Estimating Wind Turbine Parameters and Quantifying Their Effects on Dynamic Behavior

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***Abstract*— Numerous models have been proposed for representing variable-speed wind turbines in grid stability studies. Often the values for model parameters are poorly known though. The paper initially uses trajectory sensitivities to quantify the effects of individual parameters on the dynamic behavior of wind turbine generators. A parameter estimation process is then used to deduce parameter values from disturbance measurements. Issues of estimation bias arising from non-identifiable parameters are considered. The paper explores the connection between the type of disturbance and the parameters that can be identified from corresponding measurements. This information is valuable in determining the measurements that are required from testing procedures and disturbances in order to build a trustworthy model.**

***Index Terms*— Wind turbine dynamics, parameter estimation, trajectory sensitivity.**

I. Introduction

WIND generation has experienced enormous growth in recent years, with that trend set to continue [1], [2]. Accordingly, the impact of wind turbine generators (WTGs) on power system dynamic performance is becoming increasingly important. Inclusion of WTGs in studies of dynamic behavior is difficult though, as many parameters are not well known. The reasons for this are varied, but include:

- Manufacturers do not wish to disclose their intellectual property.
- Some wind turbine manufacturers have disappeared, yet their turbines continue to operate.
- Often manufacturers have very detailed models, but deriving simplified models that are suited to grid stability studies is far from straightforward.
- Planning studies require typical values for proposed WTGs.

Consequently, parameter values are frequently unknown or uncertain. Yet discrepancies may lead to erroneous conclusions regarding dynamic performance.

Not all parameters are influential though. In some cases, parameters can be varied over a relatively large range without causing any appreciable change in the dynamic response. Other parameters, however, exert quite an influence, with small perturbations giving rise to large deviations in the dynamic behavior. It is also quite common for parameters to be influential during certain disturbances but inconsequential for others. The paper uses trajectory sensitivity concepts [3], [4] to quantify the effect of parameter variations on large-disturbance behavior.

Parameters that are significant, in the sense that they exert a non-negligible influence on system dynamics, need to be known quite accurately. If they are not otherwise available, then they should be estimated from measurements of WTG response during disturbances. Interestingly, parameters that are influential will also be identifiable from measurements [5], [6]. Conversely, parameters that are not identifiable tend not to be particularly important. The paper uses a nonlinear least squares formulation to estimate significant, but poorly known, parameters.

The paper is organized as follows. Section II presents the wind turbine generator model that is used throughout the paper. Parameter sensitivity analysis techniques are discussed in Section III, and parameter estimation is described in Section IV. Conclusions are provided in Section V.

Research supported by the National Science Foundation through grant ECCS-0725710, and PSerc through the project "Impact of Increased DFIG Wind Penetration on Power System Reliability and Consequent Market Adjustments".

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II. Wind Turbine Generator Model

A. Overview

The examples presented in the paper refer to a variable-speed wind turbine that is based on doubly-fed induction generator (DFIG) technology. The model used throughout the paper is very similar to that developed in [7]. It is highly simplified from an actual WTG, and is designed to represent only the dynamics of interest in large-scale grid stability studies [8]. (For example, the model can only tolerate voltage deviations to 0.7 pu.) Although a DFIG wind turbine was selected for illustration, the concepts presented are nevertheless applicable to other types of turbines.

It is convenient to divide a wind turbine system into various subsystems, as shown in Figure 1. The physical device is composed of the wind turbine connected through the drivetrain to the electromechanical power conversion equipment. The Supervisor Controller (SC) fulfills two main goals:

1) Maximize real power production (within equipment rating).

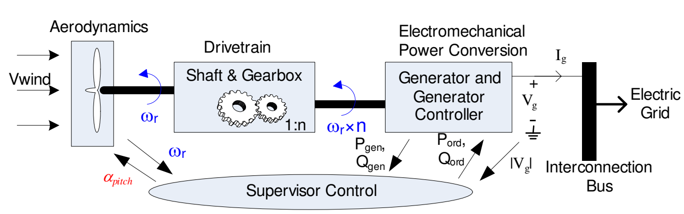


Fig. 1. Wind turbine generator subsystems.

