Neurocontroller for Power Electronics-Based Devices

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Abstract. This paper presents the Static Synchronous Compensator's (StatCom) voltage regulation by a B-Spline neural network. The fact that the electric grid is a non-stationary system, with varying parameters and configurations, adaptive control schemes may be advisable. Thereby the control technique must guarantee its performance on the actual operating environment where the StatCom is embedded. An artificial neural network (ANN) is trained to foresee the device's behavior and to tune the corresponding controllers. Proportional-Integral (PI) and B-Spline controllers are assembled for the StatCom's control, where the tuning of parameters is based on the neural network model. Results of the lab prototype are exhibited under different conditions.

Keywords: Artificial neural network, B-Spline, StatCom, FACTS.

1 Introduction

Power systems are highly nonlinear, with time varying configurations and parameters [1-3]. Thus, PI controllers based on power system's linearized model cannot guarantee a satisfactory performance under broad operating conditions. Thus, in this paper the use of a control, adjustable under different circumstances, is suggested.

StatCom requires an adaptive control law which takes into account the nonlinear nature of the plant and adapts to variations of the environment to regulate the bus voltage magnitude. The aim of this paper is the utilization of an adaptive B-Spline neural network controller. The fundamental structure of such device is based on a Voltage Source Converter (VSC) and a coupling transformer, which it is used as a link with the electric power system, Fig. 1. E_{ST} represents the StatCom's complex bus voltage, and E_k the power system complex bus voltage [4-7]; all angles are measured with respect to the general reference.

The model is represented as a voltage variable source E_{ST}. Its magnitude and phase angle can be adjusted with the purpose of regulating the bus voltage magnitude. The magnitude V_{ST} is conditioned by a maximum and a minimum limit, depending on the VSC's capacitor rating.

In this paper a B-Spline neurocontroller is utilized due to its ability to adapt its performance to different operating conditions. A PI controller is also utilized for comparison purposes. Tuning the prototype's controllers is a tedious task since

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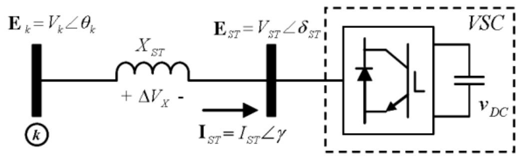

Fig. 1. StatCom's schematic representation

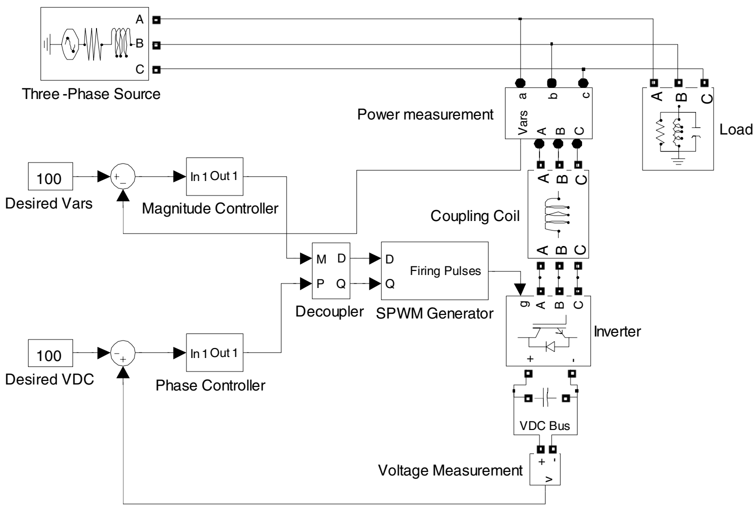

Fig. 2. Assembled prototype block diagram

trial-and-error strategy may be a long process. Thus, a StatCom´s model is developed to haste all tests and predict the device's behavior.

B-Spline controller is chosen because the PI is not self adaptable when the operating condition change. If the operating condition is changed the PI will not function properly because it would be out of the region for which it is designed. Once the B-Spline controller is designed and its effectiveness is tested by simulation [8]-[9], it is assembled.

A StatCom-based SPWM is a multiple-input multiple-output (MIMO) system. Its input signals are the magnitude and phase of the 60-Hz modulating signal in conjunction with a 3000-Hz triangle carrier signal generate the six firing signals to operate every gate of a six-IGBT inverter. Two output signals are controlled: (*a*) the reactive power flowing into or out of the device and, (*b*) the capacitor's DC voltage, Fig. 2. Thus, in this paper the reactive power flow is controlled through the amplitude of the modulating signal, while the DC voltage is controlled through the phase of the modulating signal.

2 B-Spline Neural Networks: A Summary

The major advantages of ANN-based controllers are simplicity of design, and their compromise between complexity and performance. The B-SNN is a particular case of neural networks that are able to adaptively control a system, with the option of carrying out such tasks on-line, taking into account non-linearities [10-12].

