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Coherency Based Partitioning of a Power System for Intelligent Wide-Area Damping Control

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SUMMARY

A variety of factors are causing an increase of slow frequency oscillations in power systems. These oscillations reduce the stability of the system, limit power transfers, and can potentially lead to loss of synchronism and widespread blackouts. These oscillations typically involve variables from distant areas accross the system; therefore, conventional local damping controllers such as power system stabilizers might lack the information needed to provide effective damping. Controllers that utilize wide-area measurements can overcome these limitations , but the techniques for developing those controllers are still under development. The use of computational intelligence for wide-area damping control of power systems has been demonstrated in small power system simulations. It has been shown that it is possible to develop intelligent controllers that adapt online to improve their performance and approach optimality over time and that are capable of dealing with the non-linear, stochastic, and time varying nature of power systems. However, the scalability of these algorithms needs to be evaluated and possibly improved if they are to be implemented in realistically sized power systems. Typically, the development of intelligent controllers begins with identifying an accurate and differentiable model of the system to be controlled. However, studies have shown that as the size of the system being identified grows, so does the model and the computational complexity of the algorithms required to tune that model. The shear size of real world power systems makes straightforward implementation of such system identification approaches intractable. The work presented in this paper explores the issue of scalability of intelligent system identification algorithms using simulations of a large portion of the Brazilian Sistema Interligado Nacional. A recently developed concept named the virtual generator is utilized to simplify the online identification of an input/output data driven dynamical model of a large portion of the power system. This model is based on dynamical artificial neural networks and can be used for intelligent online adaptation of controller parameters. Only the system identification methodology is presented.

KEYWORDS

Virtual generator; wide-area monitoring; power system equivalents; generator coherency; interarea oscillations; power system identification; artificial neural networks

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1. Introduction

Increasing electrical energy demand coupled with reduced ivestment in transmission systems are forcing utilities to operate power systems closer to their stability limits. Also, market deregulation in certain countries has resulted in operating regimes that were not necessarily accounted for during the power system planning and design stages. It is expected that these trends will result in the emergence or worsening of low frequency oscillations, where weakly coupled machines tipically far away from each other oscillate against each other [1]. These oscillations can be difficult to mitigate using local measuments and local control signals alone [2].

The wide-spread deployment of phasor measurement units (PMUs) and more sophisticated communication infrastructures will allow the implementation of wide-area control algorithms due to the availability of time-synchronized measurements from distant areas of the power system. However, the control design techniques neded to make use of this wide-area information are still being refined by the research community [3].

The use of computational intelligence for wide-area damping control of power systems has been demonstrated in small power system simulations[4]. It has been shown that reinforcement learning mechanisms such as adaptive critic cesigns (ACDs) coupled with the approximating and system identification capabilities of artificial neural networks (ANNs) can result in adaptive controllers that adapt online to improve their performance and approach optimality over time and that are capable of dealing with the non-linear, stochastic, and time varying nature of power systems [4]. These controllers can outperform other more conventional approaches for wide-area damping applications in power systems [5].

Typically, the development of intelligent controllers begins with identifying an accurate and differentiable model of the system to be controlled. However, studies have shown that as the size of the system being identified grows, so does the model and the computational complexity of the algorithms required to tune that model [6]. The shear size of real world power systems makes straightforward implementation of such system identification approaches intractable. This paper explores this issue of scalability of intelligent system identification algorithms using simulations of a large portion of the Brazilian sistema interligado nacional (SIN) implemented in DIgSILENT PowerFactory. A new concept named the virtual generator (VG) is utilized to allow the identification of an input/output data based dynamical model of a large portion of the power system. This model is based on recurrent ANNs and can be used for intelligent online adaptation of controller parameters.

The VG concept borrows heavily from techniques comonly used for creating power system dynamic equivalents. However, in contrast to such techniques (which are used offline for simplifying simulation studies), the VG calculation is performed online and allows wide-area controllers to treat several generators as a single unit in real-time for damping control purposes.

