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An Adaptive Neural Network Identifier for Effective Control of a Static Compensator Connected to a Power System

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Abstract- A novel method for nonlinear identification of a Static Compensator connected to a power system using Continually Online Trained (COT) Artificial Neural Networks (ANNs) is presented in this paper. The identifier is successfully trained online to track the dynamics of the power network without any need for offline data and can be used in designing an adaptive neurocontroller for a Static Compensator connected to such system.

I. INTRODUCTION

Static Compensators (STATCOMs) are power electronic based shunt connected Flexible AC Transmission System (FACTS) devices which can control the line voltage V at the point of connection to the electric power network. Regulating reactive and active power injected by this device into the network provides control over the line voltage and over the DC bus voltage inside the device respectively [1]. A power system containing generators and FACTS devices, is a nonlinear system. It is also a non-stationary system since the power network configuration changes continuously as lines and loads are switched on and off.

In most of the papers in the recent years, linear control techniques have been used to model STATCOMs and consequently to design their controllers. In such an approach the system equations are linearized at a specific operating point and based on the linearized model, PI controllers are tuned in order to have the best possible performance [2, 3]. However STATCOMs are highly nonlinear devices, the rest of the power system is also nonlinear and continually changes topology, and the drawback of designs based on linear techniques is that their performance degrades as the system operating conditions change. Controllers that use nonlinear models on the other hand can give good control capability over a wide range of operating conditions, but they have a more sophisticated structure and are more difficult to implement compared to linear systems.

A nonlinear neural network based neurocontroller can solve this problem and a possible control scheme appears

in Fig. 1. The neurocontroller needs a model of the plant being controlled, but because the power system is a nonlinear and nonstationary process, a continually variable model is needed. A second neural network can be used to continually identify this model, shown as the ANN identifier in Fig. 1. It can be trained online without requiring large amounts of offline data [4, 5].

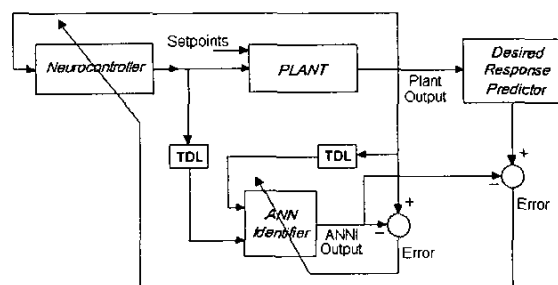


Fig 1. Neural indirect adaptive control scheme

This paper deals with designing a continually online trained (COT) artificial neural network identifier (ANNI) in order to model/identify a STATCOM connected to a power system. It considers a power system network consisting of a single machine infinite bus system (SMIB) together with a STATCOM connected to the middle of the transmission line. Multilayer Perceptron (MLP) neural networks are used to identify/model the power system network called the plant. Such identifiers can be used for designing an adaptive neurocontroller [6] for the STATCOM.

II. STATCOM IN A SINGLE MACHINE INFINITE BUS SYSTEM

Fig. 2 shows a STATCOM connected to a single machine infinite bus system, and it is simulated in PSCAD. The generator is modeled together with its automatic voltage regulator (AVR), exciter, governor and turbine dynamics all taken into account [7]. The generator is a 37.5 MVA, 11.85 kV (line voltage) machine and real parameters are used for the entire system.

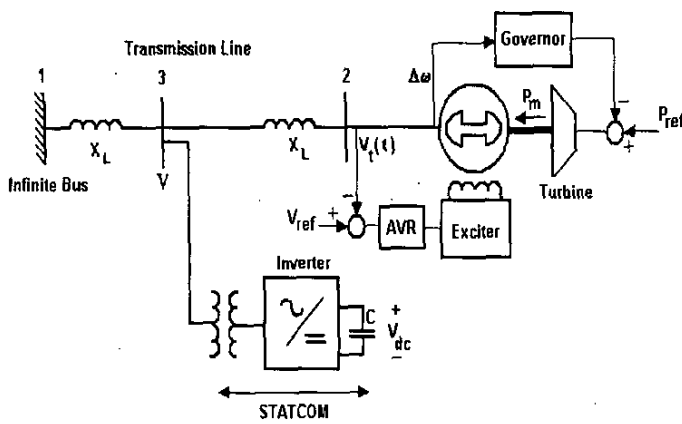


Fig 2. STATCOM connected to SMIB system (plant)