Additionally, through B-SNN it is possible to bound the input space by the basis functions' definition. The most important feature of the B-Spline algorithm is the output's smoothness that is due to the shape of the basis functions. The bus voltage magnitude must attain its reference value through the B-Spline adaptive control scheme. That is, control must drive the StatCom's modulation ratio m and the phase angle α to the desired value in order to regulate the injected voltage of the shunt converter.

The B-Spline neural network output can be expressed as [13],

$$y = \sum_{i=1}^{p} a_i w_i \tag{1}$$

where w_i and a_i are the i^{th} weight and the i^{th} B-spline basis function output, respectively; p is the number of weights. Let us define:

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

Thereby, eqn. (1) can be rewritten as:

$$\mathrm{y} = \sum_{i=1}^{p} a_i w_i = a^T w \tag{2}$$

The last expression can be rewritten in terms of time as:

$$\mathrm{y}(t) = a^T(t)w(t-1) = a^T\big(x(t)\big)w(t-1) \tag{3}$$

where a is a p-dimensional vector which contains the function basis outputs, w is the vector containing the weights, and x is the input vector.

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 to train large layered networks in general [13], and for non stationary tasks in particular. In this paper, the neurocontroller is trained on-line using the following error correction instantaneous learning rule [14],

$$\Delta w(t-1) = \frac{\gamma e_y(t)}{\|a(t)\|_2^2} a(t) \tag{4}$$

where: γ is the learning rate and $e_y(t)$ is the instantaneous output error.

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, (4) should be applied for each input-output pair in each sample time; the updating occurs if the error is different from zero. Hence, the B-SNN training process is carried out continuously on-line, while the weights' value are updated using the feedback variables. The proposed controller is based on (4). Inside the Spline block the activation function is located; in this case an Spline function.

3 Test Results

A lab StatCom prototype has been implemented in order to validate the proposition. The major elements of the scheme are the following, Fig. 3: (*i*) source voltage – 85 volts RMS, (*ii*) transmission line inductance – 3.1 mH, (*iii*) LC filter – Capacitors 5μF and inductors 3.1 mH, (*iv*) asynchronous motor – squirrel cage 1.5 HP. The Voltage Source Converter (VSC), which is the main component, has been controlled by a DSP TMS320F2812. This DSP possesses 6.67 ns instruction cycle time (150 MHZ), 16 channel, 12-bit ADC with built-in dual sample and hold, an analog input from 0 to 3 V.

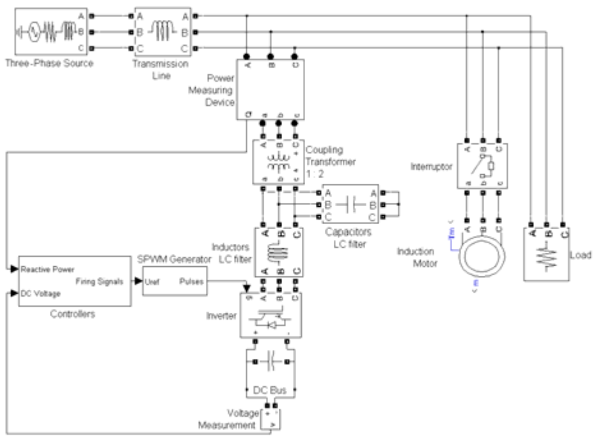

Fig. 3. Circuit arrangement

The synchronizing circuit utilized for the six IGBT VSC has been implemented in the DSP, collecting the data with a global Q of 11, which means that it reserves 21 bits for the data´s integer part and 11 bits for the fractional one. In this application the selected sampling frequency is 3000 Hz, thus 50000 clock cycles available between successive samples can be accomplished. In open loop, reactive power and DC voltage measurements are carried out. Feeding this set of measurements into the 40,60,2 scheme feed forward neural network, back propagation type, and training the created network by 800 epochs, a suitable model of the prototype is accomplished. The proposed ANN which will simulate the prototype Statcom is a 40,60,2 scheme feed forward, BP type. It means that it will have a 40 neurons first layer, a middle layer of 60 layers of a sigmoid transfer function, and two neurons in the output layer. The ANN is trained with four vectors of 229 elements each, two vectors for the input and two vectors for the output.

3.1 Proportional-Integral Controller

Firstly, two PI controllers are tried: (a) one for the reactive power flow, and (b) one for the DC voltage, Fig. 3. Two different conditions are analyzed:

(a) *Case 1*. The outputs' reference values are: 100 Vars flowing outward the StatCom, and 97.92 DC volts at the inverter´s capacitors.
(b) *Case 2*. The outputs' reference values are: 114 Vars flowing outward the StatCom, and 97.00 DC volts at the inverter´s capacitors.