The paper is organized as follows: Section 2 briefly describes the development of the DIgSILENT simulation of the South, Southeast, and Midwest portions of the SIN. Section 3 explains the VG concept, motivates its use for improving the scalability of dynamical system identification algorithms, and applies it to the simulated system. Section 4 gives a brief introduction to ANN based dynamical system identification, presents the ANN topology selected, and discusses the training procedure used. Section 5 presents conclusions and some of the current research into wide-area damping control using the concepts of this paper.

2. SIN Power System Simulation

The diagram shown in Fig. 1 illustrates the South, Southeast, and Midwest portions of the Brazilian SIN. It was generated by the national electric system operator (ONS). A DIgSILENT simulation model of this system was developed using data from a model previously developed in Simulight, a Brazilian power system electromechanical transient simulation package. The single line diagram of the resulting DIgSILENT model is shown in Fig. 2.

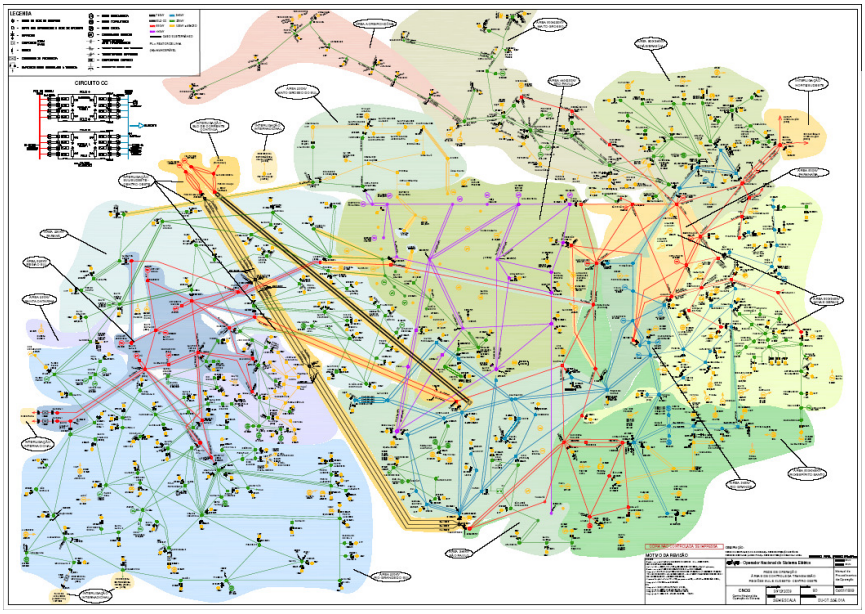

Figure 1. ONS Diagram of South, Southeast, and Midwest portions of the SIN

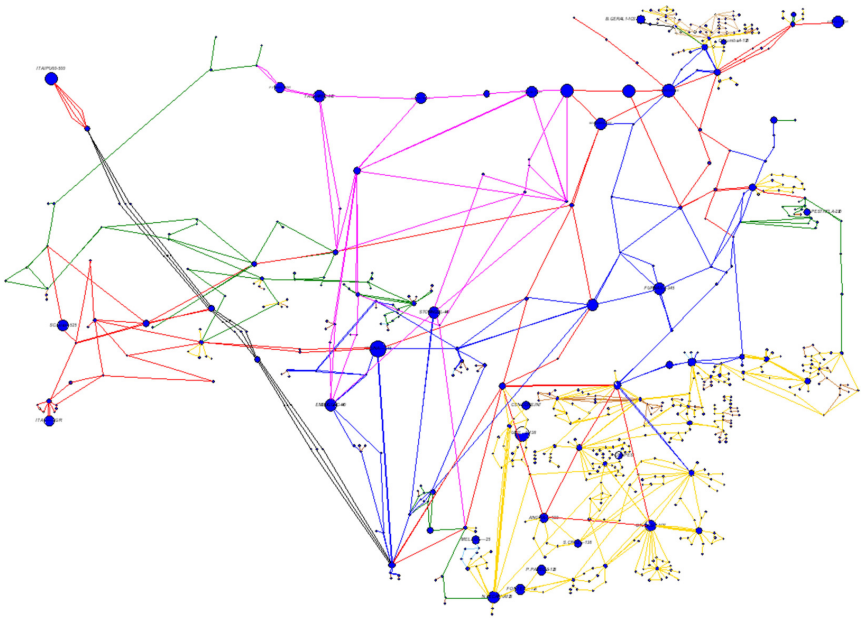

Figure 2. DIgSILENT diagram of the South, Southeast, and Midwest portions of the SIN

