Decentralized estimation of power system dynamic models

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Abstract: The paper proposes a new framework for decoupled on-line estimation of power system dynamic components in the form of input-output models. Feasibility of the framework is illustrated in the paper by successful parameter estimation of traditional generator dynamic models in a 39 bus power system.

Key words: power system dynamics, model estimation, power system stability.

I. INTRODUCTION

A large-scale power system model consists of two sets of equations: (I) network equations which represent the power-flow through the transmission network and the power balance at the network buses, and (II) models of components such as generators, loads and control devices. It is very useful to note that generators (and loads) that are connected to different buses, are decoupled from one another by themselves, and the coupling is only through the transmission network. In this paper, we exploit this property in proposing a decentralized scheme for on-line estimation of models for individual dynamic components.

II. PROPOSED FRAMEWORK

With the quasi-stationary phasor assumption (i.e. by assuming the dynamics under study to be sufficiently slower than the 60 Hz carrier frequency), the network equations (I) can be conveniently represented in the phasor domain in the form of nonlinear algebraic network equations. Excellent techniques have been developed in the past for a) reliable representation of the network equations, and b) for least-square type estimation of the appropriate solution for the network equations from on-line measurements in a real power system operating environment.

Regarding component models for generators, loads and control devices, excellent dynamic models have been developed in the past. Since load at any one of the network buses may consist of thousands of subcomponents, loads are usually represented by lumped dynamic models of their overall input-output responses, while looking from the network bus.

On the other hand, the models for generators and control devices are generally motivated by mathematical representation of their physical subcomponents and their dynamic responses. For instance, a typical generator model consists of generator electromagnetics, electromechanics, voltage exciter control, speed governor control, power system stabilizer control and various types of protective limiters. Indeed, emphasis in power industry is towards representing each of the subcomponents with detailed dynamic models. On the other hand, recent post-mortem studies [1,2] of large-scale disturbances in the western american power system have shown that many of these detailed device models may be out-dated and with incorrect dynamic parameters. An elaborate exercise that is also very expensive is being undertaken by the western utilities wherein the dynamic models of generators are estimated individually from off-line studies conducted by specialized consultants.

Previous approaches in power system model parameter estimation have been based on explicit processing of model equations [????]. Our recent research [3,4] has been aimed at developing automatic methods for on-line estimation of dynamic models from routine measurements, like the tools available for estimation of network equations (I). In the emerging deregulated power system, there may be a very large number of smaller generators connected throughout the network, and the nature and the behavior of these generators may also be unknown from the network side. Therefore, there is a clear need for developing methods for on-line estimation of power system component models.

Again, we note that components such as generators and loads at one node interact with elements at other nodes only through the network as noted earlier. Therefore, for modeling the behavior of the large-scale network, it is sufficient to represent the input-output behavior of components looking from the network side. Owing to the complexity of their subcomponents, consumer loads are at present represented by nonphysical input-output models. We postulate that a similar approach may be effective for modeling generators and other components as well, towards facilitating on-line estimation and analysis. In other words, if effective on-line estimation methods can be developed for accurate modeling of input to output responses of generators, there may not be a need for detailed physical representation of their subcomponents.

Detailed device models may still be necessary for large generators for tuning of internal subcomponents of the devices in off-line studies. On the other hand, empirical models for individual components derived from on-line measurements of their input-output responses, may be quite sufficient for studying the large-scale network properties. Unlike physical models which are very diverse in nature, the empirical models can be chosen as suited for the problem under study.

Summarizing the discussion so far, we propose a dynamic representation of the large-scale power system in the form of "structural models" which consist of (I) actual network equations from measurement based estimates which represent the network structure rather accurately, and (II) empirical dynamic models for individual components including generators, loads and control devices, which strictly represent their input to output behavior. A theory base needs to be developed for construction of such empirical models and for their estimation from on-line measurements.

In this paper, we illustrate the feasibility of on-line estimation of generator models by monitoring only their input to output responses. As a first step, we represent the generators by standard detailed physical representations of their subcomponents. We show that many of the sensitive parameters of even the detailed models can be extracted by monitoring the voltage phasor input and the respective real and reactive power outputs.

III. ESTIMATION PROBLEM FORMULATION

For studying the generator responses, routine tests are initiated near the generators whose parameters are to be estimated. Here we assume that we can measure the terminal voltage magnitude and the phase angle, active and reactive power outputs at each of the generator buses under study. As noted earlier, the input-output estimation problem is decoupled among different generators, and there is no need for synchronous measurement of voltage phasors among different generators. We only require that the input, the voltage phasor, and the output, the power phasor, are measured synchronously at each network node which is a local problem. Therefore, on-line model estimation problem has been nicely decoupled into separate estimations at various generators, each of which can be solved locally and effectively. This approach makes on-line dynamic estimation manageable in terms of time and accuracy.