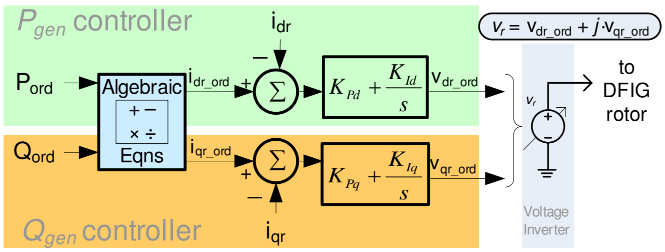


Fig. 2. Generator control.

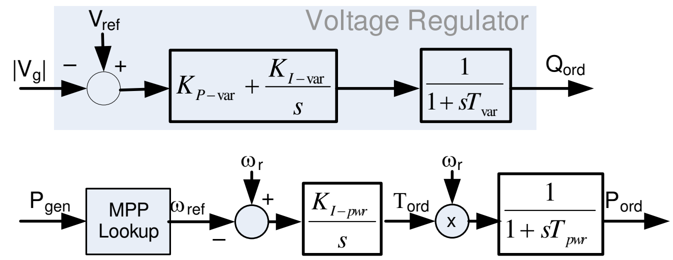


Fig. 3. Supervisor control. "MPP Lookup" provides a lookup table (or polynomial fit) of optimal (P_{gen}, ω_r) pairs resulting in maximum power [10].

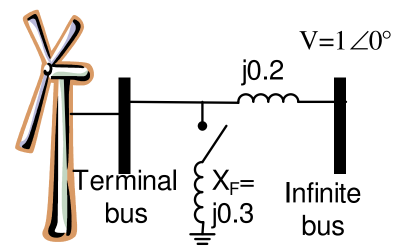


Fig. 4. WTG test network.

2) Control reactive power. Older DFIG WTGs usually controlled reactive power to a specified power factor. Newer designs are capable of regulating the terminal bus voltage [9]. The paper focuses on the latter case.

Models for the aerodynamic block [10], the drivetrain block [9], [10], and the generator [11], [12] are well-established from the underlying physics, and do not warrant reproduction. Two simplifications that are common in grid stability studies have been used though:

1) The drivetrain is modeled as a single lumped-mass inertia.
2) The induction generator model neglects stator transients. (This is common practice for grid simulations [12].)

Models for the Supervisor Controller (SC) and the Generator Controller (GC) are not well established [13]. Both the SC and GC contain custom control loops designed by the wind turbine manufacturers. The models used here are provided for example purposes only, and may not be reflective of an actual wind turbine.

B. Generator control

The GC regulates the DFIG rotor excitation so that the active and reactive power delivered by the WTG match the setpoint values P_{ord} and Q_{ord}. Unlike traditional synchronous machines, the DFIG requires AC rotor excitation [14]. Varying the rotor voltage magnitude $|V_r|$ and phase $\angle V_r$ allows complete control over complex power generation. The frequency of the rotor voltage cannot be set independently, but must equal the difference between rotor speed and synchronous grid frequency. Physically, the GC consists of a voltage-source inverter, together with a controller, as shown in Figure 2.

The controller of Figure 2 is conceptually similar to [15], and consists of two proportional-integral (PI) rotor current regulators. Variables are expressed in d-q notation [11]. Active and reactive power controls are virtually decoupled when a reference frame is chosen such that the d-axis aligns with the stator voltage vector V_g, and the q-axis leads the d-axis by 90^o. The "algebraic equations" block in Figure 2 represents the fact that there is a direct, algebraic relationship between rotor current and machine power[1] [16].

C. Supervisory control

The SC has three major roles. As illustrated in Figure 3, inputs ω_r and P_{gen} are used to determine the active power setpoint P_{ord} that maximizes generated power. Also, the reactive power setpoint Q_{ord} is adjusted to drive the terminal bus voltage $|V_g|$ to its setpoint V_{ref}. This SC model is similar to models found in the literature [17], particularly [7].

The third function, which is not illustrated in Figure 3, is to adjust the blade pitch angle (α_{pitch}) if high winds risk overloading the generator. This blade pitch control system has not been modeled. (During simulations, wind speed has been capped to eliminate the need for a working pitch mechanism.) Detailed of such models can be found in [7], [13].

