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Decentralized Interaction Estimators in Large Scale Power Systems with Neural Networks

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In This paper a new method for designing decentralized interaction estimators for interconnecting large-scale systems is proposed. A local estimator is designed for each local area, to estimate the incoming interactions from other area using only the local output measurements. In fact, these interactions are the information of other subsystems. A new scheme is developed to construct an approximate model for the interaction dynamics based on neural network theory and design a local estimator. An ANN is developed to construct the approximate model of the interaction dynamics and designing a local estimator. The designed local estimator exploits the actual inputs and outputs to produce a good estimation of unknown states and interactions.

Keywords: ANN, Estimation, Large Scale Systems. .

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I INTRODUCTION

In decentralized control strategy, a simple local controller uses only its area's state measurements. It does not exploit any feedback information from other subsystems. Therefore the incoming interactions of other subsystems are unknown for each local controller. In the most control strategies the interactions are considered as external disturbances [1, 2]. While this paper addresses a method to reconstruct the interactions, which can be used in the control stage to yield better results.

State estimation in power systems has been traditionally done at regional control centers with limited interaction. However, due to the deregulation of energy markets, large amounts of power are transferred with high rate and several long distance lines control areas [3]. These so-called tie lines, originally constructed for emergency situations which are now fully operational and must be accurately monitored. The advances in metering infrastructure are unprecedented: phasor measurement units (PMUs) provide finely-sampled voltage and current phasors, synchronized across the grid; smart meters reach at the distribution level; and networked processors are being installed throughout the power system [3, 4]. The abundance and diversity of measurements offer advanced monitoring capabilities, but processing them constitutes a major challenge, which is exacerbated in the presence of malicious data attacks and bad data [5, 6].

In the classical decentralized control schemes, it is assumed that all of the state variables are available [7, 8]. However, this assumption is not usually pragmatic in the most large-scale systems. So, a state estimator has to be designed. This estimator uses the actual inputs and outputs to produce a good estimation of unknown states. The uncertainties of interactions between subsystems make the complexity of controller or estimator design in large-scale systems. In the classical decentralized schemes, the interactions are unknown for the local observer or controller. Therefore interaction reconstruction may be very helpful to achieve less conservative performance for the local observers and controllers.

The main idea of this paper is to introduce a scheme to estimate the interactions in a decentralized approach based on neural network theory. The decentralized observation problem was considered in [9]. Necessary and sufficient conditions on the subsystems were derived in [10] which the observers could be designed. In [11] an output-decentralization and stabilization scheme were proposed, which could be directly used to construct asymptotic state estimators for linear large-scale systems. The problem of robustness of a Luenberger observer applied to a given large-scale system was addressed in [12].

In [13] a decentralized filter was obtained by identifying the dynamics of the interaction variables, and estimating the local states and interactions by using local information. An indirect method for decentralized estimation of interconnected large-scale systems was presented in [14]. In [14], structure of the estimators were obtained in two steps. In the first step, an approximate model for the desired local variables in an indirect method was derived. In the second step a local filter was derived using the obtained model and local measurements.

In the latest published papers [13–16], either the interactions have been treated as disturbances or the local state vector and the interaction variables are assumed to be available. While in practical problems, the interaction variables are not accessible and there is no measurement on them. In [17] only local output feedback is introduced a new method for designing decentralized estimators to estimate the states and interactions. The estimated interactions are used to load frequency control of a large scale power system using robust adaptive theory

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in [18, 19].

In this paper, the complex behavior of the interaction signals and and uncertainty on the system model and parameters caused to use a neural network estimator instead of a classical estimator. A large-scale system can be split into the two systems, the ith subsystem and the residue system (aggregation of other subsystems). Note that, the dynamics of the residue system make the interactions with the ith subsystem. In classical manner, we should incorporate the dynamics of the residue system to have a good estimation. If the dynamics of the residue system is added to the estimator dynamics, the result of the designed filter becomes very high. So this estimator design is very difficult with classic method. We introduce ANN solution to solve this problem, because in this case the dynamics of the subsystems are not needed.