In this case, the same controller structure is employed for both loops. To tune the PI's controller parameters is the first objective. Its structure is defined as follows,

$$\frac{y(s)}{u(s)} = K_p + \frac{K_i}{s} \tag{5}$$

In such process an intensive use of the ANN previously trained is done. The following parameters produce under damped response without overshoots: K_{im} = 0.9; K_{pm} = 2.0; K_{if} = 3e-4; K_{pf} = 1.0e-3. K_{im} is the integral gain and K_{ip} is the proportional gain for the magnitude controller. K_{if} and K_{pf} are the gains for the phase controller, respectively. The system is feeding the resistive load only, Fig. 3. Fig. 4 depicts the reactive power and DC voltage obtained by simulation. The physical realization is displayed in Fig. 5. At t = 19 s the induction motor is started and turned out immediately. At t = 29 s it is started again and after several cycles it is turned out. Notice that during this time output signals do not reach their reference value. Under this condition the amplitude and phase of the modulating signal reach their maximum.

However, if the desired values and the initial state are modified, the PI controlled StatCom ´s output exhibits a different behavior, Fig. 6. In this simulation the desired values are 114 Vars delivered and 97.00 DC volts. Now, the new initial state, *Case 2*, is such that the output voltage lags 1.8 degrees with respect to the grid´s voltage, by a modulation index of 90%.

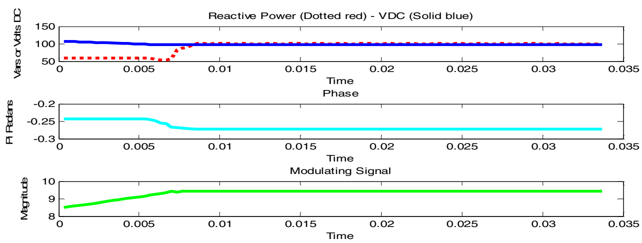

Fig. 4. *Case 1*. Simulated ANN response for Kim = 0.9; Kpm = 2.0; Kif = 3e-4; Kpf = 1.0e-3. From top to bottom: (*a*) reactive power and DC voltage, (*b*) phase, and (*c*) magnitude of the modulating signal.

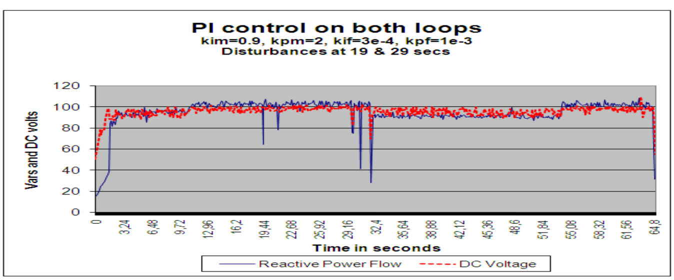

Fig. 5. *Case 1*. Prototype's response (Var and DC voltage) for Kim = 0.9; Kpm = 2.0; Kif = 3e-4; Kpf = 1.0e-3

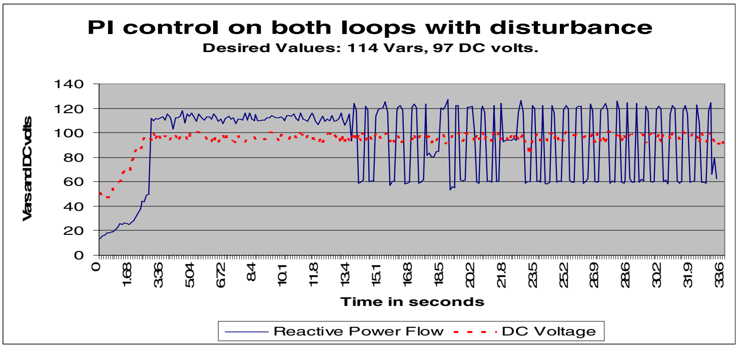

Fig. 6. *Case 2*. Prototype's response. PI behavior under a disturbance.

Then, with different initial states the PI controllers are tested. Under Case 2, a fast change in the DC voltage due to the induction motor starting compels the system to oscillate, Fig. 6. Hence, the tuned PI parameters that exhibited a satisfactory performance in Fig. 4 are not able to work well when the StatCom migrates to another operating point.

3.2 B-Spline Controller

The proposed B-Spline controller is now simulated with the StatCom´s ANN model. Originally, the desired values are as in the PI case (*initial state*): 100 Vars flowing outward the StatCom, and 97.92 DC volts at the inverter´s capacitors. The StatCom´s *initial state* generates an output voltage lagged 0.4 degrees with respect of the grid´s voltage; the inverter´s output voltage presents a modulation index of 85%. Fig. 7 shows that the references are reached with both loops based on B-Spline controllers. The slower loop is the DC voltage loop; it is handled through the learning factor Nf. In the present case Nf = 0.1. Both desired values are reached in 35 ms and the response signal exhibits an overshoot. The responses with PIs are improved, Fig. 4.