D. Disturbance models

Three different disturbances are used for various tests throughout the paper:

- **Wind speed:** Ramp decrease in wind speed,
$$\nu_{wind} = \begin{cases} 11.5 & t < 1 \\ 18 - 6.5t & 1 \le t \le 2 \\ 5 & t > 2 \end{cases} \tag{1}$$
where ν_{wind} is the wind speed in m/s.
- **Voltage reference:** Step change in V_{ref} from 0.99 pu to 0.95 pu at $t = 0.5$s.
- **Fault:** The test system, shown in Figure 4, consists of a WTG connected to an infinite bus through a line with reactance 0.2 pu. A fault, with reactance $X_F = 0.3$ pu is applied at the terminal bus of the WTG, and is cleared after 0.23 s.

III. Parameter Analysis Techniques

A. Trajectory sensitivities

The time evolution of system quantities following a disturbance is referred to as a trajectory, and can be compactly expressed as $z(t)$. In the case of a WTG, quantities of interest

[1] This assumes that stator transients are neglected.

include currents, voltages, power measurements, rotor speed ω_r, and pitch angle α_{pitch}. The generated complex power is of particular importance in subsequent discussions, so for convenience, P_{gen} and Q_{gen} shall be ordered first among the system quantities,

$$\begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix} = \begin{bmatrix} P_{gen}(t) \\ Q_{gen}(t) \end{bmatrix}. \tag{2}$$

System constants are called *parameters*, and are denoted by θ. WTG systems include numerous parameters, with Figures 2 and 3 showing various control system parameters. Subsequent investigations will focus on a subset of the parameters, namely

$$\theta = [K_{Pvar} \;\; K_{Ivar} \;\; K_{Ipwr} \;\; K_{Pd} \;\; K_{Id} \;\; K_{Pq} \;\; K_{Iq} \;\; H]^T. \tag{3}$$

An actual trajectory depends on the choice of parameter values. This parameter dependence is commonly expressed in terms of the system *flow*, $\phi(t, \theta)$, with

$$z(t) = \phi(t, \theta) \tag{4}$$

implying that for a particular value of θ, the point on the trajectory z at time t is given by evaluating the flow ϕ at that time. Generally ϕ cannot be written explicitly, but instead is obtained numerically by simulation.

Trajectory sensitivities provide a useful way of quantifying the effect that individual parameters have on overall system behavior [18]. A trajectory sensitivity is simply the partial derivative of the trajectory, or equivalently the flow, with respect to the p parameters of interest,

$$\begin{aligned} S_i(t, \theta) &= \frac{\partial \phi_i}{\partial \theta}(t, \theta) \\ &= \begin{bmatrix} \frac{\partial \phi_i}{\partial \theta_1}(t, \theta) & \frac{\partial \phi_i}{\partial \theta_2}(t, \theta) & \cdots & \frac{\partial \phi_i}{\partial \theta_p}(t, \theta) \end{bmatrix} \end{aligned} \tag{5}$$

where ϕ_i refers to the i-th element of the vector function ϕ, and θ_j is the j-th parameter. The ordering given by (2) implies

$$S_1(t, \theta) \equiv \frac{\partial P_{gen}}{\partial \theta}(t, \theta), \qquad S_2 \equiv \frac{\partial Q_{gen}}{\partial \theta}(t, \theta). \tag{6}$$

Trajectories are obtained by numerical integration, which generates a sequence of points at discrete time steps $t_0, t_1, ..., t_N$ along the actual trajectory. The discretized trajectory will be described using the notation

$$\mathbf{z} = [z(t_0) \;\; z(t_1) \;\; \ldots \;\; z(t_N)]^T. \tag{7}$$

Trajectory sensitivities can be calculated efficiently as a byproduct of numerical integration [4]. The corresponding discretized sensitivities can be written,

$$\mathbf{S}_i(\theta) = \begin{bmatrix} S_i(t_0, \theta) \\ S_i(t_1, \theta) \\ \vdots \\ S_i(t_N, \theta) \end{bmatrix}. \tag{8}$$

Unfortunately, few of the commercial simulation packages currently calculate trajectory sensitivity information. Approximate sensitivities must be generated by varying each parameter in turn by a very small amount, re-simulating, determining the difference in trajectories, and thus finding the sensitivity. The disadvantage of this method is that it is computationally expensive, and requires an additional simulation for each parameter.