This paper is organized as follows: Section II formulates the problem. The system under study is described in Section III. Section IV is devoted to present the main contributions of this paper namely as: 1) introducing an ANN for interaction dynamics identification, 2) developing a new decentralized states and interactions estimator which uses the identified model. In Section V, the simulation results in a three-area power system show the effectiveness of the proposed algorithm.

II Problem Statement

Consider the large-scale LTI system S, composed of N subsystem S_i $(i = 1, \cdots, N\ )$ described by:

$$\begin{aligned}\dot{\boldsymbol{x}}_i &= \boldsymbol{A}_{ii}\boldsymbol{x}_i + \boldsymbol{h}_i + \boldsymbol{B}_i\boldsymbol{u}_i + \boldsymbol{G}_i\boldsymbol{w}_i \\ \boldsymbol{y}_i &= \boldsymbol{C}_i\boldsymbol{x}_i + \boldsymbol{v}_i\end{aligned} \tag{1}$$

where, h_i is the interaction from other subsystems,

$$\boldsymbol{h}_i = \sum_{\substack{j=1\\ j\neq i}}^{N} \boldsymbol{A}_{ij}\boldsymbol{x}_j \tag{2}$$

where $\boldsymbol{x}_i \in R^{n_i}$ is the state vector of ith subsystem and $\boldsymbol{u}_i \in R^{p_i}$ is its control function [17]. Furthermore $\boldsymbol{w}_i \in R^{g_i}$ is the disturbance and $\boldsymbol{v}_i \in R^{q_i}$ is the measurement noise, which are assumed to be bounded. $\boldsymbol{A}_{ii}$, $\boldsymbol{B}_i$, $\boldsymbol{C}_i$ and $\boldsymbol{G}_i$ describe the dynamics of the isolated ith subsystem,$\boldsymbol{A}_{ij}$ describes the interaction matrix from the jth subsystem, which are assumed to have appropriate dimensions. It is assumed that $(\boldsymbol{C}_i, \boldsymbol{A}_{ii})$ is observable and $(\boldsymbol{A}_{ii}, \boldsymbol{B}_i)$ is controllable.

The goal of this paper is to design an estimator NN_i for each subsystem to estimate the interactions from other subsystems, $\boldsymbol{h}_i$, and the states of ith subsystem using neural network theory. As seen in Fig. 1, the estimator NN_i constructs the estimate of interaction, $\hat{\boldsymbol{h}}_i$, and state estimation from the input and output of S_i. These estimations are very helpful for the local controller to control the ith subsystem

III Proposed Method

In this section the neural network dynamic equivalent technique is applied to large scale systems in order to identify the interaction signals and states. For this purpose, the complete system is divided in two parts: the local subsystem (the subsystem under study) and the external system (the aggregation of other subsystems). Each proposed local estimator uses only local information; it means inputs and outputs of the related subsystem. The equivalent realized estimator is an ANN, where its outputs are the estimation of local states and incoming interactions of the external system. In fact, in this scheme the local subsystem will preserve its dimension, order and complexity, while the external system will be replaced with the ANN.

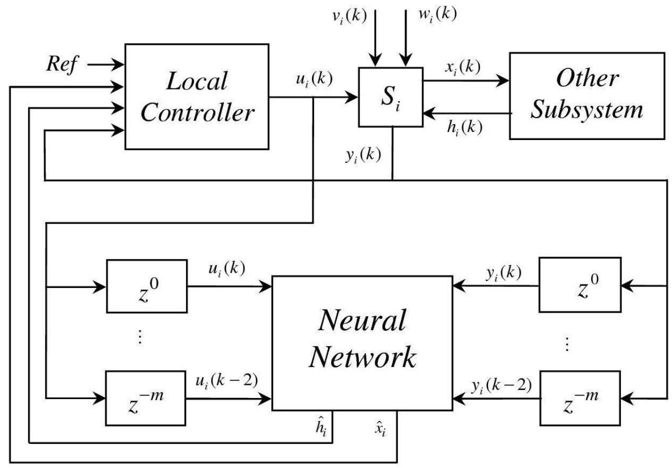

Figure 1: State and interaction estimation diagram at ith subsystem.

