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Recommended Citation

S. Mohagheghi et al., "A Dynamic Recurrent Neural Network for Wide Area Identification of a Multimachine Power System with a FACTS Device," *Proceedings of the 13th International Conference on, Intelligent Systems Application to Power Systems, 2005*, Institute of Electrical and Electronics Engineers (IEEE), Jan 2005.

The definitive version is available at <https://doi.org/10.1109/ISAP.2005.1599266>

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A Dynamic Recurrent Neural Network for Wide Area Identification of a Multimachine Power System with a FACTS Device

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Abstract— Multilayer perceptron and radial basis function neural networks have been traditionally used for plant identification in power systems applications of neural networks. While being efficient in tracking the plant dynamics in a relatively small system, their performance degrades as the dimensions of the plant to be identified are increased, for example in supervisory level identification of a multimachine power system for Wide Area Control purposes. Recurrent neural networks can deal with such a problem by modeling the system as a set of differential equations and with less order of complexity. Such a recurrent neural network identifier is designed and implemented for supervisory level identification of a multimachine power system with a FACTS device. Simulation results are provided to show that the neuroidentifier can track the system dynamics with sufficient accuracy.

Index Terms— Multimachine power system, Recurrent neural networks, Static Compensator, Supervisory level identification, System modeling, Wide area control.

I. INTRODUCTION

A POWER system consists of components such as generators, lines, transformers, loads, switches and compensators. The compensators are shunt or series elements such as capacitors and inductors or converter controlled *Flexible AC Transmission System* (FACTS) devices.

Manuscript received April 1st, 2005. Financial support by the National Science Foundation (NSF), USA under grants ECS #0400657 and ECS #0348221, and from the Duke Power Company, Charlotte, North Carolina, USA, for this research is greatly acknowledged.

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All the internal control schemes, whether for the synchronous generator or FACTS devices, focus on controlling each component from an internal point of view, i.e., providing appropriate signals for the device in order to control some local quantity such as voltage or line power flow. However, with a number of these controlled devices close to one another in a power network, the issue of interaction between them arises. Moreover, each one attempts to be a good local controller, but has no information on the overall control objective of the entire system. Interactions between these local controllers (*agents*) might therefore at times lead to adverse effects causing inappropriate control effort by different controllers.

This interaction between agents could be avoided by using a coordinated control strategy, also referred to here as supervisory level control or *Wide Area Control* (WAC) which has prior knowledge of each agent's effect on the network. The WAC coordinates the actions of the agents by for example using SCADA or other available data. The WAC would receive data from the power system and based on the defined objective functions, would send appropriate control signals to the agents in the power network, in order to optimize the overall system performance.

In order to achieve this, the WAC needs some knowledge of the dynamics of the system, in terms of knowing how variables throughout the entire system will react to the actions of the different agents (individual local controllers). Clearly a mathematical solution, such as a set of differential equations is not easy to obtain and requires extensive computer resources. In order to overcome this, the WAC objectives could be implemented by neural networks which are well suited to identify a highly nonlinear non-stationary plant, in a noisy environment with uncertainties [1]. Such a neural network based identifier (*neuroidentifier*) will exchange information with the WAC module (Fig. 1).

Several papers have focused on designing multilayer perceptron (MLP) neural networks based identifiers for learning the dynamics of power system components for local control purposes [2],[3]. In an earlier paper, the authors have also investigated the efficiency of such a structure for identification of a small power system from the supervisory level [4]. While all these designs prove efficient in a relatively small power system with limited number of plant inputs/outputs, their performance degrades as the size of the network and/or the number of the

inputs and outputs are increased. Furthermore, the traditional MLP structure loses accuracy when required to learn the dynamics of a non-stationary system with fast changing dynamics.

Dynamic recurrent neural networks can be a solution to these problems. Recurrent networks are neural networks with one or more feedback loops. The application of feedback enables recurrent networks to acquire state representations, which make them suitable architectures for adaptive nonlinear prediction [5],[6].