The inputs for each generator are terminal voltage and angle. The outputs are active power and reactive power. Inputs and outputs for other devices can be similarly formulated as determined by their effect on the network. Figure 1 shows the input-output diagram for a generator.

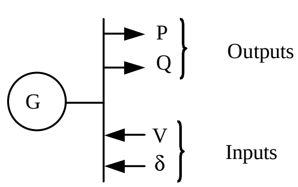

Figure 1. Input-output diagram

The dynamic model for any generator can be represented by a set of first-order differential equations of the form

$$\dot{x} = f(x, p, V) \qquad (1)$$

Here V is the terminal voltage phasor, which could be measured by readily available phasor measurement units. In the current technology, many of the newer digital protective relays can accurately compute the voltage and power phasor signals from the three-phase measurements of instantaneous voltage and current signals. Therefore, we can safely assume the availability of voltage phasor V and the real and reactive power outputs P and Q respectively. In equation (1), x stands for the state variables of the generator dynamic model and p is a set of dynamic parameters that we want to estimate. More generally, the problem can be formulated in terms of estimating an empirical model structure itself. In this paper, as a first step, we study the estimation of parameters in pre-specified dynamic models.

The parameter estimation problem can then be formulated as an optimization problem (2) over the parameter space P.

$$\min_{p \in P} E(p) \qquad (2)$$

where

$$E(p) = \sum_{k=1}^{n} (P_m(t_k) - P_c(t_k, p))^2 + (Q_m(t_k) - Q_c(t_k, p))^2$$

and

p:	a set of parameters in the parameter space P
P:	parameter space
t_k:	the k-th sampling point
n:	total number of sampling points
$E(p)$:	error function in p
$P_m(t_k)$:	measurement value of active power at t_k
$P_c(t_k, p)$:	model based active power at t_k with p
$Q_m(t_k)$:	measurement of reactive power at t_k
$Q_c(t_k, p)$:	model based reactive power at t_k with p

The estimation scheme is as follows.

1. Determine the initial values for the state variables from the pre-test measurements and the assumed values of p.
2. Carry out the simulation with assumed parameters by using voltage phasor measurements as inputs.
3. Compute error *E(p)* between measurements and computed values over the time window.
4. Minimize the error using proper optimization methods. The minimum point is assumed to be the estimated set of parameter values.

We will illustrate how the estimation scheme works on a 39-bus test system in the next section

IV. TEST SYSTEM AND TEST CASES

The test system used is the New England 39-bus system. We modified the power flow data and we have replaced the dynamic data with standard detailed generator models for the purpose of studying our estimation methodology.

The selected parameters to be estimated are the exciter control parameters K_A, T_A, K_F and T_F (see Figure A.2) for

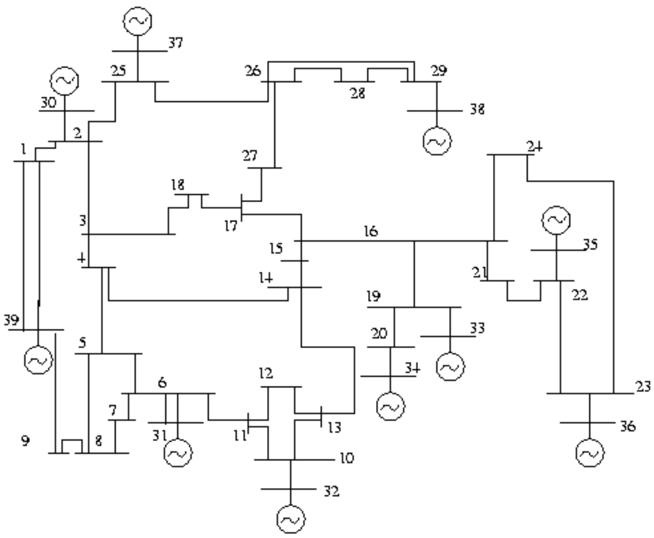

Figure 2. The New-England 9G 39B system

generators 31 and 32. A routine event of 200 MVAR shunt capacitor bank insertion at Bus 6 is used as the disturbance for obtaining the input-output response of the generators. The "measurements" here are simulated by using a commercial simulation package ETMSP [5] with the "correct set" of parameters. The exciter control parameters K_A, T_A, K_F and T_F are then assumed to be unknown for generators 31 and 32, and they are estimated at each of the generators in a decoupled fashion by processing of their respective measurements.