The network uses the local inputs and outputs at times t, $t - \Delta t$ and $t - 2\Delta t$, to estimate local states and interactions at time t, where Δt is the sampling time. We need neither the external system structure nor its state variables. This procedure can be integrated with common transient simulation codes where differential and algebraic equations of the internal system are retained while equations modeling external system are replaced by the equivalent neural network. The neural network will be interfaced with the study system through the interconnection variables and providing the external system dynamic behavior. The presented neural network in this work can be called as equivalent dynamics for interaction estimation.

The equivalent neural network model will be more accurate if the training set is large enough. In order to achieve a good level of accuracy and generalization, the training set has to be composed by several perturbations which occurring in different locations with different amplitude and load conditions. However large training sets need more neurons in inner layers and more computational resources. On the other hand, if the network is too big for the size of the input data, the network will memorize the input-output relations in the training set, and causes to loose generalization capability. Because of the complexities in large scale systems, it is necessary for our neural network to have a good generalization behavior, i.e., the neural network has to provide a good estimation not only for the training data set but also the out side date of the training set. Therefore, choosing the size of the network is a really difficult to involve generalization capability, accuracy and low training time. The over-fitting problem arises when the training process is too long and the er-

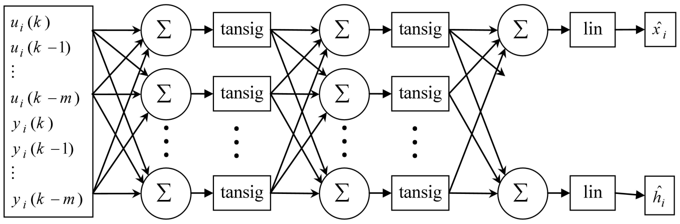

Figure 2: Structure of the proposed network.

ror of estimation for the training is driven to a very small value. In this case, early stopping prevents the over-fitting problem, so the training process should be stopped before reaching to a small error estimation.

The proposed neural network uses three feed forward layers. This kind of net has a good behavior in terms of fast training and good generalization properties. The first two layers are composed with nonlinear functions (sigmoid), while in the output layer, linear functions are used.

The training data set is obtained by doing some tests on the original system. Several faults or perturbations are implemented to the system in different points. Then we can store the waveform of signals by measuring the voltages and currents at the interconnection nodes in a fixed time window $[0,\ T_f]$.

The training data set at time t is formed for i-th area by the input vector : $\begin{bmatrix} \boldsymbol{Y}_i^T(t) & \boldsymbol{U}_i^T(t) & \boldsymbol{H}_i^T(t) \end{bmatrix}^T$, and output vector $\boldsymbol{h}_i$, which are defined as:

$$\begin{aligned} \boldsymbol{Y}_i(t) &= \begin{bmatrix} \boldsymbol{y}_i^T(t) & \boldsymbol{y}_i^T(t-\Delta t) & \cdots & \boldsymbol{y}_i^T(t-m\Delta t) \end{bmatrix}^T \\ \boldsymbol{U}_i(t) &= \begin{bmatrix} \boldsymbol{u}_i^T(t) & \boldsymbol{u}_i^T(t-\Delta t) & \cdots & \boldsymbol{u}_i^T(t-m\Delta t) \end{bmatrix}^T \\ \boldsymbol{H}_i(t) &= \begin{bmatrix} \boldsymbol{h}_i^T(t) & \boldsymbol{h}_i^T(t-\Delta t) & \cdots & \boldsymbol{h}_i^T(t-m\Delta t) \end{bmatrix}^T \end{aligned} \tag{3}$$

where m is the size of tapping delay line, containing past values of signals $\boldsymbol{y}_i$, $\boldsymbol{u}_i$ and $\boldsymbol{h}_i$ in this work it is considered as $m = 1$. Fig. 2 shows the structure of the proposed network.