The model contains 73 generators modelled in detail, each with automatic voltage regulator (AVR), turbine and governor models. Some of these generators represent several parallel connected machines at a generating station. 38 of these generators are equipped with power system stabilizers. 53 other generators are modelled as power injections at a number of locations across the system. The 50 Hz generators at Itaipu and the HVDC transmission link connecting them to Ibiuna are modelled as a 4.8 GW power injection at Ibiuna. Loads are modelled as constant impedances. Electromagnetic transients are ignored by representing the power network via algebraic equations. The interconnection to the North/Southeast portions of the SIN is modelled by a synchronous generator supplying 2.6 GW with no AVR and constant mechanical power input.

Figure 3 presents a generic AVR that illustrates the addition of a wide area control signal (u_{WADC}) to be used for damping control purposes. However, each generator in the SIN model is equipped with a different AVR model.

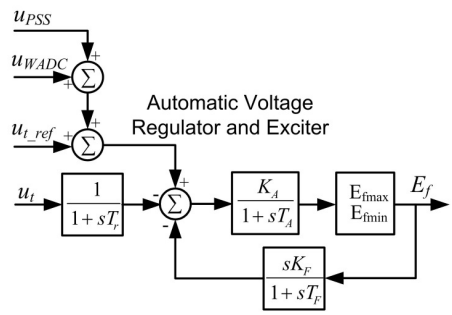

Figure 3. Generic Automatic Voltage Regulator with wide-area input signal (u_{WADC})

The goal of the strategies demonstrated throughout this paper is to allow the development of intelligent wide area controllers to damp low frequency oscillations in realistically sized power systems such at the SIN. These controllers are expected to improve the stability and reliability of the system, and potentially increase the power transfer limits between distant areas of a power system.

3. Generator Coherency and Virtual Generators

The VG representation relies on the concept of coherency described in section 3.1. Section 3.2 presents the method used for identifying coherent generators, and illustrates its results for the SIN simulation. Section 3.3 describes the VG and its justification. Section 3.4 uses the coherency identification results to develop VG representations of a portion of the SIN.

3.1. Generator Coherency

Coherency in power systems is defined as the tendency of groups of generators to "swing together" after disturbances. Swinging together refers to generators oscillating in phase with each other, at the same angular speed, and maintaining the same rotor angle deviation. This tendency has been attributed to a variety of factors such as the stiffness of the interconnection between generators and the ratio between the synchronizing torque coefficients and the inertias of the generators within a group [7].

3.2. Coherency Identification

A variety of methods have been developed to identify groups of coherent generators. Three of these methods were evaluated in [8], namely weak links (WL), two-time scale (TS), and linear time simulations (LS). The authors of that paper concluded that all three methods produced good generator grouping for creating equivalents. Of the three methods, the LS is considered the classical method to identify coherent generators. It consists of simulating a linearized model of the power system with classical generator models and ignoring non-generator dynamics. Once the generators' swing curves (time-domain waveforms of the rotor angles) are obtained, clustering algorithms can be used to find groups of generators that exhibit strong similarity in their swing curves. The details of the LS coherency identification algorithm can be found in [9].

A more advanced technique based on modal analysis and accounting for the effect of voltage dynamics was presented in [10], but the additional clustering accuracy gains that can potentially result from that approach are considered unnecessary in the present work.

The approach in this paper is similar to the LS method; however, the full order model of the system (not a simplified and linearized version of it) is used to generate the generator swing curves. Hierarchical clustering based on these curves is then completed using tools available in MATLAB's Statistics Toolbox. This approach to generator clustering will be called *full simulation hierarchical clustering* (FSHC) in this paper. Figure 4 presents the dendrogram resulting from FSHC of the generators in the SIN. Dendrograms allow the selection of different clusters given a particular tolerance level for the dissimilarity betweent generator waveforms. Higher tolerances result in a lower number of clusters at the cost of less similarity between the generators in those clusters. Lower tolerances increase similarity but increase the number of clusters.