Details of the dynamic models are as follows. Generators 31 and 32 (say G31 and G32 respectively) are represented by two-axis flux decay models with one amortisseur winding on q-axis. We neglect the rotor saturation effect. We use IEEE DC1A [6] exciter models for the field controls. Governor-turbine model used is the WSCC type GW [5]. The block diagrams of the exciter model and governor-turbine model are given in Appendix. Power System Stabilizer is not represented in G31 and G32. The whole set of dynamic equation for each of thee generators is summarized below for the sake of completeness.

Generator rotor equations and swing equations:

$$\dot{q} = (w-1)*377 \tag{3}$$

$$\dot{w} = \frac{1}{2H}(P_T - P_e - D(w-1)) \tag{4}$$

$$\dot{E}'_q = \frac{1}{T'_{d0}}(-E'_q - (x_d - x'_d)I_d + E_{fd}) \tag{5}$$

$$\dot{E}'_d = \frac{1}{T'_{q0}}(-E'_d + (x_q - x'_q)I_q) \tag{6}$$

Exciter equations:

$$\dot{V}_R = f \tag{7}$$

$$\dot{E}_{fd} = \frac{1}{T_E}(V_R + E_{fd} - R_x(E_{fd} + A_e \cdot e^{B_e \cdot E_{fd}})) \tag{8}$$

$$\dot{V}_F = \frac{1}{T_F}(-V_F + K_F \dot{E}_{fd}) \tag{9}$$

$$\text{where } f = \begin{cases} 0 \quad if \;\; f > 0 \; and \; V_R > V_{R\max} \\ (-V_R + K_A(V_{ref} - V_T - V_F))/T_A \\ 0 \quad if \;\; f < 0 \; and \; V_R < V_{R\min} \end{cases}$$

Governor-Turbine equations:

$$\dot{G}_1 = \frac{1}{T_1}(-G_1 + ((w-1) + T_2\dot{w})/R) \tag{10}$$

$$\dot{G}_2 = \frac{1}{T_3}(-G_2 + G_1 + T_4\dot{G}_1) \tag{11}$$

$$\dot{G}_3 = -G_3 + G \tag{12}$$

$$P_T = P_{\max} \cdot (K_1 G + K_3 G3) \tag{13}$$

$$\text{where } G = \begin{cases} G_{\max} \quad \text{when } P_{ref} - G_2 \ge G_{\max} \\ P_{ref} - G_2 \\ G_{\min} \quad \text{when } P_{ref} - G_2 \le G_{\min} \end{cases}$$

Here I_d and I_q are d-axis and q-axis components of the generator terminal current, which can be computed as follows:

$$\begin{aligned} V_d &= V\cos(q - d) \\ V_q &= V\sin(q - d) \end{aligned} \tag{14}$$

$$\begin{bmatrix} I_d \\ I_q \end{bmatrix} = \frac{1}{R_a^2 + x'_d x'_q}\begin{bmatrix} -x'_d & R_a \\ R_a & x'_q \end{bmatrix}\begin{bmatrix} E'_d - V_d \\ E'_q - V_q \end{bmatrix} \tag{15}$$

where V and δ are the measured terminal voltage magnitude and angle. The active power P and reactive power Q outputs of the generator are

$$\begin{aligned} P &= V_d I_d + V_q I_d \\ Q &= V_q I_d - V_d I_q \end{aligned} \tag{16}$$

In the parameter estimation problem, notice that our goal is to minimize $E(p)$ as in (2). Our way of calculating $E(p)$ is to first integrate (3)-(13) by using numerical integration methods, next compute Pc and Qc from (16), and then to compute the value of $E(p)$ by (2). Once we have a method for evaluating $E(p)$, we can apply various kinds of optimization techniques for minimizing the error. For gradient-based methods such as the conjugate gradient method and Quasi-Newton method [8], we compute the gradient by using center differentiation,

$$\nabla E(p) = \left[\frac{\partial E(p)}{\partial p_i}\right]_{n\times 1} = \left[\frac{E(p+\Delta p_i) - E(p-\Delta p_i)}{2\cdot\Delta p_i}\right]_{n\times 1} \tag{17}$$

For function-value based methods such as the genetic algorithm [7], the error E(p) itself contains enough information for their use.