IV System Description

In order to demonstrate the effectiveness of the proposed decentralized interaction estimation, numerical simulations have been carried out on load frequency system of IEEE 14-bus standard system. A single line diagram of the IEEE 14-bus standard system extracted from [20] is shown in Fig. 3. It consists of five synchronous machines with IEEE type-1 exciters three of them are synchronous compensators used only for reactive power support. There are 11 loads in the system totaling 259 MW and 81.3 Mvar. The dynamic data for the generators exciters was selected from [21].

A synchronous machine

The models of a synchronous machine may be varied from elementary classical models to more detailed ones. In this work, detailed models containing transient and sub-transient phenomena are considered as [22, 23]. This model standard 6th ordered synchronous machine model, consist of sate variables $[\delta, \omega, e'_q, e'_d, e''_q, e''_d]^T$, where, ω and δ represent the rotational speed and rotor angle, respectively; e'_q, e'_d, e''_q and e''_d correspond to the transient and sub-transient generated voltage in the

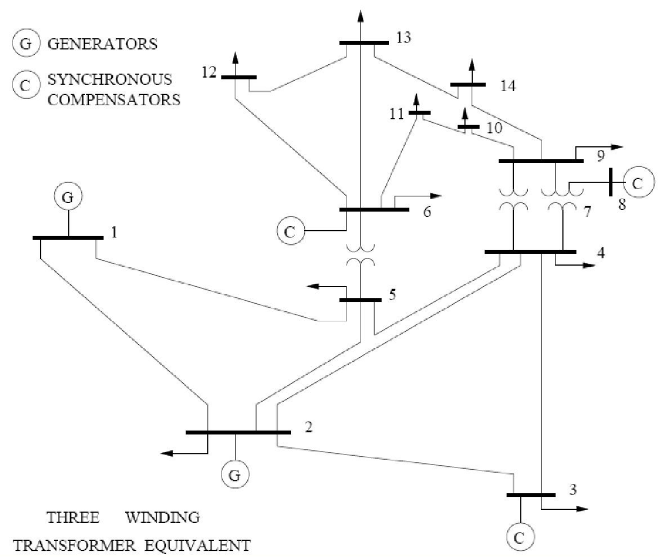

Figure 3: IEEE 14-bus test system.

direct and quadrature axes. The dynamical equations of the system are described as follows:

$$\begin{aligned} \dot{\delta} &= \omega - 1 \\ \dot{\omega} &= \frac{1}{M}(P_m - P_e - D(\omega - 1)) \\ \dot{e}'_q &= (-f_s(e'_q) - (x_d - x'_d - \frac{T''_{d0}}{T'_{d0}}\frac{x''_d}{x'_d}(x_d - x'_d))i_d \\ &\quad + (1 - \frac{1}{T'_{d0}})v_f)/T'_{d0} \\ \dot{e}''_q &= (e'_q - e''_q - (x'_d - x''_d - \frac{T''_{d0}}{T'_{d0}}\frac{x''_d}{x'_d}(x_d - x'_d))i_d \\ &\quad + (1 - \frac{1}{T'_{d0}})v_f)/T''_{d0} \\ \dot{e}'_d &= (-e'_d - (x_q - x'_q - \frac{T''_{q0}}{T'_{q0}}\frac{x''_q}{x'_q}(x_q - x'_q))i_q)/T'_{q0} \\ \dot{e}''_d &= ((x'_q - x''_q - \frac{T''_{q0}}{T'_{q0}}\frac{x''_q}{x'_q}(x_q - x'_q))i_q \\ &\quad - e''_d + e'_d)/T''_{q0} \end{aligned} \tag{4}$$

where the electrical power P_e is defined as:

$$P_e = (v_q + r_a i_q)i_q + (v_d + r_a i_d)i_d \tag{5}$$

and the algebraic constraints are as follows:

$$\begin{aligned} 0 &= v_q + r_a i_q - e''_q + (x''_d - x_l)i_d \\ 0 &= v_d + r_a i_d - e''_q - (x''_d - x_l)i_q \end{aligned} \tag{6}$$

The parameters and variables all are listed in Table 1.

B Automatic Voltage Regulator

Automatic Voltage Regulators (AVRs) define the primary voltage regulation of synchronous machines. Several AVR models have been proposed and realized in practice. For more precise simulation, it is also necessary to consider the effects of AVRs. So the standard IEEE Type II is considered for the model of AVRs [24].

