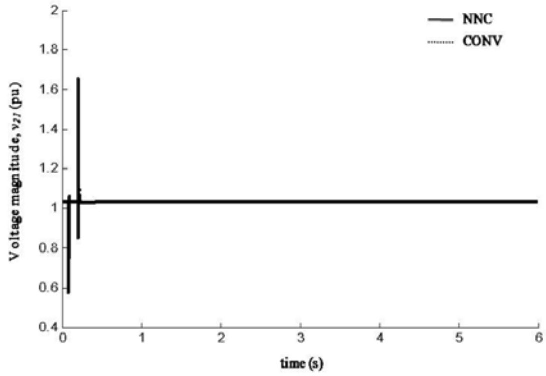

Fig. 6. Bus-21 voltage response, *Case 1*.

5.2 Case 2

This case illustrates the system evolution when in t = 0.1 s the generator's active power is increased 15 percent, except generator-13 which is the slack bus, while the loads are increased 25 percent, both reactive and active power. Fig. 7 displays the voltage at bus-21, where satisfactory coordinated performance can be appreciated. The NNC has the ability of being updated to the new operating condition, improving the WPSS and the CONV performance. That is, in spite of being subject to a new operative condition, the neurocontroller responds appropriately. The NNC and CONV control technique have a similar performance for the bus-21 voltage support, but the global performance in other variables is degraded. On the other hand, with only PSSs the voltage drops and the oscillations last more time, Fig. 7. This case emphasizes the use of the StatCom with the neurocontroller.

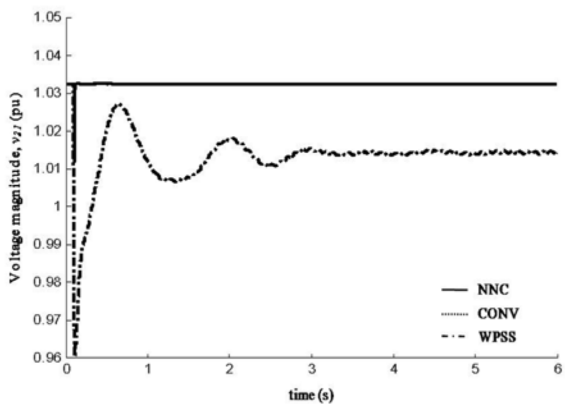

Fig. 7. Bus-21 voltage response, *Case 2*.

5.3 Case 3

The third case validates the appropriate neurocontroller performance considering that the StatCom is currently installed at bus-35, and the system is subjected to a three-phase fault at bus-34 in t = 0.05 s with a duration of 100-ms. After this time the fault is cleared by tripping line 33-34. Fig. 8 depicts the active power at generator 1.

The performance of the three control techniques is in accordance with *Case 1* and *2*. The NNC exhibits satisfactory performance, adapting itself easily to present circumstances. Obviously, the major impact of the StatCom is in those buses close to that where the device is connected.

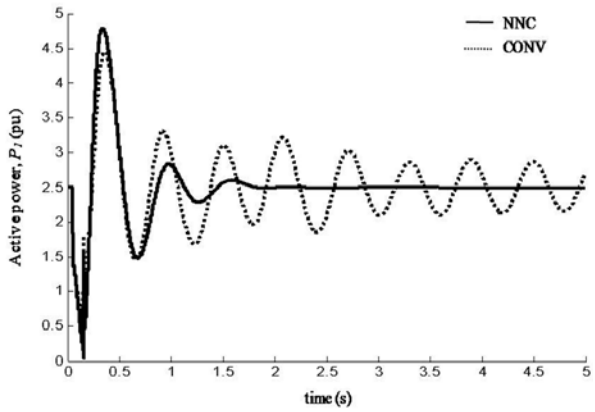

Fig. 8. Active power at generator 1, *Case 3*.0

4 Conclusion

This paper proposes the inclusion of one StatCom, controlled by a B-Spline neural network, in a power grid that includes additional control devices. The performance and applicability of the proposition are proved by digital simulation on a multimachine power system. This strategy allows appropriately controlling the bus voltage magnitude where the StatCom is connected, but also it helps to limit the oscillations and overshoots in other relevant signals. Thus, the feedback signals to the NNC are pertinent for a suitable control of the StatCom, exhibiting a positive interaction with other controllers.

The proposed control strategy does not depend on the FACTS location and does not depend on the PSSs location and their tuning, since the neurocontroller is able to adapt by itself to different operating conditions. Future papers will exhibit results on practical applications.

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