V. ESTIMATION RESULTS

Capacitor insertion at a bus will cause the terminal voltage magnitudes of nearby generators to increase and the reactive power outputs of the generators will decrease accordingly. In this test scenario, exciters on generators near bus 6 will notice the disturbance and take control actions as implied by the change in their terminal voltages. Most of the exciter parameters will be sensitive to this test for generators close to the bus where capacitor bank switching occurs. The parameters such as exciter hardlimits will be difficult to estimate in this test since the hardlimits are not reached unless there is a large disturbance. All the generator dynamic parameters for G31 and G32 are listed in Table 1, 2, 3 and 4. Again, the parameters to be estimated are K_A, T_A, K_F and T_F for their exciters. These are the most critical parameters that can be changed by the local generator operators as part of operating control measures.

Table 1. Generator parameters for G31 and G32.

	R_a	x_d	x_q	x'_d	x'_q
G31	0.0068	0.905	0.63	0.3	0.4
G32	0.0113	0.865	0.58	0.274	0.212
	x_l	T'_{d0}	T'_{q0}	H	D
G31	0.15	6	0.1	3.85542	0
G32	0.165	7.4	0.05	3.16168	0

Table 2. Exciter parameters for G31 and G32.(IEEE DC1A)

	K_A	T_A	T_E	A_e	B_e
G31	**20**	**0.2**	0.378	0.121	0.45
G32	**400**	**0.05**	0.95	0.0022	2.693
	K_F	T_F	R_{max}	R_{max}	
G31	**0.076**	**1.0**	1.0	-1.0	
G32	**0.04**	**1.0**	3.0	-3.0	

Table 3. Governor parameters for G31(WSCC GW)

P_{max}	R	T_1	T_2	T_3	T_4
1.149	0.05	66.66	10.0	1.5	0
G_{max}	G_{min}	T_w	K_1	K_3	
1.0	0.0	0.91	-2.0	3.0	

Table 4. Governor parameters for G32 (WSCC GH)

P_{max}	R	T_G	T_P	T_D	D_D
1.11215	0.05	0.2	0.04	3.5	0.4
G_{max}	G_{min}	T_w	V_{ELC}	V_{ELO}	
1.0	0.0	0.5	0.022	0.033	

From ETMSP simulation with the true parameter values, “measurements” over a 20 second time window are recorded. The first 10-second window is then used in our study for our estimation.

Two different optimization techniques [4] are used in deriving the estimated parameters. The first method is based on an improved version of a quasi-Newton type algorithm called the BFGS method [8] and the other is a genetic algorithm, specifically GENCOP III [9]. The estimation results using the two techniques are shown in Tables 5 and 6 respectively.

From the tables, it can been seen that the BFGS method has convergence problems when the initial set of parameter values is not properly selected. The algorithm has difficulty in finding the minimum point that satisfies the convergence criterion for generator G32. However, the estimated value is fairly accurate when it converges in estimating the parameter values for G31. Note that G32 is farther away from the capacitor insertion bus 6 than G31. The sensitivities of the error *E(p)* to the parameters *p*, i.e. the gradient, are not large enough for generator G32, which causes the difficulty in convergence of its parameters. This is a weakness of the BFGS optimization algorithm rather than that of the proposed estimation methodology as we show next.

Table 5. Estimation results using BFGS method

G31	Initial value	Estimated value	True value
K_A	**100**	**20.1276**	**20**
T_A	**0.1**	**0.2041**	**0.2**
K_F	**0.1**	**0.0770**	**0.076**
T_F	**1.0**	**1.0095**	**1.0**
Minimized Error	/	**0.0024**	/
G32	Initial value	Estimated value	True value
K_A	**100**	Does not converge within the maximum iterations	**400**
T_A	**0.1**		**0.05**
K_F	**0.1**		**0.04**
T_F	**1.0**		**1.0**
Minimized Error	/	/	/

Table 6. Estimation results using GENOCOP III

G31	Estimated value	True value
K_A	**34.4**	**20**
T_A	**0.525**	**0.2**
K_F	**0.0788**	**0.076**
T_F	**0.783**	**1.0**
Minimized Error	**0.0064**	/
G32	Estimated value	True value
K_A	**428.4**	**400**
T_A	**0.0273**	**0.05**
K_F	**0.04**	**0.04**
T_F	**0.989**	**1.0**
Minimized Error	**0.0009**	/

The error minimization of the genetic algorithm is relatively robust due to its selective competition property [9]. While it may be computationally expensive, it will find a point close to the global minimum when the algorithm is well-formulated. With fine-tuning, the algorithm can reach the global minimum, as it did for G32.

This paper is intended to propose the new decoupled generator model estimation methodology. As such, results of Tables 5 and 6 show that it is possible to estimate the internal dynamic parameters of the generators by observing only its inputs namely, voltage magnitude and voltage phasor angle, and its outputs namely, real and reactive power generations. Better optimization algorithms for error minimization can be developed in the future.