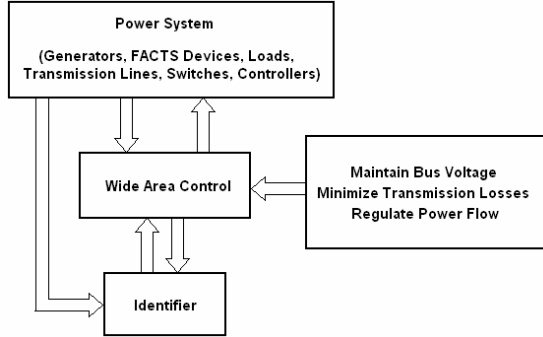


Fig. 1. Wide area control schematic diagram.

This paper deals with designing a recurrent neural network as a Wide Area Identifier of a multimachine power system with a shunt FACTS device. Simulation results are presented to show that the proposed design is efficient in learning the dynamics of the plant.

II. STATCOM IN A MULTIMACHINE POWER SYSTEM

Figure 2 shows a STATCOM connected to a multimachine power system. The system is a 10 bus, 500 kV, 5000 MVA power network and is simulated in the PSCAD environment. The generators are modeled together with their automatic voltage regulator (AVR), exciter, governor and turbine dynamics taken into account. Detailed parameters of the network can be found in [7].

A STATCOM is a shunt FACTS device which is connected in parallel to the transmission line and can

control the line voltage by injecting reactive power into the network [8]. Generally speaking the local internal controller of the STATCOM consists of two control loops, one for controlling the line voltage and another for the DC link voltage regulation. The details of the conventional STATCOM controllers implemented in this study can be found in [9].

III. DYNAMIC IDENTIFICATION OF A PLANT

Nonlinear control considers a dynamical system S that can be described by the state equations:

$$\begin{aligned} S: x(k+1) &= f[x(k), u(k)], \\ y(k) &= h[x(k)], \end{aligned} \quad (1)$$

where $u \in R^m$, $x \in R^n$ and $y \in R^r$ are the input, state and output vectors respectively. Various techniques exist in the literature for controlling such a system when its state vector is fully or partly accessible [10]. However, this is not the case for most of the practical applications, where the input and output measurements are the only pieces of information available. These are the class of problems where the well established control designs cannot be directly applied. The first step in control of such systems is to identify their dynamics using the available signal measurements.

In general for a nonlinear system shown in (1) with relative degree of d , the output at time step $(k+d)$ can be determined as a nonlinear function of the past values of inputs and outputs:

$$y(k+d) = F[y(k), \dots, y(k-n+1), u(k), \dots, u(k-n+1)], \quad (2)$$

where n is the order of the nonlinear system. Such a model is called the nonlinear autoregressive moving average (NARMA) representation of the plant.

Neural networks are among the most efficient techniques for identifying a nonlinear system with unknown dynamics. Given the set of measured inputs and outputs of the nonlinear plant, a neural network can be effectively trained in order to learn its NARMA equation [1]. Static feedforward neural networks have been widely applied for I/O representation of nonlinear plants [1]-[4].

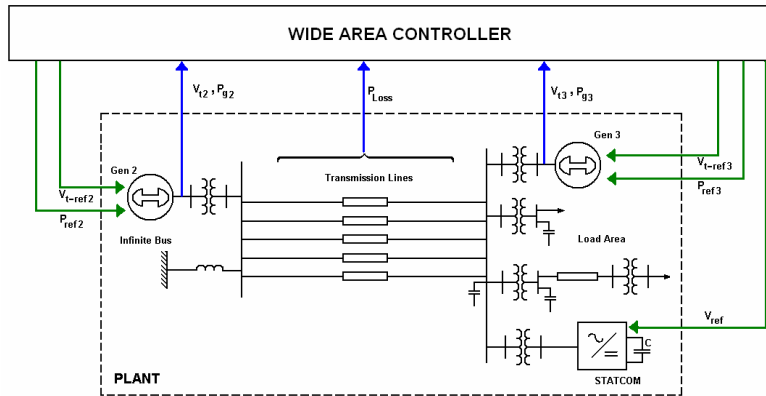


Fig. 2. Multimachine power system with a STATCOM.