TABLE I

PARAMETER SENSITIVITY NORMS FOR V_{ref} DISTURBANCE.

	K_{Pvar}	K_{Ivar}	K_{Ipwr}	K_{Pd}	K_{Id}	K_{Pq}	K_{Iq}	H
$\|\mathbf{S}_1.\|$	≈ 0	0.01	0.62	1.57	1.49	0.68	0.36	0.05
$\|\mathbf{S}_2.\|$	0.03	0.31	0.08	0.20	0.19	1.92	0.69	≈ 0
Sum	0.03	0.32	0.70	1.77	1.68	2.60	1.05	0.05

B. Quantifying parameter effects

Trajectory sensitivities can be used directly to identify significant parameters in a model. Parameters that have a large associated trajectory sensitivity (for part or all of the simulation time) have a larger effect on the trajectory than parameters with smaller sensitivities. This relative significance can be quantified by using an appropriate norm. Considering the sensitivity of the i-th system quantity (trajectory) to the j-th parameter, given by $S_{ij}(t, \theta)$, the 2-norm (squared) is given by

$$\|S_{ij}\|_2^2 = \int_{t_0}^{t_N} S_{ij}(t, \theta)^2 dt \tag{9}$$

where the period of interest is $t_0 \leq t \leq t_N$. In terms of the discrete-time approximation provided by simulation, the equivalent 2-norm can be written

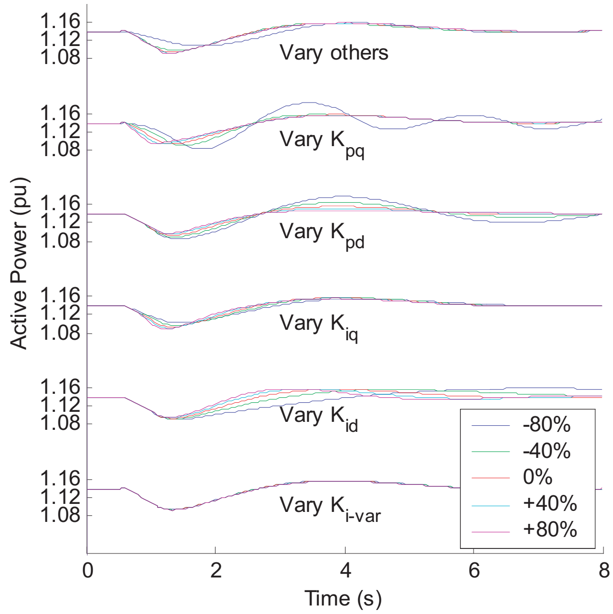
$$\|\mathbf{S}_{ij}\|_2^2 = \sum_{k=0}^{N} S_{ij}(t_k, \theta)^2. \tag{10}$$

For illustration, Table I tabulates the sensitivity norms for the voltage reference disturbance described in Section II-D.

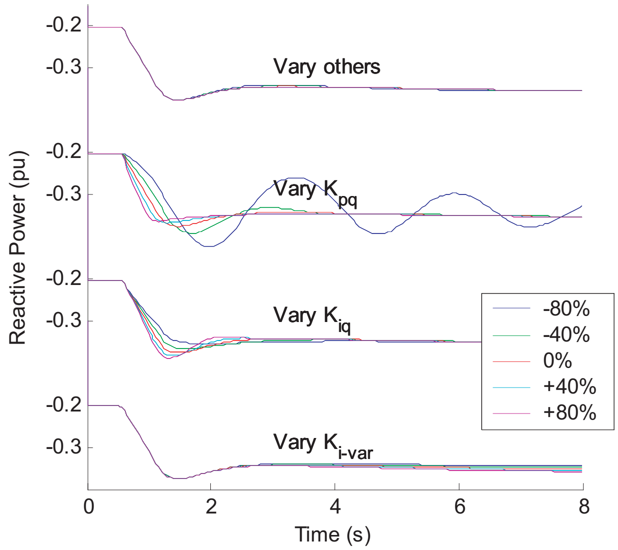
From this table, it can be seen that parameters K_{Pvar}, K_{Ivar}, and H have much smaller sensitivities, and thus are likely to have minimal effect on the simulation trajectory, while parameters K_{Ipwr}, K_{Pd}, K_{Id}, K_{Pq} and K_{Iq} are likely to have a larger effect on the trajectory. Figure 5 verifies this conclusion. Notice that parameters K_{Pd}, K_{Id}, K_{Pq} and K_{Iq} all have a significant influence on the P_{gen} trajectory, in good agreement with Table I. Parameters K_{Pq}, K_{Iq}, and to a lesser extent K_{Ivar} all affect the Q_{gen} trajectory, also in good agreement with Table I.