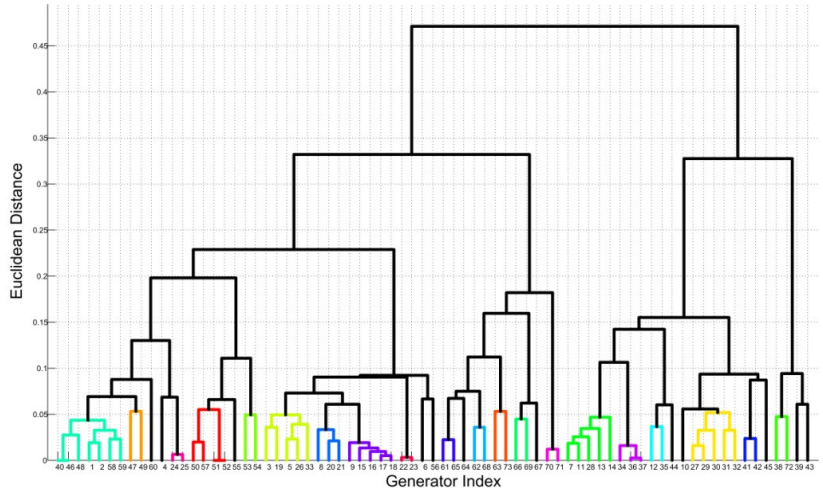

Figure 4. Dendrogram for hierarchical clustering of coherent generators in the SIN

Choosing the appropriate tolerance level for clustering is not strightforward. However, careful inspection of the generator waveforms allows for an informed selection. Figure 5 presents the speed waveforms for 5 groups of generators resulting from the dendrogram shown in Fig. 4 with each group plotted in a different color.

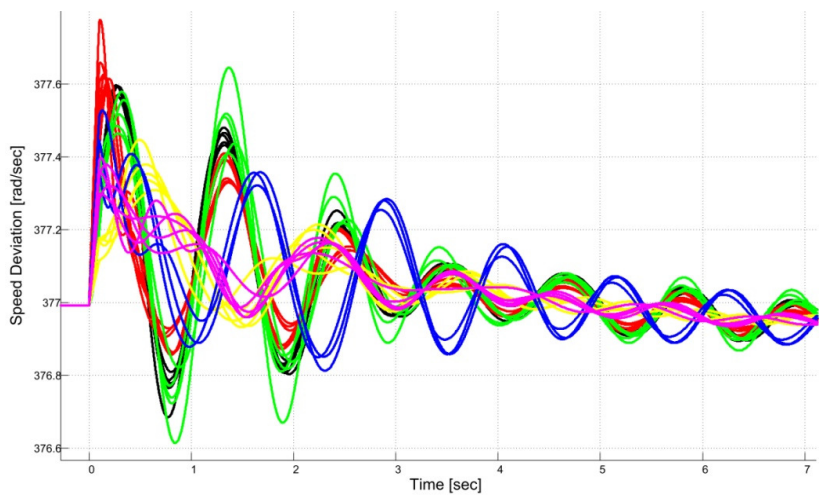

Figure 5. Speed waveforms for generators in 5 of the clusters

3.3. Virtual Generators

In [9]-[11] it was demonstrated that, for certain kinds of power system studies, coherent behavior can be exploited to generate simplified dynamic equivalents of portions of power systems while maintaining acceptable simulation accuracy. These equivalents represent a number of coherent generators using a single generator model, thus greatly reducing the complexity of the simulation. Typically, these equivalents are used to represent portions of the system that are outside of the area being studied, and disturbances are applied at locations electrically far away from the equivalent.