The neural network based NARMA model, although efficient in certain applications, has several deficiencies associated with it:

A. Order of the System

The NARMA model is derived under the assumption that the linearized model of the nonlinear system is observable [1]. It has been shown that almost any system of the form (1) is observable if $2n+1$ measurements of the output are taken [11]. However, most of the times, the information about the nonlinear plant and the order of the system are not known beforehand. Hence, the correct number of time delayed inputs/outputs is not easy to obtain and are mostly found by trial and error. While a small number of measurements might lead to insufficient data and therefore failure in identification, a large number of data samples will cause extensive computational effort.

B. Static Modeling

As long as the underlying input-output mapping is static, and the training data set is sufficiently large and representative of the normal operation of the system under study, it is commonly believed that the *Multilayer Perceptron Neural Network* (MLPN) is good and simple to use. However, there are many problems occurring in nature, science, or engineering, which are more suitably modeled using a dynamic model, i.e., one which takes into account any possible temporal correlation of the data. [6]

C. Size of the Neural Network

The size of a static neural network, such as a MLPN will drastically increase as the number of plant inputs/outputs is increased in order to provide sufficient identification accuracy. For a system of order n , any additional measurement will add n input nodes and even more hidden nodes to the structure of the neural network.

D. Trivial Solution

A NARMA model neuroidentifier with a relatively small sampling time might give the misconception of satisfactory performance. This is due to the fact that the trivial solution $y(k+d) = y(k)$ might seem reasonable, yet in actual fact it is meaningless.

Dynamic Recurrent Neural Networks (DRNN) can be an alternative solution to the above problems. These are networks consisting of dynamic neurons with forward and backward connections. A dynamic neuron is one whose output can be described by a differential equation (or a difference equation in the case of discrete systems). Various models of a dynamic neuron are explained in [12].

DRNN's are powerful neural structures that can model the nonlinear plant as a set of differential equations. Figure 3 shows a typical diagram of a DRNN. The hidden layer outputs that are fed back to the input layer are the states of

the system. The number of these states determines the order of the model. Because of the beneficial effects of the global feedback, DRNN's may be better than feedforward structures in control, prediction and identification applications [5],[15].

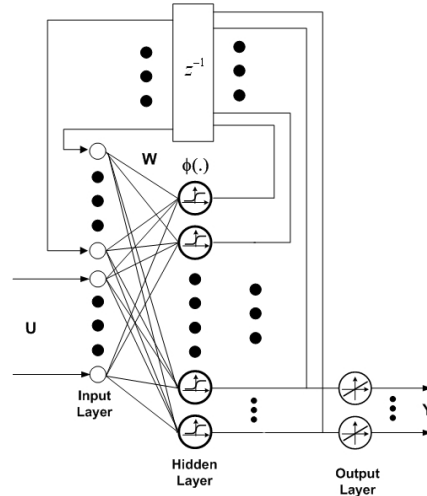


Fig. 3. Schematic diagram of a dynamic recurrent neural network.

The dynamic behavior of the DRNN can be written as:

$$\begin{aligned} x(k+1) &= \phi[W(k) \begin{bmatrix} x(k) \\ u(k) \end{bmatrix}], \\ y(k) &= C.x(k), \end{aligned} \quad (3)$$

where W is the input layer synaptic weight matrix, and $x \in R^N$ is the state vector of the plant, i.e. the output of the hidden layer neurons. $\phi(\cdot)$ is the nonlinear activation function of the hidden neurons, which in this study is considered to be a hyperbolic tangent function:

$$\phi(\cdot) = \tanh(\cdot) \quad (4)$$

It can be shown that a dynamic recurrent neural network of the form (3) can approximate the nonlinear system (1) with the number of states $N \geq n$ [13].

IV. WIDE AREA NEUROIDENTIFIER

A. Neuroidentifier Structure

The "Plant" in Fig. 2 consists of the synchronous generators, transmission lines, STATCOM and their corresponding local internal controllers or agents. These agents are left as integral components of the plant, but the following reference signals to the agents are considered as the inputs to the plant as shown in Fig. 4. These are:

- V_{ref} ; Line voltage reference at the point where the STATCOM is connected to the network,
- P_{ref2}, P_{ref3} ; Power reference values at the inputs of the generator turbines ,

- V_{t-ref2}, V_{t-ref3} ; Terminal voltage reference values at the inputs of the generator AVRs.