Parameters that had little effect on the trajectory resulted in nearly identical plots, and so are shown by one representative graph labeled "Vary Others." The parameters included in this category are K_{Pvar}, K_{Ivar}, and H in Figure 5(a), and parameters K_{Pvar}, K_{Ipwr}, K_{Pd}, K_{Id} and H in Figure 5(b).

Keep in mind that the sensitivities in Table I were obtained for a single disturbance, and thus are applicable only for similar disturbances. Different forms of disturbances may excite the system in ways that accentuate the impact of other parameters. As a general rule, more severe disturbances yield higher sensitivities.



(a) P_{gen} trajectories.



(b) Q_{gen} trajectories.

Fig. 5. Effect of varying parameters by $\pm 80\%$, for the V_{ref} disturbance.

IV. Parameter Estimation

A. Gauss-Newton solution method

It is often possible to deduce parameter values from disturbance measurements. In the case of WTGs, simply measuring the generated real and reactive power during a disturbance may yield sufficient information to accurately estimate several model parameters. The aim of parameter estimation is to determine parameter values that achieve the closest match between the measured samples and the model trajectory.

Disturbance measurements are obtained from data acquisition systems that record sampled system quantities. Let a measurement of interest be given by the sequence of samples

$$m = [m_0 \;\; m_1 \;\; \ldots \;\; m_N]^T \tag{11}$$

with the corresponding simulated trajectory being given by

$$\mathbf{z}_i = [z_i(t_0) \;\; z_i(t_1) \;\; \ldots \;\; z_i(t_N)]^T , \tag{12}$$

which is the i-th column of $\mathbf{z}$ defined in (7). The mismatch between the measurement and its corresponding (discretized) model trajectory can be written in vector form as

$$e(\theta) = \mathbf{z}_i(\theta) - m \tag{13}$$

where a slight abuse of notation has been used to show the dependence of the trajectory on the parameters θ.

The best match between model and measurement is obtained by varying the parameters so as to minimize the error vector $e(\theta)$ given by (13). It is common for the size of the error vector to be expressed in terms of the cost,

$$\mathcal{C}(\theta) = \|e(\theta)\|_2^2 = \sum_{k=0}^{N} e_k(\theta)^2. \tag{14}$$

The desired parameter estimate $\breve{\theta}$ is then given by

$$\breve{\theta} = \underset{\theta}{\operatorname{argmin}}\; \mathcal{C}(\theta). \tag{15}$$

This nonlinear least squares problem can be solved using a Gauss-Newton iterative procedure [19]. At each iteration j of this procedure, the parameter values are updated according to

$$\mathbf{S}_i(\theta^j)^T \mathbf{S}_i(\theta^j) \Delta\theta^{j+1} = -\mathbf{S}_i(\theta^j)^T e(\theta^j) \tag{16}$$

$$\theta^{j+1} = \theta^j + \alpha^{j+1} \Delta\theta^{j+1} \tag{17}$$

where $\mathbf{S}_i$ is the trajectory sensitivity matrix defined in (8), and α^{j+1} is a suitable scalar step size[2].

An estimate of θ which (locally) minimizes the cost function $\mathcal{C}(\theta)$ is obtained when $\Delta\theta^{j+1}$ is close to zero. Note that this procedure will only locate local minima though, as it is based on a first-order approximation of $e(\theta)$. However if the initial guess for θ is good, which is generally possible using engineering judgement, then a local minimum is usually sufficient.