The STATCOM is first controlled using a conventional PI controller as described in [2] (Fig. 3). D-axis and Q-axis voltage deviations are derived from the difference between actual and reference values of the power network line voltage V and the DC bus voltage V_{dc} (inside the STATCOM) respectively, and are then passed through two PI controllers, whose output values Δe_d and Δe_q in turn determine the modulation index m_a and inverter output phase shift α applied to the PWM module as in (1).

$$m_a = \frac{\sqrt{\Delta e_d^2 + \Delta e_q^2}}{V_{dc}} \quad (1)$$

$$\alpha = \cos^{-1} \left(\frac{\Delta e_d}{\sqrt{\Delta e_d^2 + \Delta e_q^2}} \right)$$

Controlling the voltage V at the point of connection to the network is the main objective of the STATCOM considered in this paper.

Parameters of the STATCOM PI controllers are derived so that the controller provides satisfactory and stable performance when the system is exposed to small changes in reference values as well as large disturbances such as a three phase short circuit on the power network.

The "Plant" indicates the generator, its controllers, transmission line, the STATCOM and the PWM module with Δe_d and Δe_q as inputs and ΔV (line voltage deviation) and ΔV_{dc} (DC bus voltage deviation) as outputs, whereas "Controller" represents line voltage and DC bus voltage control loops.

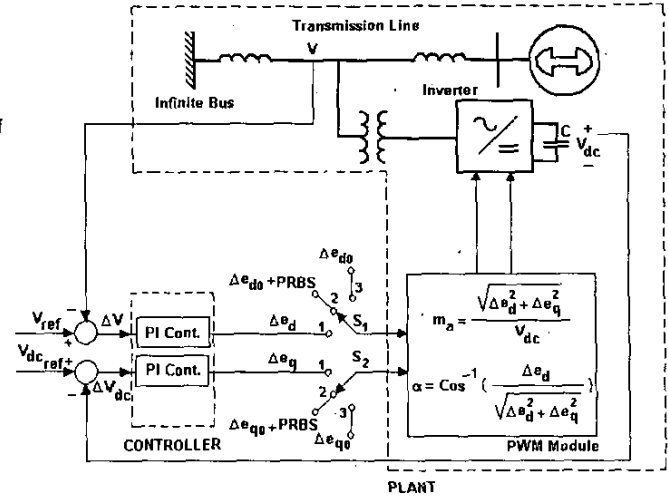


Fig 3. STATCOM controller

III. ADAPTIVE NEURAL NETWORK IDENTIFIER

A schematic diagram of the ANN identifier (ANNI) connected to the plant is shown in Fig. 4. The ANNI is a three layer MLP type neural network having a single hidden layer with sigmoidal activation function and the backpropagation algorithm is used for its training. The number of neurons in the hidden layer is heuristically chosen to be fourteen.

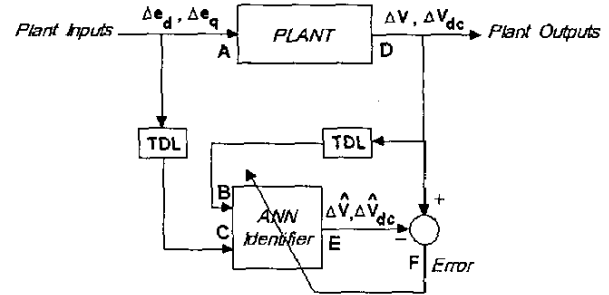


Fig 4. Plant / Adaptive ANN Identifier

The inputs of the ANNI are the plant inputs Δe_d and Δe_q and outputs ΔV and ΔV_{dc} at times $(t-1)$, $(t-2)$ and $(t-3)$ along with a constant threshold input and the sampling time step is $250 \mu s$ (Fig. 5).

For the combination of inputs shown in Fig. 5, the ANNI generates estimated values of the plant outputs ($\hat{\Delta V}$ and $\hat{\Delta V}_{dc}$) at time t . The estimated outputs are then compared with their corresponding actual values at time t and the difference forms the training error which is used to update the weight matrices using the backpropagation algorithm with a small learning gain of 0.03 [5].

Feedforward operation and the backpropagation training algorithm for a multilayer perceptron neural network (MLPN) appear in the Appendix.