In turn the plant outputs in this study are the following five measured wide area quantities: the active power output and terminal voltage values of the synchronous generators, as well as the transmission line losses. If necessary, more measurements from the plant could be used in order to control more variables than only the four listed above.

A DRNN with *Backpropagation Through Time* (BPTT) method as the training algorithm, is used for wide area identification of the power network in Fig. 2 [5],[14]. The plant inputs are fed into the neuroidentifier along with the previous values of the actual plant outputs. In turn the neuroidentifier predicts the values of the plant outputs at one step ahead, i.e., at time step $t+1$ (Fig. 4).

The number of neurons in the hidden layer is heuristically chosen as twenty five, with a learning gain of 0.01. The hidden layer outputs are fed back to the input layer as the states of the dynamical system. All the inputs to the neuroidentifier are normalized, i.e., they are in per unit value, so that all input signals have the same weight in training the neural network.

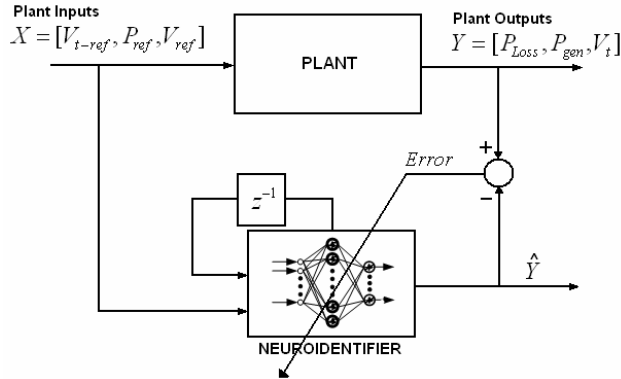


Fig. 4. Wide Area Neuroidentifier schematic diagram.

The actual values of the plant outputs are compared with the estimated values generated by the neural network, to form an error vector, which is applied to modify the weight matrices using BPTT training algorithm.

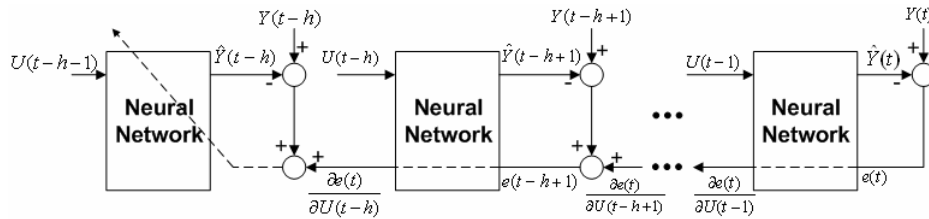


Fig. 5. Backpropagation through time learning algorithm.

B. BPTT Training Procedure

The main difficulty in training recurrent networks lies in the fact that the output of the network and the weight modifications depend on the values of the network inputs since the beginning of the training as well as the initial state [16]. This makes the training of DRNN more difficult than the static MLP and RBF neural networks for online training purposes.

The BPTT algorithm for training a recurrent neural network is an extension of the standard backpropagation algorithm. It may be derived by unfolding the temporal operation of the network into a layered feedforward network whose topology grows by one layer at every time step [5].

In order to apply this method in real time applications, a truncated BPTT can be implemented which looks at the history of the network input and state data for a fixed number of time steps, called the *truncation depth* h . The truncation depth h defines the size of the moving window by which the temporal behavior of the network is analyzed. Selecting an appropriate number is critical for achieving desirable performance. Figure 5 shows the schematic diagram of BPTT with the truncation depth h .

At any time step the DRNN estimated output is subtracted from the desired output, forming an error vector. The error is then backpropagated through the neural network without updating its synaptic weight matrices. This backpropagated error is now added to the error vector at one step before, forming the next error vector to be backpropagated through the neural network. This process is repeated h times, and the final error vector is used for updating the synaptic weights of the neural network using ordinary backpropagation algorithm (Fig. 5). All the neural networks in the BPTT algorithm shown in Fig. 5 have the same input/output synaptic weights, but have different input/target vectors at various time steps. Each of these networks represents the neural network at a specific time step. The truncation depth of two is selected in this study.