B. Parameter conditioning

Often there is insufficient information in a measured trajectory to estimate all the parameters. In Section III it was seen that some parameters have little effect on trajectory shape. These parameters are usually not identifiable.

When developing a parameter estimation algorithm, it is necessary to separate identifiable parameters from those that are not, in order to avoid spurious results. This can be achieved using a *subset selection* algorithm [21], [22]. This algorithm considers the conditioning of the matrix $\mathbf{S}_i^T \mathbf{S}_i$ that appears in (16). If it is well conditioned, then its inverse will be well defined, allowing (16) to be reliably solved for $\Delta\theta^{j+1}$. On the other hand, ill-conditioning of $\mathbf{S}_i^T \mathbf{S}_i$ introduces numerical difficulties in solving for $\Delta\theta^{j+1}$, with the Gauss-Newton process becoming unreliable.

The subset selection algorithm considers the eigenvalues of $\mathbf{S}_i^T \mathbf{S}_i$ (which are the same as the singular values of $\mathbf{S}_i$.)

[2]Numerous line search strategies for determining α are available in [20], for example.

TABLE II

Parameter conditioning. (An '×' denotes well-conditioned.)

	K_{Pvar}	K_{Ivar}	K_{Ipwr}	K_{Pd}	K_{Id}	K_{Pq}	K_{Iq}	H
ν_{wind}			×	×	×			×
V_{ref}		×	×	×	×	×	×	
Fault				×	×	×	×	

Small eigenvalues are indicative of ill-conditioning. The subset selection algorithm therefore separates parameters into those associated with large eigenvalues (identifiable parameters) and the rest which cannot be identified. The latter parameters are then fixed at their initial values.

Interestingly, the diagonal elements of $\mathbf{S}_i^T\mathbf{S}_i$ are exactly the values given by the 2-norm (10). If the trajectory sensitivities corresponding to parameters were orthogonal, then $\mathbf{S}_i^T\mathbf{S}_i$ would be diagonal, and separating the influences of parameters would be straightforward. This is not generally the case though, with the impacts of parameters often being partially correlated. For that reason, large values of (10) are not sufficient to guarantee parameter identifiability.

From a numerical (and practical) standpoint, it is best to initially estimate parameters using a disturbance that results in the highest number of well-conditioned parameters. Having too many ill-conditioned parameters can prevent good estimation. Even though each individual ill-conditioned parameter has little effect on the trajectory, when several ill-conditioned parameters take incorrect initial values, they may irrecoverably bias the estimation process.

Table II summarizes parameter conditioning for the three disturbance scenarios described in Section II-D. A V_{ref} disturbance results in the fewest ill-conditioned parameters, and thus this disturbance was used first in parameter estimation. Notice that the results in Table II are fairly intuitive. A change in V_{ref} predominantly disturbs the WTG reactive power control system. All GC parameters are well-conditioned because of the coupling that occurs through the "algebraic equation" block, see Figure 2. Parameter K_{Ipwr} is on the borderline of the conditioning classification, and in fact is ill-conditioned for slightly different V_{ref} disturbances.

In the first row of Table II, a ν_{wind} disturbance affects only turbine active power production, thus only parameters associated with active power are well-conditioned.

The justification for the last row in Table II is less obvious but relates to response time. A fault is a relatively quick disturbance, compared to the other two. In WTGs, it is typical for the SC to have time constants that are far slower than GC controller time constants [23]. For the particular parameter values chosen in this paper, the SC is so slow that it does not even "notice" the fault; P_{ord} and Q_{ord} remain almost constant throughout the entire simulation.

C. Parameter estimation results

Unfortunately no measurements of actual wind farms were available for use in this paper. Measurement data was therefore fabricated by simulation, using a certain set of parameters henceforth called "actual" parameters. White noise of magnitude 0.02 pu was added to make the measurements slightly more realistic.

TABLE III

Parameter estimation using V_{ref} disturbance. (Asterisk denotes ill-conditioned.)