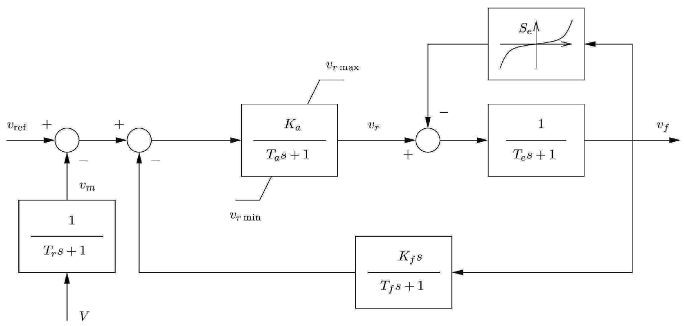

Figure 4: Exciter Type II.

The AVR Type II is indicate in Fig. 4 and described by the following equations:

$$\begin{aligned}
\dot{v}_m &= (V - v_m)/T_r \\
\dot{v}_{r1} &= (K_a(v_{ref} - v_m - v_{r2} - \frac{K_f}{T_f}v_f) - v_{r1})/T_a \\
\dot{v}_{r2} &= -(\frac{K_f}{T_f}v_f + v_{r1})/T_f \\
\dot{v}_f &= -(v_f(1 + S_e(v_f)) - v_r)/T_e
\end{aligned} \tag{7}$$

in which

$$v_r = \begin{cases} v_{r1} & if \quad v_{r\min} \le v_{r1} \le v_{r\max} \\ v_{r\max} & if \quad v_{r1} \ge v_{r\max} \\ v_{r\min} & if \quad v_{r1} \le v_{r\min} \end{cases} \tag{8}$$

In above equation, the ceiling function S_e is described by

$$S_e(v_f) = A_e(e^{B_e|v_f|} - 1) \tag{9}$$

where A_e and B_e are constant coefficients. Table 3 described the data format of AVR Type II which are used in (6).

C Turbine and Governor Models

The following simple linear models are considered for all generators.

$$\begin{aligned}
T_m &= v_p + \tau_t \frac{dv_p}{dt} \\
v_p &= \omega + \tau_g \frac{d\omega}{dt}
\end{aligned} \tag{10}$$

where T_m is mechanical input torque, v_p is the position of steam valve, ω is generator speed, τ_t and τ_g are time constants for turbine and governor. In our simulation we have considered $\tau_t = 0.2\ sec$ and $\tau_g = 1.8\ sec$.

V SIMULATION RESULTS

In this section, numerical simulations have been carried out to demonstrate the effectiveness of the proposed decentralized interaction estimation. The proposed method is implemented to IEEE 14-bus standard power system which is described in last the section.

According to physical specifications of the system, the overall system is divided to five area based on the position of each generator. A three layer neural network is used for estimating the interactions between subsystems. Since there isn't any interaction signals for state variables δ,v_r1, v_{r2} and v_f from other subsystems for convenience and saving the processing time of estimation, we can consider only the effectiveness variables. In other word, just the variables $[\omega, e'_q, e'_d, e''_q, e''_d, v_m]$ are affected by other subsystems. According to Fig. 1 the input and output signals of each area construct the inputs of estimators. The input-output variables for each area and $i = 1, 2, \cdots, 5$, are considered as follows.

Table 1: Specification of Boost Converter.

Area	Layer Neurons	Activation	Function
1	1	12	Sigmoid
	2	25	Sigmoid
	3	5	Linear
2	1	12	Sigmoid
	2	25	Sigmoid
	3	6	Linear
3	1	12	Sigmoid
	2	25	Sigmoid
	3	6	Linear
4	1	12	Sigmoid
	2	25	Sigmoid
	3	6	Linear
5	1	12	Sigmoid
	2	25	Sigmoid
	3	6	Linear

$$\begin{aligned} y_i &= [\ v_{t_i} \quad \delta_i \quad \omega_i \quad v_{f_i} \quad P_{Gen_i}\ ]^T \\ u_i &= P_{M_i} \end{aligned} \tag{11}$$

where $v_{ti}, \delta_i, \omega_i, v_{fi}, P_{gen_i}$ and P_{M_i} are voltage terminal, rotor angle, rotor speed, excitation voltage, real generated power, and mechanical input power, respectively for ith area.