One of the equivalencing methods is called slow coherency aggregation and can be found in [12]. The idea is to define the center of angle of a group of coherent machines as a slow variable, and their inter-machine oscillations as a fast variable. The definitions of these variables for a group of say 2 machines for example, are shown in (1) and (2).

$$\delta_{slow} = \frac{H_1\delta_1 + H_2\delta_2}{H_1 + H_2} \qquad (1)$$

$$\delta_{fast} = \delta_1 - \delta_2 \tag{2}$$

The constant H_i is the per unit inertia of generator i with all generators in the group referred to the same power base. Equation (1) can be differentiated to obtain:

$$\dot{\delta}_{slow} = \frac{H_1\dot{\delta}_1 + H_2\dot{\delta}_2}{H_1 + H_2} = \omega_{slow} = \frac{H_1\omega_1 + H_2\omega_2}{H_1 + H_2} \tag{3}$$

Generalizing for groups of N coherent generators results in:

$$\omega_{slow} = \frac{\sum_{i=1}^{N}(H_i\omega_i)}{\sum_{i=1}^{N}(H_i)} \tag{4}$$

The coherency assumption results in the vanishing of the fast variable in (2) to a small value that is neglected. Also, the availability of PMU data allows the real-time calculation of (4) as the system operates. As a consequence, large portions of the system containing a number of coherent generators can be represented as a single generator for wide-area damping control purposes. The resulting "equivalent" generator is called a "virtual generator" (VG) from now onwards. The virtual speed of the VG is defined as in (5).

$$\omega_{VG} = \omega_{slow} = \frac{\sum_{i=1}^{N}(H_i\omega_i)}{\sum_{i=1}^{N}(H_i)} \tag{5}$$

The validity of the coherency assumption, and consequently the validity of the VG representation, varies with the system operating condition and with the type of disturbance applied. This fact has to be considered during control design but is not discussed any further in this paper. However, there are ways of enforcing coherency that can mitigate this phenomenon.

3.4. Simplifying the System Via Virtual Generators

Virtual generators allow intelligent controllers to treat large portions of the system in a simplified way; thus, reducing computational complexity, and improving scalability. Figure 6 presents the tipical speeds of the generators inside of a coherent cluster and the speed of the VG used to represent them after a 100 ms 3-phase short circuit fault. The VG representation results in minimal loss in accuracy.

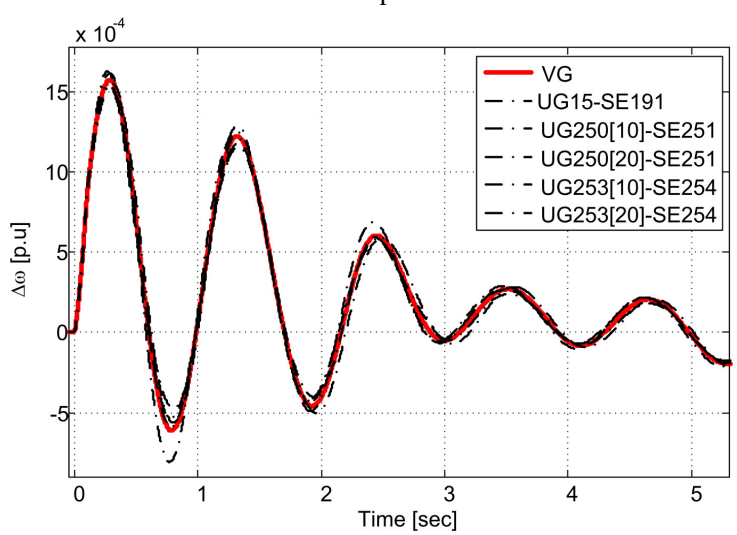

Figure 6. Typical speeds for generators in a cluster and the VG representing them

The main obstacle for the effective use of VGs for control is obtaining an accurate model that describes the dynamical input/output relationship between the speed of the VG and the available inputs into the system. Section 4 explains how ANNs can be used to circumvent this obstacle.

4. Artificial Neural Networks Based System Identification

Proven universal approximation capabilities coupled with the availability of effective parameter adaptation algorithms (training algorithms) make ANNs good candidates for non-linear dynamical system identification [13]. The neuro-identification task is illustrated in Fig. 7 and can be summarized as: given a sequence of present inputs and outputs of an unknown plant, provide one-step-ahead predictions of the plant outputs. It is assumed that once the network is capable of generating accurate predictions of the future outputs, it has "learned" or identified the underlying principles governing the dynamic input/output mapping of the plant. An accurate identifier network thus represents a model of the plant and is capable of answering the question: how do the inputs into the system affect the future outputs of the system?