	K^*_{Pvar}	K_{Ivar}	K_{Ipwr}	K_{Pd}	K_{Id}	K_{Pq}	K_{Iq}	H^*
Actual	20	2	0.6	0.3	0.5	0.3	0.5	4.64
Initial	20	4	0.2	0.5	0.7	0.15	0.2	6
Estim	20	1.99	0.76	0.28	0.54	0.31	0.46	6

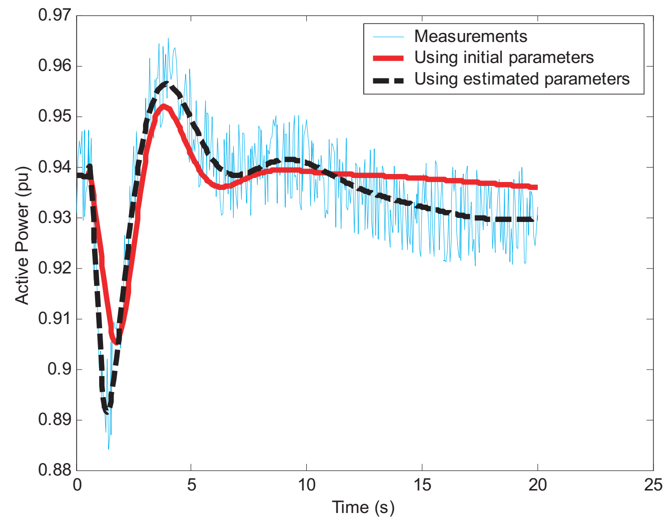


Fig. 6. Measured and simulated P_{gen} for a V_{ref} disturbance. (Results from Table III.)

A simulation was run where V_{ref} was changed according to Section II-D. The wind speed during the entire simulation was steady at 11.5 m/s. The resulting turbine output active and reactive power trajectories were corrupted with noise, and saved as the measurement vector m. The estimation process was then initialized with the parameter values shown in the second row of Table III. After five iterations, the process converged to the values given in the third row of Table III. The results are promising, with accurate estimation of most well-conditioned parameters. The exception is K_{Ipwr}, where its marginal conditioning led to reduced accuracy. Figure 6 shows that these estimated parameters yielded a good match in trajectories. Ill-conditioned parameters are denoted with an asterisk in Table III, and were maintained at their initial (typical) values.

Whilst the parameter values in Table III yield a good model for V_{ref} disturbances, the error in H, and to a lesser extent K_{Ipwr}, may prevent accurate replication of other events. Figure 7 shows the results of using Table III "estimated parameters" to model a wind disturbance. The model does not perform near as well.

The solution to this problem is to estimate more parameters. According to Table II, if the model in intended to predict WTG response to a wind disturbance, then both K_{Ipwr} and H should be estimated because these parameters are influential. However, if the model is intended for fault studies only, then the parameters in Table III should be sufficient, because the

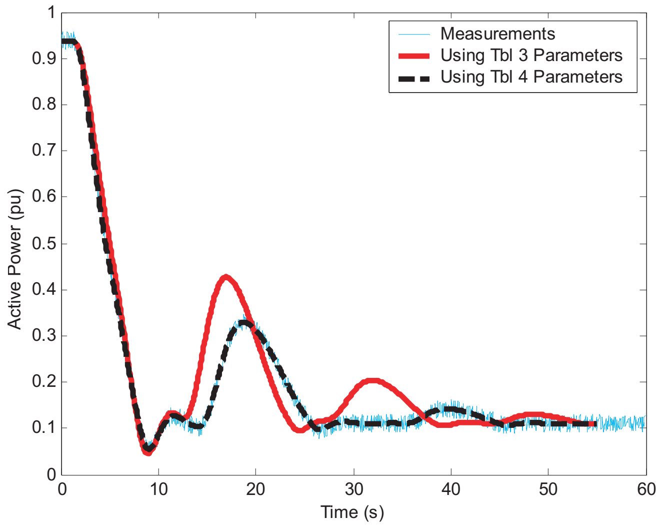


Fig. 7. Measured and simulated P_{gen} for a ν_{wind} disturbance. (Comparison of results from Tables III and IV.)

TABLE IV
PARAMETER ESTIMATION USING ν_{wind} DISTURBANCE. (ASTERISK DENOTES ILL-CONDITIONED.)