These variables are measured and used for estimating the input interaction signals coming from other area by an appropriate neural network. In training stage, the desired network outputs are obtained from (2), by assuming that the state variables are available. In this work, the training of each estimator is done by using back-propagation method [25]. The Marquart-Luenberg technique is also used for increasing the rate of training. The specifications of the proposed network are listed in the Table 3. As it is shown in the Table 3, sigmoid activation functions are considered for first and second layer of each area, while a linear function is applied to output layer. According to (9), each estimator has 6 variable inputs and because of delay in one step, there are 12 neurons in the input layer. When training is accomplished, the proposed decentralized estimator is implemented to the system for comparing the actual interactions with estimated interactions under following disturbances.

- An three phase short circuit with error impedance $1+j(pu)$ is occurred in bus bar 13 within 5 sec.
- Then within 5.01 sec. the protection equipment of attached lines to bus bar 13 including the line between bus bar 12-13, 13-6, and 13-14, disconnect the lines.
- Within 6 sec., the short circuit error is removed.
- Within 6.01 sec., the breakers of lines 12-13, 6-13, and 14-

13 are closed.

- A similar short circuit with lower error impedance 0.01j (pu) is occurred in bus bar 12 within 9 sec.
- Within 9.01 sec., key lines 12-13 and 12-6 are opend by protection equipments.
- The short circuit error is removed within 10 sec., at the same time another short circuit is occurred at bus bar 4 with impedance$0.1j(pu)$.
- Within 10.01 sec., the breakers of connected lines to bus bar 12 are closed and the key lines of 2-4, 7-4, 5-4, 3-4, and 9-4 are opened.
- The short circuit error of bus bar 4 is removed within 11 sec.
- The breakers of connected lines to bus bar 4 are closed within 11.01 sec.
- Within 12 sec., the load on bas bar 6 and generator 5 is decreased by opening the keys of lines 6-11, 6-13, and 6-12.
- Within 15 sec., the keys of lines 2-4, 2-5, and 2-1 are opened, so the load on bus bar 2 and generator 3 is decreased.
- The load on bus bar 6 is returned to previous state within 20 sec.
- Finally the load on bus bar 2 is also returned to previous state within 21 sec.

Following figures show the effectiveness of the proposed method. Because of the large number of interaction signals, only the interaction signals of first and second area are shown in the figures. Simulation results show that the other areas have the same properties. As we can see from the figures, the estimated signals tracked the actual signal with acceptable deviations. Appropriate and fast convergence is the main advantage of the proposed method. It should be noted that the estimation of interactions is the main goal of this paper and no control input signals are considered for each area.

VI CONCUSION

In this paper, the design of decentralized estimators for interconnected large-scale systems was investigated. Local estimators were designed to estimate the interactions and states of each subsystem using only the local output measurement.

We outlined a new ANN to construct an approximated model for the interaction dynamics. The neural network model can substitute the external system preserving the internal system behavior with good accuracy. Simulations have shown that, using a suitable neural network and training the ANN with a good training set, it is possible to obtain a large scale system dynamic equivalent through a neural network approach with good accuracy. The results showed that, in the proposed ANN the errors of estimation are globally and ultimately bounded with respect to a specific bound.

VII APPENDIX: MAIN SYMBOLS

Tables 2 and 3 show the list of main symbols which were used in the paper.