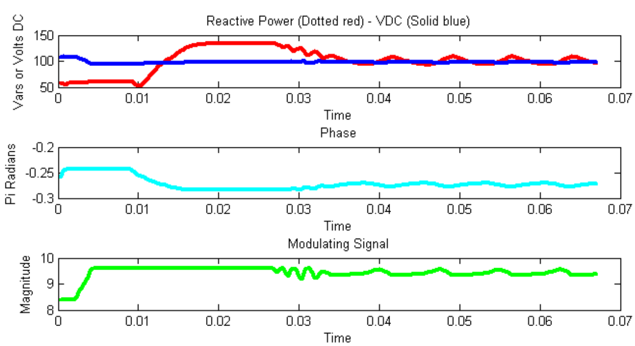

Fig. 7. *Case 1*. Simulated ANN B-Spline response for Wm=12636, Nm=40, Wf=-0.3621, Nf=0.1. From top to bottom: (*a*) reactive power and DC voltage, (*b*) phase, and (*c*) magnitude of the modulating signal.

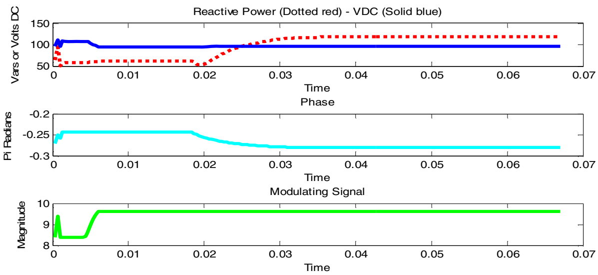

Fig. 8. *Case 2*. Simulated ANN B-Spline response for Wm=12636, Nm=40, Wf=-0.3621, Nf=0.1. From top to bottom: (*a*) reactive power and DC voltage, (*b*) phase, and (*c*) magnitude of the modulating signal.

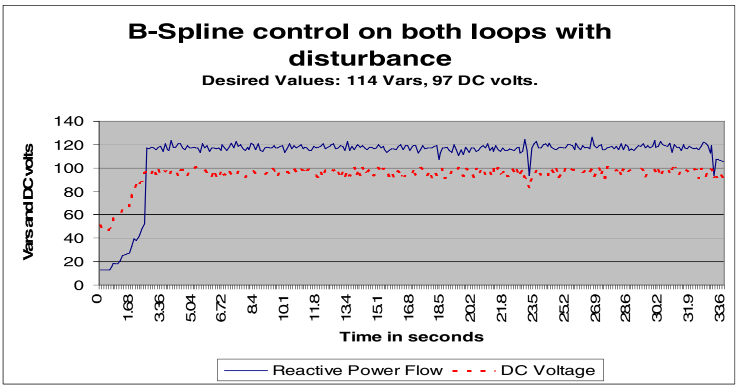

Fig. 9. *Case 2*. Prototype's B-Spline response (Vars and DC voltage) showing its adaptability

A new initial state is taken into account: 114 Vars delivered and 97.00 DC volts. Under this initial state the StatCom exhibits the output behavior in Fig. 8.

The PI's parameters for an *initial state* may not be the appropriate ones for another one. In this example the StatCom gets into a non stable region and the B-Spline controller exhibits a slower response compared with the first *initial state*; the desired values are reached without stability problems. The B-Spline performance is depicted in Fig. 9. The controllers' parameters are the same: for the magnitude controller an initial condition of 12636 DSP units and learning factor of 400 DSP units, while for the phase controller an initial condition of -0.3621 pi radians and a learning factor (Nf) of 0.1. Both references are attained. Finally, the B-Spline controller's performance displayed in Fig. 9 proved the adaptability of the B-Spline controller by rejecting the disturbance related to the starting motor on a different operational point respect to the one it is tuned. At t = 23 s and at t = 33 s, the induction motor is started.

4 Conclusions

The proposed neurocontroller represents a pertinent choice for on-line control due to it possesses learning ability and fast adaptability, robustness, simple control algorithm, and fast calculations. Unlike the PI control technique, the B-Spline NN control exhibits adaptive behavior since the weights can be adapted on-line responding to inputs and error values as they take place. These are desirable characteristics for practical hardware on power station platforms. Simulating the StatCom´s behavior with an ANN reduces the tuning time and offers a predictive view of the systems response. Lab results for different disturbances and operating conditions demonstrate the effectiveness and robustness of the NN control.

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