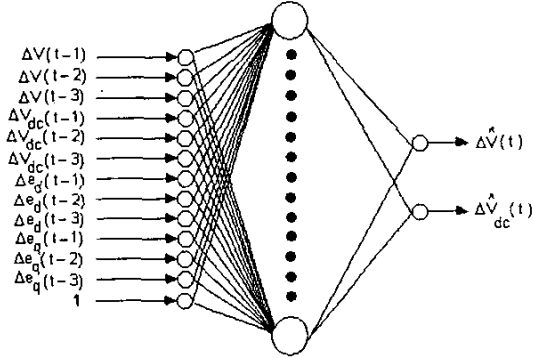


Fig 5. Artificial Neural Network Identifier structure

IV. IDENTIFIER TRAINING

Two sets of training results are presented in this paper. The first set which is called *forced-training*, shows how the ANNI tracks the plant dynamics when it is perturbed using Pseudorandom Binary Signals (PRBS). The second set, called *natural training*, shows the identifier tracking when the PRBS is stopped and the system is exposed to a large disturbance such as a three-phase short circuit [4].

The flowchart for training the identifier is shown in Fig. 6. It is first trained using forced training until sufficient accuracy is achieved and then PRBS is stopped and the natural training process takes place.

A. Forced Training

In order to train the ANNI, the entire system is simulated under normal mode (controlled by its PI controllers) until it reaches steady state (i.e. the values of controller outputs Δe_d and Δe_q become constant at 8 sec) after PSCAD is initialized; then the PI controllers are deactivated and their outputs Δe_d and Δe_q held constant at Δe_{d0} and Δe_{q0} respectively. PRBS signals are then added to the Δe_{d0} and Δe_{q0} from an external source. The PRBS signal magnitudes (Figs. 7 and 8) are limited to $\pm 10\%$ of the controller constant outputs Δe_{d0} and Δe_{q0} .

The modulation index m_a applied to the inverter as the result of the PRBS disturbances is shown in Fig. 9. The inverter output phase shift command α contains similar deviations.