Table 2: Synchronous Machine Data Description

Variable	Description	Unit
S_n	Power rating	MVA
V_n	Voltage rating	kV
f_n	Frequency rating	Hz
x_l	Leakage reactance	$p.u.$
r_a	Armature resistance	$p.u.$
x_d	d-axis synchronous reactance	$p.u.$
x'_d	d-axis transient reactance	$p.u.$
$x"_d$	d-axis subtransient reactance	$p.u.$
T'_{do}	d-axis open circuit transient time constant	sec
$T"_{do}$	d-axis open circuit subtransient time constant	sec
x_q	q-axis synchronous reactance	$p.u.$
x'_q	q-axis transient reactance	$p.u.$
$x"_q$	q-axis subtransient reactance	$p.u.$
T'_{qo}	q-axis open circuit transient time constant	sec
$T"_{qo}$	q-axis open circuit subtransient time constant	sec
M	Mechanical starting time	$\frac{kWs}{kVA}$
H	Inertia constant	$\frac{kWs}{kVA}$
K_ω	Speed feedback gain	$p.u.$
K_p	Active power feedback gain	$p.u.$
γ_p	Active power ratio at node	$[0,1]$
γ_Q	Reactive power ratio at node	$[0,1]$
T_{AA}	d-axis additional leakage time constant	sec
	First saturation factor	$[0,1]$
	Second saturation factor	$[0,2]$

Table 3: Data format of AVR Type II

Variable	Description	Unit
2	Exciter type	
V_{rmax}	Maximum voltage regulator	$p.u.$
V_{rmin}	Minimum voltage regulator	$p.u.$
K_a	Amplifier Gain	$p.u.$
T_a	Amplifier Time Constant	sec
K_f	Stabilizer Gain	$p.u.$
T_f	Stabilizer time constant	sec
T_e	Field circuit time constant	sec
T_r	Measurement time constant	sec
A_e	1st ceiling coefficient	
B_e	2st ceiling coefficient	

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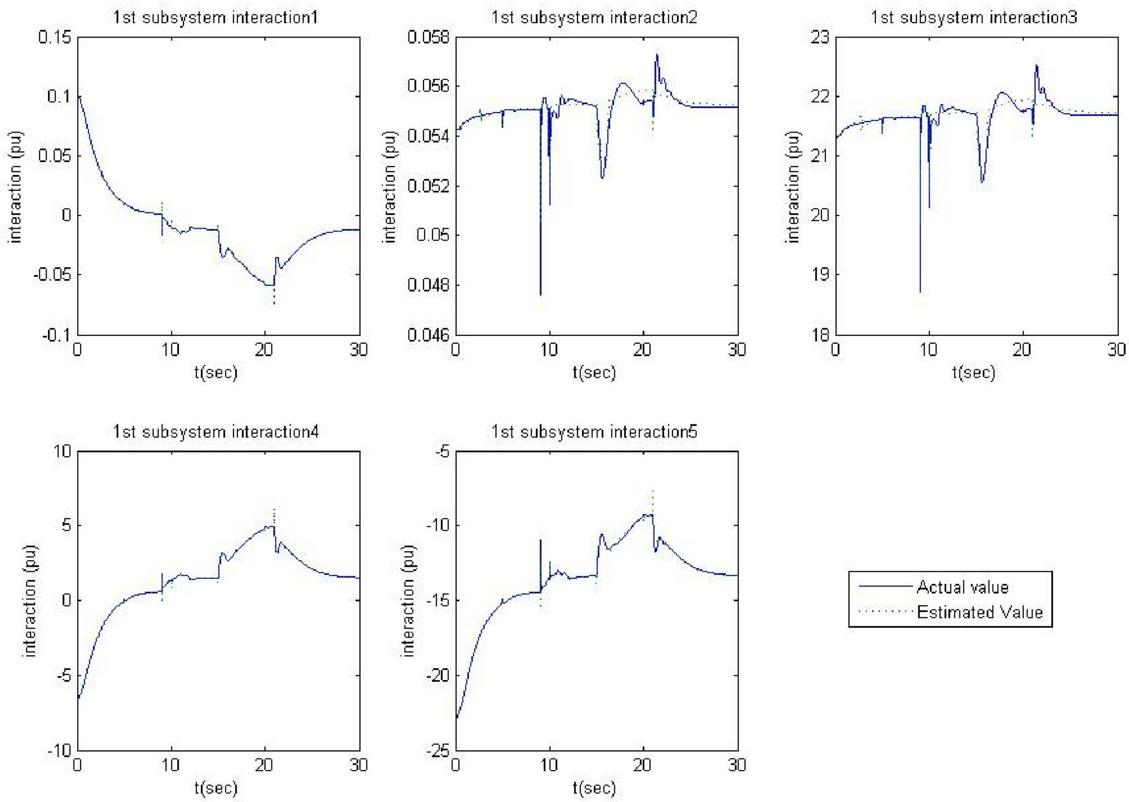

Figure 5: Actual and estimated interaction signals in first area.