Since the estimation problem is decoupled among the generators, the estimations can be carried out either locally at the generators or in parallel at the network control center. Even computationally expensive optimization methods such as the genetic algorithm of Table 6 can be affordable in terms of CPU time.

It was earlier observed in the paper that for the proposed generator model estimation framework, there is no need for synchronous measurements of voltage phasors across the network. It is sufficient to observe the four measurements namely, *V, d, P and Q*, at each generator bus synchronously in a decoupled fashion. The useful information for estimation purposes is how the bus voltage phasor angle ***d*** changes during the measurement period in comparison to its power outputs *P* and *Q*. We can observe this fact readily from the input-output relationships of the generator, for instance, by inspecting the generator dynamic equations in Section IV.

We further illustrate this fact in Table 7 by repeating the parameter estimation for G31 after assuming different angle references for the voltage phasor angle ***d*** of generator G31. Specifically, an arbitrary fixed perturbation value d_0 is added to each of the ***d*** angle measurements, and the estimation is repeated with the same set of real and reactive power measurements. As expected, the estimation results are not affected by any fixed error d_0 in the measurement of the voltage phasor angle ***d***. This is important in our framework since we do not assume synchronized measurements across the network and the phase angle error d_0 will be different at different nodes of the network.

Table 7. Estimation Results with changes in the angle reference

δ_0(degrees)	**0**	**60**	**120**	**180**
K_A	20.1276	20.1307	20.1395	20.1374
T_A	0.2041	0.2042	0.2044	0.2041
K_F	0.0770	0.0770	0.0770	0.0770
T_F	1.0095	1.0095	1.0092	1.0093
δ_0(degrees)	**-30**	**-90**	**-120**	**-180**
K_A	20.1390	20.1402	20.1284	20.1306
T_A	0.2044	0.2044	0.2041	0.2041
K_F	0.0770	0.0770	0.0770	0.0770
T_F	1.0092	1.0092	1.0094	1.009

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Appendix. Block Diagrams of Dynamic Models

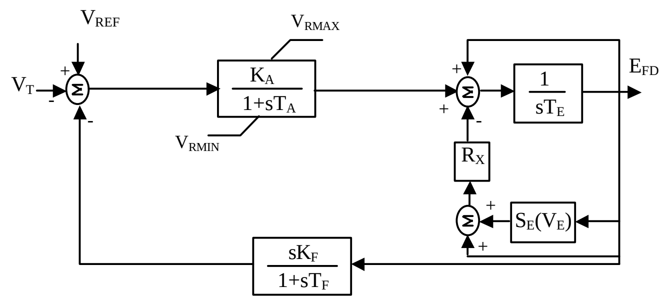

Figure A1. IEEE Type DC1A Exciter

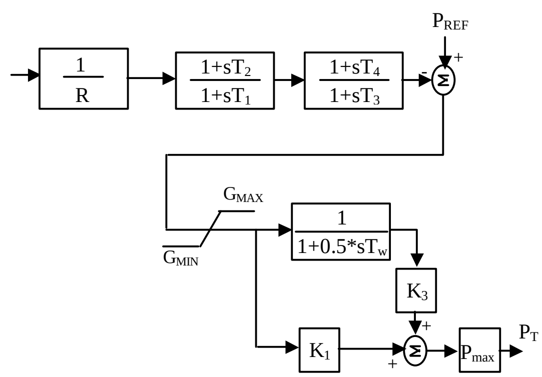

Figure A2. WSCC GW Governor-Turbine

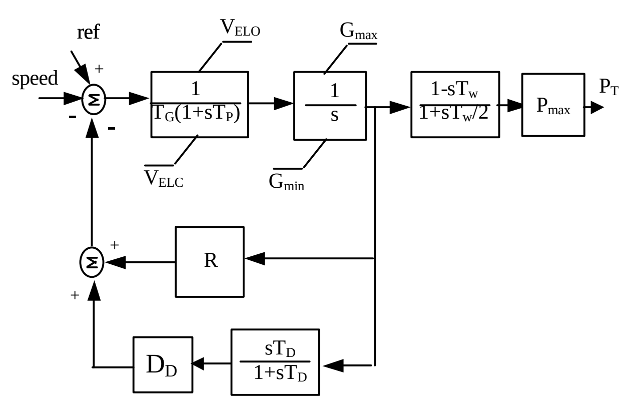

Figure A3. WSCC GH Governor-Turbine