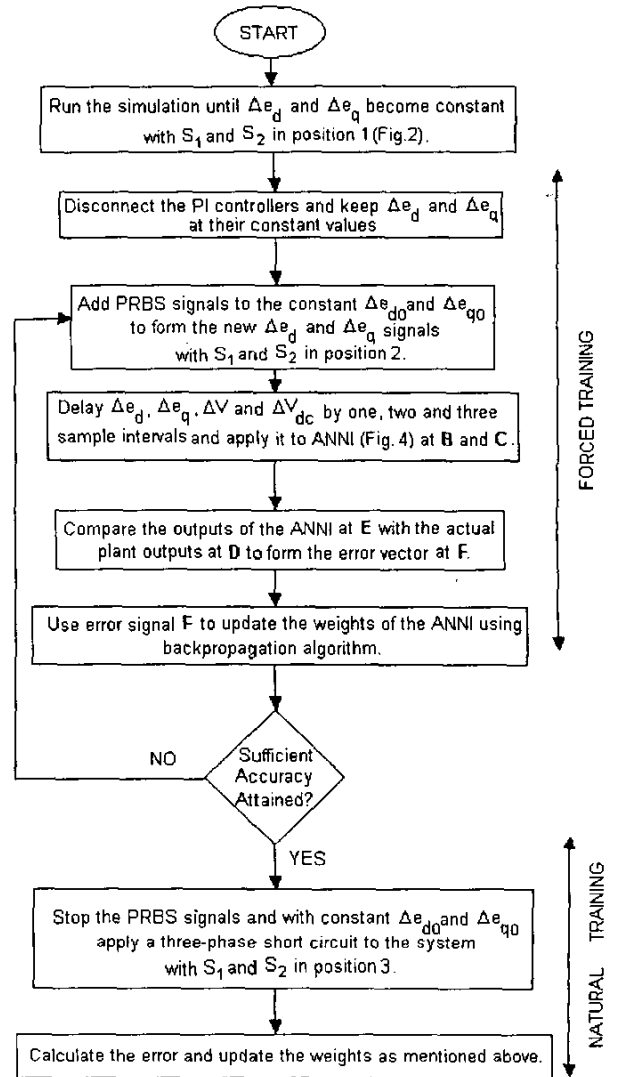


Fig 6. Flowchart for training the identifier

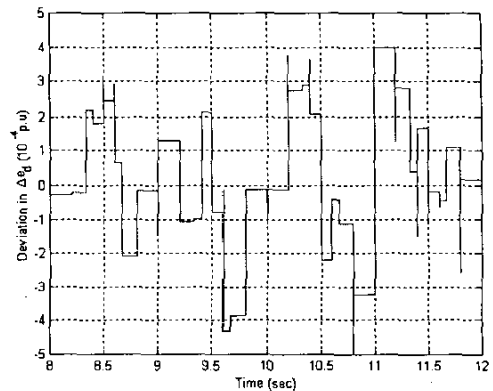


Fig 7. Forced PRBS training signal Δe_d applied to the plant

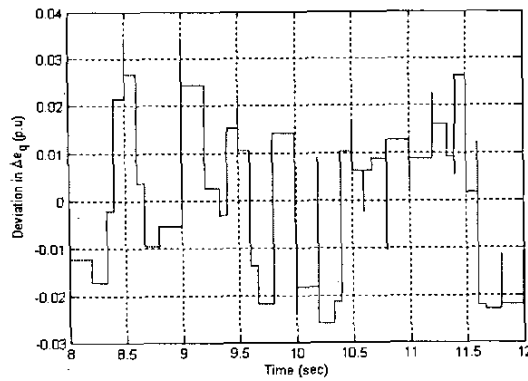


Fig 8. Forced PRBS training signal Δe_q applied to the plant

Simulation results of the identifier tracking the plant dynamics are shown in Figs. 10 and 11. The difference between the plant outputs and the ANNI outputs are negligible. The error between ΔV and $\hat{\Delta V}$ is limited to 0.005% while the maximum error between ΔV_{dc} and $\hat{\Delta V}_{dc}$ is 0.15%.

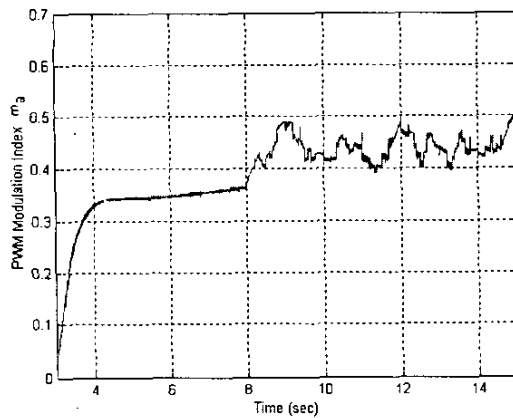


Fig 9. Modulation Index applied to the STATCOM

The ANNI is then trained with the PRBS signals at a few more operating points to ensure that it can track the dynamics of the system over a wide range of the operating conditions. After being trained at each operating point, final values of the weights are saved and used as initial weights for training at the new operating point. Figs. 12 and 13 show the simulation results when a 5% increase is applied to the reference voltage of the generator's exciter which changes the operating point of the system to a new point. The results show that the identifier correctly tracks the plant's dynamics when the operating point changes.