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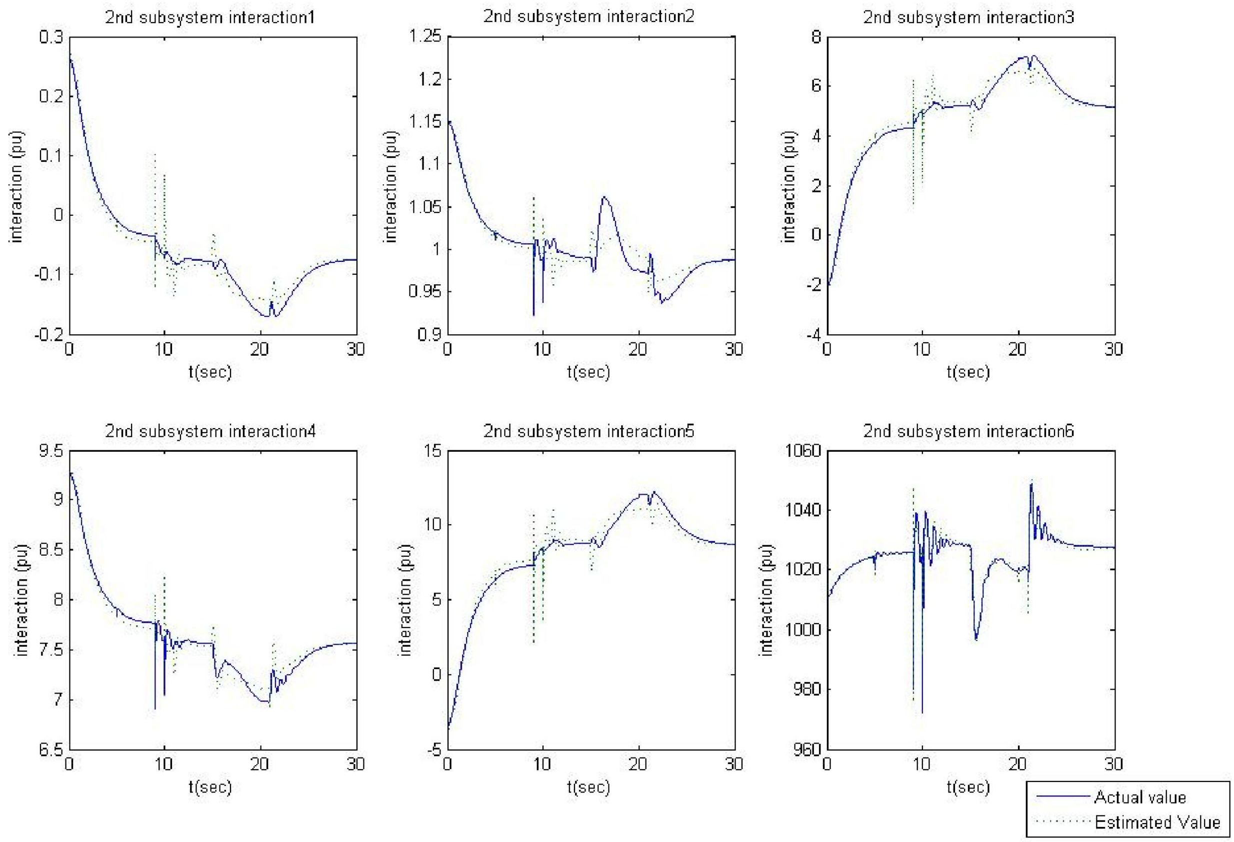

Figure 6: Actual and estimated interaction signals in second area.

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