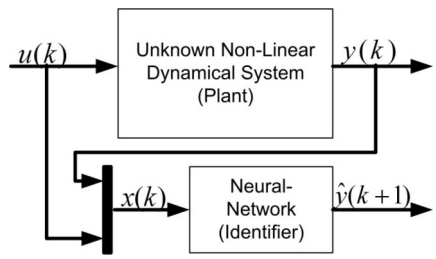

Figure 7. Neuro-identification task

When coupled with the VG concept, ANNs can simplify the development of intelligent controllers for wide area damping. Figure 8 shows the proposed system identification methodology. Note that the plant to be controlled has a single output (the speed of the VG), and that the ANN is charged with finding the relationship between N inputs (u_{WADC1}-u_{WADCN}) and the value of that output at the next time step. The sampling frequency of the ANN is set to 20 Hz. The signal D[k] represents unmeasured disturbances that affect the behavior of the plant.

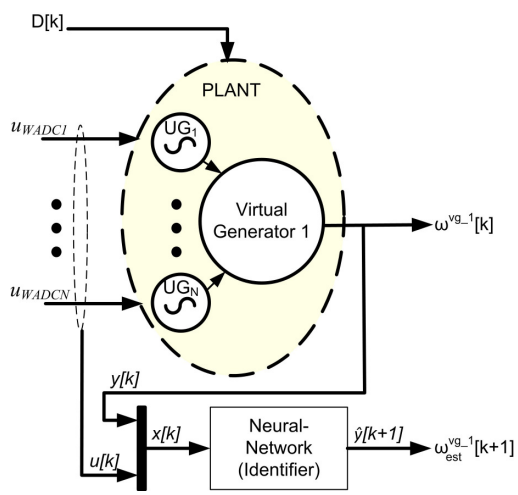

Figure 8. Setup for identifying dynamical input/output model of VG using ANNs

4.1. Globally Recurrent Neural Network (GRNN) Training

There are countless dynamical neural network architectures. Reference [6] explores the capabilities of the two commonly used architectures: the Time Delay Neural Network (TDNN), and the Elman Recurrent Neural Network (ERNN). The authors found that both networks provide similar performance for power system identification. The ERNN, although known to be more powerful for

dynamic system identification, results in larger computational costs; however, an appropriate software implementation can overcome those costs.

The globally recurrent neural network (GRNN) selected in this study is illustrated in Fig. 9 and its output equation is defined in (6). Note the presence of time-delayed feedback loops between the outputs and inputs of the hidden layer. These loops provide the network with memory, and give it the capability to accurately represent arbitrary dynamical systems as demonstrated in [14].

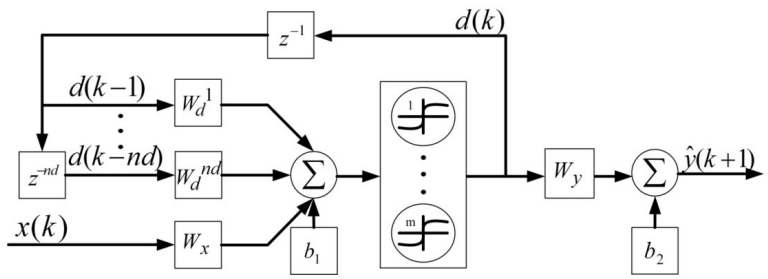

Figure 9. Gobally recurrent neural network (GRNN) topology

$$\hat{y}(k+1) = f\begin{pmatrix} W_x x(k) + \\ W_d^1 d(k-1) + \\ W_d^2 d(k-2) + \\ \vdots \\ W_d^{nd} d(k-nd) + \end{pmatrix} W_y + b_2 \qquad (6)$$

A C++ based object oriented library implementing the GRNN, gradient calculations, and training algorithms is developed for this study. Reference [15] provides some of the concepts needed for such implementations. The gradient calculations follow the approach outlined in [16]. Arguably the most important factor for achieving acceptable performance when using ANNs, is the training algorithm since although the capability of the GRNN to represent arbitrary dynamical systems has been proven mathematically, no method is currently available to ensure full harnessing of those capabilities.

The GRNN weight updates are performed online using a sliding input/output data window.