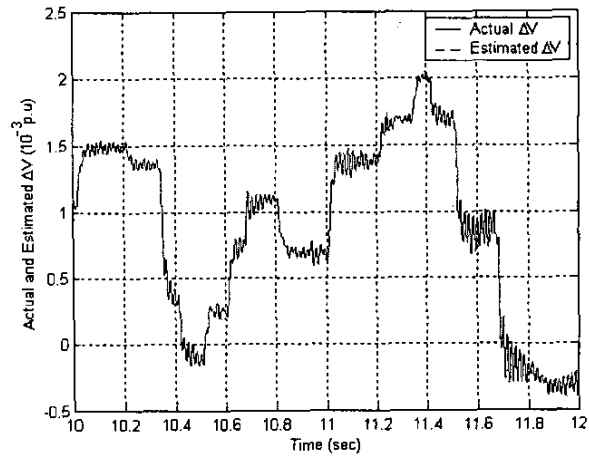


Fig 10. Actual and estimated values of ΔV

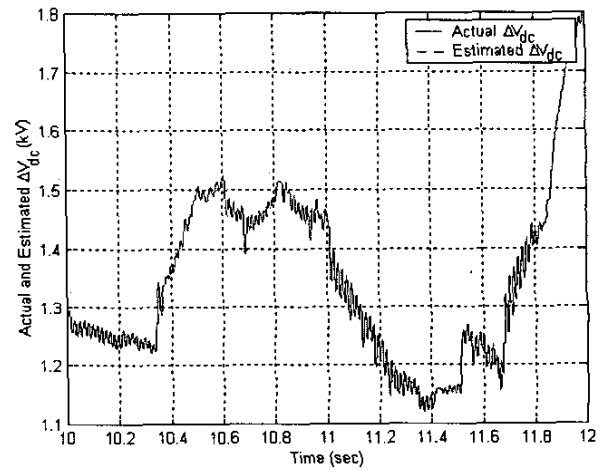


Fig 11. Actual and estimated values of ΔV_{dc}

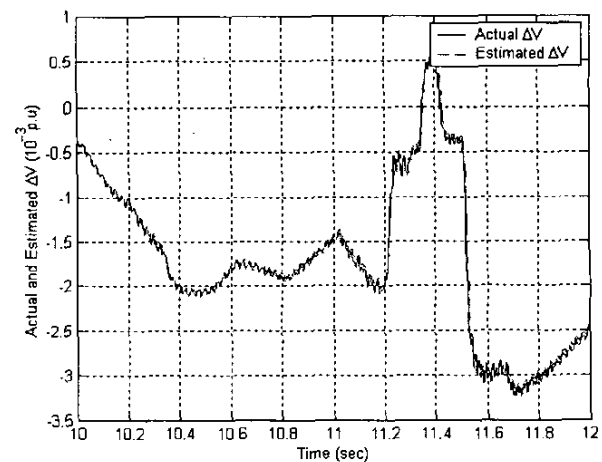


Fig 12. Actual and estimated values of ΔV with 5% change in the V_{ref} of the Exciter

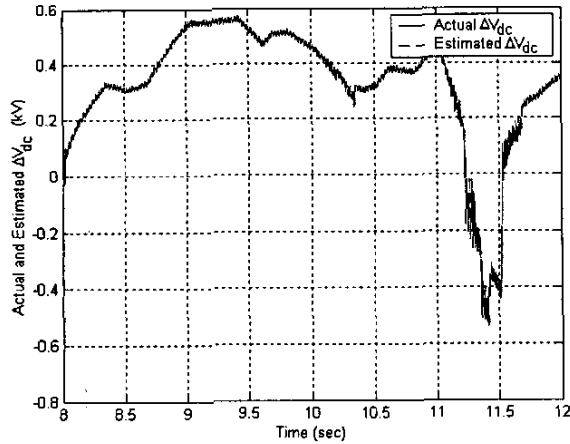


Fig 13. Actual and estimated values of ΔV_{dc} with 5% change in the V_{ref} of the Exciter

B. Natural Training

After training the identifier with the PRBS signals, the PRBS is removed at $t=20$ sec, and with the controller outputs still held constant at their steady state values Δe_{d0} and Δe_{q0} . ANNI weights derived from the forced training stage above are therefore used as the initial values for weight matrices in this test. Using switches S_1 and S_2 now in position 3, a three-phase short circuit is applied for 100 ms at the bus 3 (Fig. 1), while ANNI training continues, and the results appear in Figs. 14 and 15.

These results show that during this large disturbance, the ANNI succeeds in identifying the plant outputs accurately. This happens because training never stops.