V. SIMULATION RESULTS

The neuroidentifier goes through a *forced training* stage, during which time the plant inputs are manually perturbed all at the same time, by adding small *pseudorandom binary signals* (PRBS) to each one. Such deviations in the inputs of the plant cause small changes/deviations in the plant outputs. The neuroidentifier is then trained, with its weight matrix being updated based on the BPTT algorithm, in order to learn the dynamics between the plant inputs and outputs.

The system in Fig. 2 is first simulated until it reaches steady state. At this point the PRBS signals are added to the plant inputs X from an external source and the neuroidentifier training begins.

Due to the slower dynamic nature of the supervisory level controller compared to the dynamics of the local internal controllers or agents, the frequencies of the PRBS signals are heuristically chosen to be 0.1, 0.2 and 0.5 Hz, while their magnitudes are limited to $\pm 5\%$ of the corresponding plant reference signals. Figure 6 shows a typical PRBS disturbance applied to the plant inputs.

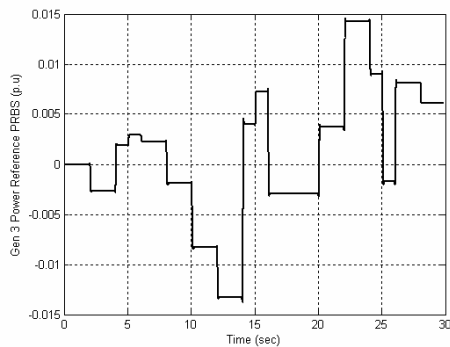


Fig. 6. PRBS applied to the turbine power reference of the generator 3.

Figures 7-9 show some sample training results. It can be seen that the neuroidentifier can track the system dynamics with high precision. This happens because the training never stops.

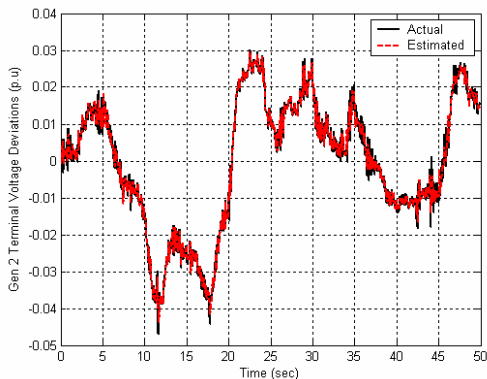


Fig. 7. Generator 2 terminal voltage deviations during forced training.

However, in a real power system, applying PRBS perturbations to the network might not be desirable or practical. An alternative solution in such a case is to apply smaller PRBS signals, or to train the identifier for a longer time during the normal operation of the continuously stochastic changing power system. However, when training the neuroidentifier under normal operating conditions (with no PRBS disturbance), steps should be taken in order to compensate for the fact that the frequency of stochastic changes during the normal performance of the power system might be low. Therefore, training might need to be

continued for a much longer period. Moreover, it is possible to define an adaptive learning gain for the identifier [4].

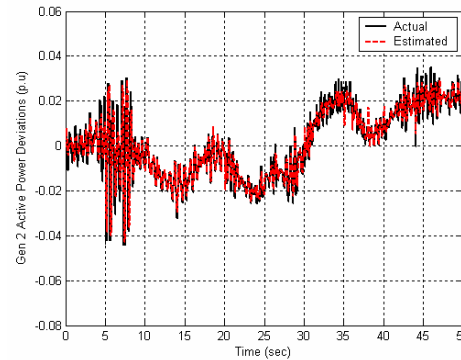


Fig. 8. Generator 2 active power output deviations during forced training.