- Pseudo-random binary signals (PRBSs) are injected at the u_{WADC} input point on the AVR (see Fig. 3) of each generator in the sub-network. Details on how to design appropriate signals for system identification are provided in [17].
- At each time step, input-output pairs are collected as training data and are imported into the C++ neural network library. The software pushes this new data into a sliding window of samples.
- The scaled conjugate gradient (SCG) [18] training algorithm finds a set of network weights that minimizes the mean square error between the outputs of the network and the measured output from the system.

In [19] a discussion of several of the currently available training algorithms is provided, and recommendations are given for the use of conjugate gradient based methods for training ANNs.

4.2. GRNN Testing

Under certain circumstances it is possible to obtain ANNs that perform well with the training data, but poorly with data not included in the training set. This phenomenon is sometimes known as overfitting. The testing stage evaluates if the ANN has learned the input/output relationship of the plant. Pseudo-random binary signals (PRBSs) are no longer applied during testing, and disturbances not present in the training set are used to excite the system. Accurate predictions of the system outputs under these conditions are considered an acceptable indicator of successful system identification.

Figure 10 presents the simulation results after a GRNN is trained to model the VG behavior shown Fig. 6. The GRNN is capable of accurately predicting one-step-ahead values of the VG speed after a variety of faults have been applied to the system.

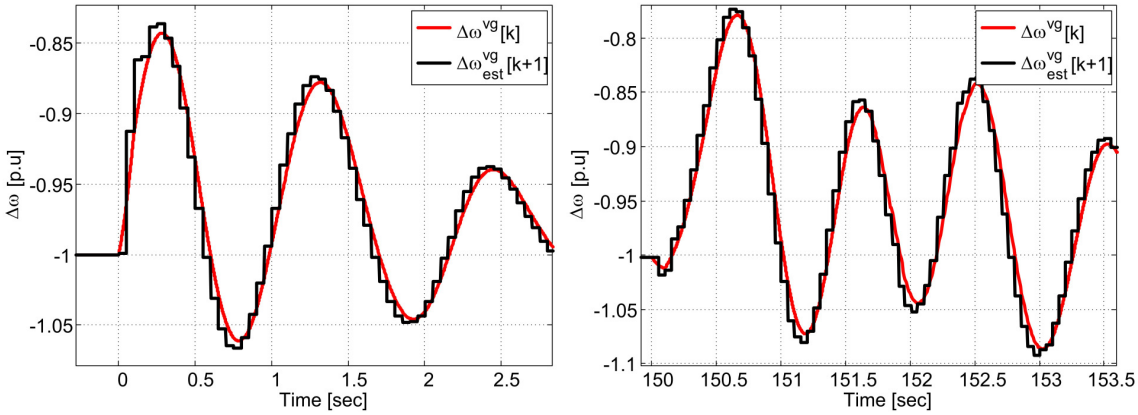

Figure 10. System model performance for 3-phase faults at different locations in the system

These results point to a successful learning procedure. Further evaluations were completed with similar results. They are not shown due to space limitations.

5. Conclusions

Intelligent control algorithms have shown much promise for power system damping control. Several researchers have shown that such controllers are capable of dealing with the time-varying, non-linear, and stochastic nature of power systems. However, past studies on the development of these controllers have been limited to small power system simulations. The unparalleled complexity of realistically sized power systems makes the straightforward implementation of intelligent controllers intractable. Therefore, the scalability of intelligent controllers for power system damping needs to be improved to address the challenges of real systems.

The work presented in this paper utilized a recently developed concept called the virtual generator to attack the scalability problem. Recognizing the tendency of generators to behave coherently and generating simplified representations online using wide-area measurements will allow intelligent controllers to treat several generators in a power system as a single unit. Although simplified, these representations retain the important information needed for wide-area damping control in the form of a virtual generator speed. In addition to the virtual generator, an accurate model relating the available inputs into the system to the virtual generator speed is critical for intelligent control adaptation. A recurrent artificial neural network can provide that model if training is done correctly. The simulation results obtained in this paper show that the model can be obtained using solely input/output data.

Future efforts will be geared towards utilizing the strategies developed in this paper coupled with adaptive critic designs to implement a wide-area damping controllers for mitigating slow frequency oscillations in the Brazilian sistema interligado nacional.

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