	K^*_{Pvar}	K^*_{Ivar}	K_{Ipwr}	K_{Pd}	K_{Id}	K^*_{Pq}	K^*_{Iq}	H
Actual	20	2	0.6	0.3	0.5	0.3	0.5	4.64
Initial	20	1.99	0.76	0.28	0.54	0.31	0.46	6
Estim	20	1.99	0.6	0.3	0.5	0.31	0.46	4.64

influential parameters K_{Pd}, K_{Id}, K_{Pq}, and K_{Iq} have already been accurately estimated.

To create the best model possible, the parameter estimation process should be repeated, this time using measurements from a wind disturbance. Initial parameter values are provided by the "estimated" values in Table III. The results of this second estimation run are given in Table IV and Figure 7. It is clear that improved estimates for K_{Ipwr} and H have been obtained.

D. Parameters that cannot be estimated

Sometimes parameters cannot be estimated from available measurements. According to Table II, K_{Pvar} is such a parameter. Table I suggests that behavior is quite insensitive to variations in K_{Pvar}. It is therefore to be expected that incorrect values for K_{Pvar} would have only a marginal impact on the model accuracy. Table V shows the effect of incorrect K_{Pvar} initialization during parameter estimation. The third and fourth rows in this table show estimation for a V_{ref} disturbance. The last two rows show a second estimation for a ν_{wind} disturbance. In this way, the results follow the same procedure used to produce Tables III and IV.

Comparing the last line of Table V with the last line of Table IV, it is clear that the estimated parameters are not as good as when K_{Pvar} was initialized correctly. This illustrates a certain compounding effect of using incorrect values for an ill-conditioned parameter. Though small, the influence of K_{Pvar} is still sufficient to bias the trajectory slightly. In striving for a better match between simulation and measurements, the estimation process adjusts other parameters to compensate for

TABLE V
PARAMETER ESTIMATION FOR INCORRECT K_{Pvar}. (ASTERISK DENOTES ILL-CONDITIONED.)

	K_{Pvar}	K_{Ivar}	K_{Ipwr}	K_{Pd}	K_{Id}	K_{Pq}	K_{Iq}	H
Actual	20	2	0.6	0.3	0.5	0.3	0.5	4.64
Init 1	30	4	0.2	0.5	0.7	0.15	0.2	6
Est 1	30*	4*	0.62	0.24	0.5	0.28	0.6	6*
Init 2	30	4	0.62	0.24	0.5	0.28	0.6	6
Est 2	30*	4*	0.6	0.31	0.5	0.28*	0.6*	4.64

the bias. This results in somewhat poorer parameter estimates. In general, parameter estimation should be repeated using different initial guesses for all non-identifiable parameters. If the results show significantly different values for estimated parameters, then the non-identifiable parameter(s) cannot be ignored.

Another interesting outcome is that K_{Ivar} became ill-conditioned during the first parameter estimation run. Apparently this is caused by the close relationship between K_{Pvar} and K_{Ivar} in the SC. It is possible for larger values of K_{Pvar} to overwhelm the K_{Ivar} integrator, causing the voltage controller to have mostly proportional response. It was noted in Table I that K_{Ivar} had relatively small sensitivity. The increase in K_{Pvar} negatively impacted the conditioning of K_{Ivar}. These observations highlight the complex manner in which parameters may interact.

V. CONCLUSIONS

It is an unfortunately reality that many parameters of wind turbine models are poorly known. In order to investigate the dynamic performance of wind turbine generators, parameter values must be assigned. Not all parameter values need to be know with the same accuracy though. Using trajectory sensitivities, it has been shown that for a particular disturbance, some parameters are much more influential than others. This pattern of influential parameters may change for different disturbances.

A subset selection method has been used to determine parameters that are well-conditioned. Such parameters may be reliably estimated from disturbance measurements. The estimation process is formulated as a nonlinear least-squares problem, which is solved using a Gauss-Newton iterative algorithm. For the case considered in the paper, a two stage estimation process was found to be useful. The first stage used a disturbance in the voltage setpoint to estimate most of the parameters. The next stage considered a wind speed disturbance in order to estimate further parameters that were not initially identifiable.

Even with such a multi-step process, some parameters are still not identifiable. Errors in the assumed values for these parameters may bias the estimation results. In such cases, it may be useful to repeat the parameter estimation process using different initial guesses for non-identifiable parameters.

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