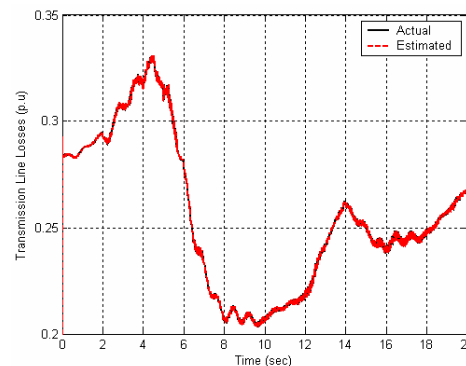


Fig. 9. Transmission line losses during forced training.

After being forced trained, the PRBS is removed and the neuroidentifier performance is tested by applying various dynamic and transient tests to the power system. During the testing stage the neuroidentifier learning gain is reduced to a very small number to prevent the network from forgetting the previously learned information.

In the first test, one of the load branches is disconnected at 5 second, during the steady state performance of the system, and switched back on after 2 seconds. Figure 10 shows the actual and estimated values of the generator 3 terminal voltage.

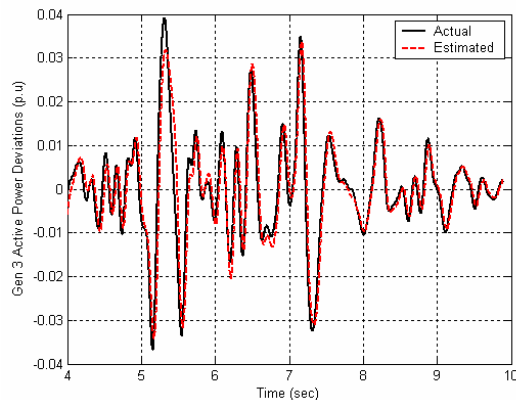


Fig. 10. Actual and estimated values of the generator 3 active power output deviations when a shunt load is switched off and back on.

The system is also tested by applying natural disturbances, such as a three phase short circuit. Figure 11 shows the estimated and the actual values of the generator 3 active power output when a 100 ms three phase short circuit occurs at its terminals.

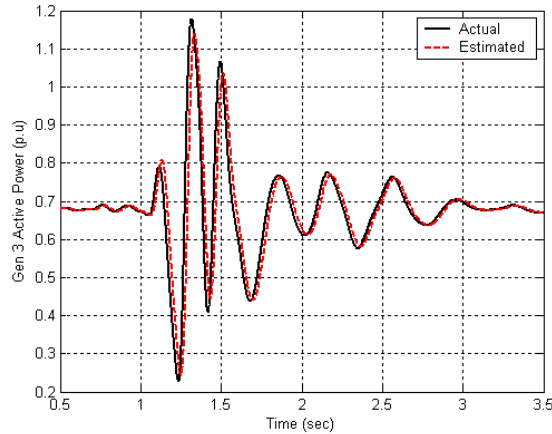


Fig. 11. Generator 3 active power output during a 100 ms three phase short circuit.

VI. CONCLUSION

Feedforward neural networks are predominantly used in the literature for NARMA modeling of components in the power network. Although these techniques are efficient in small systems and for local agents in a network, their efficiency is degraded by an increase in the size of the plant/agent to be modeled. Moreover, the input-output mapping might fail in a highly dynamic system.

Dynamic recurrent neural networks are alternative solutions to the above problems. They can model any nonlinear dynamic system with enough number of global feedbacks. Due to the state space modeling structure, they never get trapped in the trivial solution, and they use smaller structure with less number of neurons compared to the conventional MLPN.

Controlling a power network from a supervisory level requires a model of the system which is dynamic and capable of analyzing large amounts of data. A multimachine power system is considered in this paper along with a shunt FACTS device which together form a highly nonlinear system. The authors tried implementing a neuroidentifier for such a system using MLPN structure. However, simulation results showed that the MLPN based neuroidentifier failed to converge even after extensive online training.

A dynamic recurrent neural network is therefore used with backpropagation through time training algorithm for

learning the dynamics of such multimachine power system. Simulation results are provided that indicate the DRNN is capable of modeling such a system efficiently in terms of state space dynamics.

Such a dynamic neural structure can serve as a plant model in a neural network based Wide Area (supervisory level) control scheme of a multimachine power system.

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