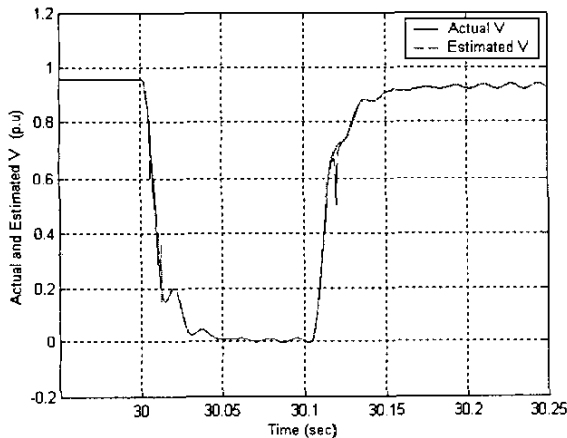


Fig 14. Actual and estimated V during a three-phase short circuit

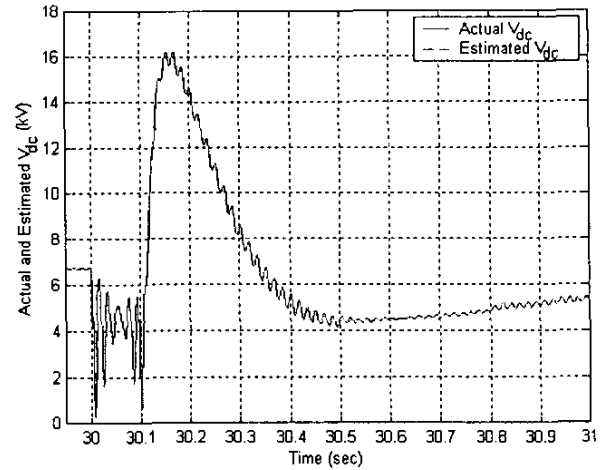


Fig 15. Actual and estimated V_{dc} during a three-phase short circuit

Similar tests at different operating points (as mentioned above) are carried out for natural training of the identifier, and the simulation results show satisfactory system identification by the ANNI at the multiple operating points.

V. CONCLUSION

A continually online trained multilayer perceptron neural network is introduced that can identify/model a STATCOM connected to a power system. Simulation results show that the identifier tracks the dynamics of the plant with high precision while no offline data is required for its training.

Conventional PI controllers have mostly been used for controlling a STATCOM, while their performance is highly dependent on the system operating point and is degraded by any changes in the operating point or the power network characteristics. A nonlinear neurocontroller can eliminate this problem but it needs an identifier such as the one described in this paper. Further research is still in progress to design STATCOM neurocontrollers and compare the results with that of a conventional controller.

VI. APPENDIX

Multilayer Perceptron Network (MLPN)

A. Feedforward Operation

Typical structure of a three layer multilayer perceptron is shown in Fig. 16 [8]. The three layers of neurons (input, hidden and output layers) are

interconnected through weight matrices W and V and map n inputs to m outputs.

Forward propagation of the input vector $x \in R^n$ through the input weight matrix $W \in R^{h \times n}$ determines the activation vector $a \in R^h$:

$$a = W \cdot x \quad (2)$$

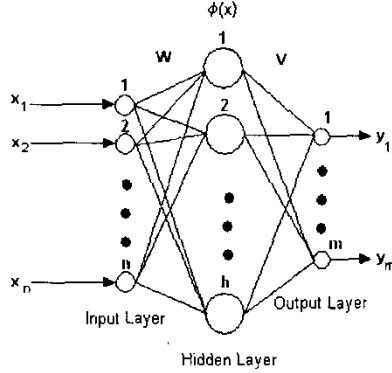


Fig 16. Three layer feedforward neural network with MLPN structure

Elements of a are then passed through a nonlinear activation function (e.g. a sigmoidal function as in (3)) to create the decision vector $d \in R^h$:

$$\phi(.) = \frac{1}{1 + e^{-(.)}} \quad (3)$$

$$d_i = \phi(a_i) \quad i = 1, \dots, h$$

By propagating the decision vector d through the output weight matrix $V \in R^{m \times h}$, the estimated output vector \hat{y} can be obtained:

$$\hat{y} = V \cdot d \quad (4)$$

B. Backpropagation Algorithm

MLPN weights are updated using the gradient decent based backpropagation algorithm. The error vector $e_y \in R^m$ is defined as the difference between the actual and estimated outputs and is then backpropagated through the output matrix V to obtain the decision error vector $e_d \in R^h$ which in turn generates the activation error vector $e_a \in R^h$:

$$\begin{aligned} e_y &= y - \hat{y} \\ e_d &= V^T \cdot e_y \end{aligned} \quad (5)$$

$$e_{a_i} = d_i \cdot (1 - d_i) \cdot e_{d_i} \quad i = 1, \dots, h$$

At each time step k the weight matrices W and V are updated using equation (6):

$$\Delta W(k) = \gamma_m \cdot \Delta W(k-1) + \gamma_g \cdot e_a(k) \cdot x^T(k) \quad (6)$$

$$\Delta V(k) = \gamma_m \cdot \Delta V(k-1) + \gamma_g \cdot e_y(k) \cdot d^T(k)$$

where γ_m and γ_g are the momentum gain and learning gain respectively.

ACKNOWLEDGEMENT

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