Data-Driven Dynamic Modeling in Power Systems

Lingling Fan, Zhixin Miao, Shahil Shah, Przemyslaw Koralewicz, Vahan Gevorgian, Jian Fu

This article introduces how to identify dynamic system models using measurement data. In power system analysis, a static model represents the time-invariant input and output relationship of a system while a dynamic model describes the behavior of the system over time, for example, how will a system transit from one steady-state operation point to another?

In the control community, learning dynamic models is a *system identification problem*. Essentially, machine learning and system identification are all about inferring models from data. Both rely on optimization. The exact processes of the inference may vary from statistic modeling to deep learning neural network. This article focuses on presenting the unique applications for deriving power system dynamic models from measurement data.

Dynamic behaviors are difficult to capture, especially for applications lack of analytic models. That is where data driven/machine learning techniques can play a critical role. Indeed, there is a long history of power system engineers building dynamics models using data-driven approaches, well before machine learning is a popular term. Integration of inverter-based resources (IBR) adds more complexity to the existing modeling framework due to underlying complex physics of the IBR systems and the strict non-disclosure requirements from original equipment manufacturers (OEM). Thus, data driven based system identification methods are playing an increasingly important role, especially for systems where physical models are elusive. For example, when representing aggregated distributed energy resources at a transmission and distribution interface, one popular approach is to use the interface measurement data to produce a DER model that can map the inputs (e.g., voltage and frequency) to the outputs (real and reactive power generation).

The article begins by introducing the classification of measurement data and models. It then reviews five commonly used, data-driven dynamic modeling applications in power systems:

1. synchronous generator model parameter identification,
2. aggregated load model parameter identification,
3. reduced-order model identification for control design,
4. admittance model identification for subsynchronous resonance (SSR) screening, and
5. electromechanical oscillation mode identification from phasor measurement unit (PMU) data.

The first two applications are different from the last three applications in terms of the outcomes of the estimation. The first two applications estimate model parameters. This means that the model structure is prior knowledge, and the estimation leads to model parameters. Compared to the last three applications, partial information of the estimation model is known, *i.e.*, the model is a ***gray-box model***. Thus, dynamic model parameter estimation problems are indeed gray-box model identification. On the other hand, if the model structure is not imposed, the estimation leads to ***black-box models***.

Next, the article discusses IBR model identification. The current practice of IBR model identification mainly focuses on obtaining frequency-domain admittance/impedance measurements using frequency scans. The resulting models are black-box models that reflect input/output relation. There are many ways to structure IBR dynamic models to map the same input/output relation. A more challenging question is can we guess model structures and figure out the model parameters based on measurements? The follow-up discussions attempt to address those questions.

Figure 1 summarizes the six applications discussed in this paper.

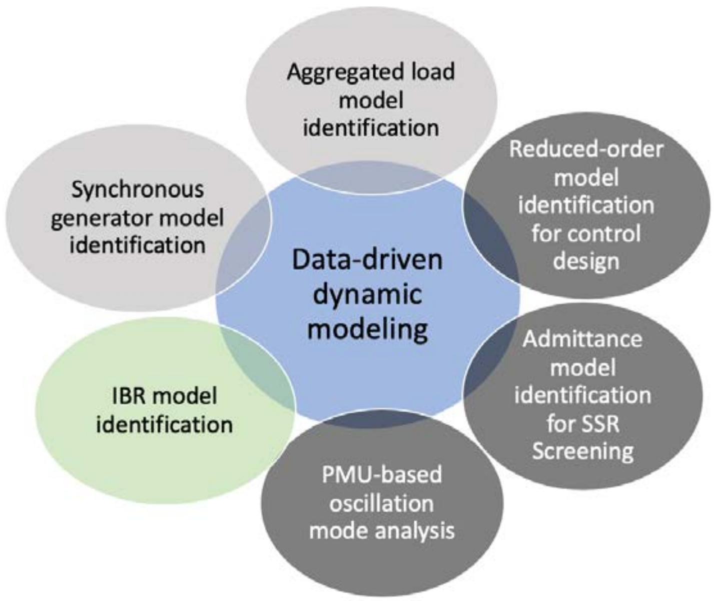


Figure 1 Measurement-based dynamic modeling: six applications. SSR stands for subsynchronous resonance. PMU stands for phasor-measurement unit.

A Brief Classification of Measurement Data and Models

Measurement data can be expressed in the time domain or frequency domain. In power grids, digital fault recorders and phasor measurement units (PMUs) capture time stamped (time-domain) dynamic response data. Frequency-domain data are usually produced via frequency scans, also known as the harmonic injection method. To measure admittance of a device, a test circuit is first built to connect the device to a controllable voltage source. A sinusoidal perturbation is injected into the input portal – the voltage source. The output port (the current)'s steady-state time-domain responses are processed via Fourier transform to extract the frequency components. Thus, the frequency response of the input/output system is measured at that frequency. This experiment can be repeated for a varying frequency.

We use a simple example of a series connected resistor-inductor-capacitor (RLC) circuit to illustrate the types of measurement data and the identified models. Figure 2 presents the procedure of estimating the parameters of the resistor R, the inductor L, and the capacitor C from time-domain dynamic response data. The time-domain dynamic response data are generated by a step change in the source voltage with the capacitor voltage measured at a sampling period of 0.001 s. White noise is imposed in the capacitor voltage measurement data to emulate the effect of noise in the measurement sensor.

The basic procedure is to first build a dynamic model to represent the RLC circuit, with R, L, C as the model parameters. The parameters are then tuned to match the estimated output with the measurement output. Figure 2 also presents the measured output data vs. the estimated output. The red line represents the estimated output based on an initial guess of the RLC parameters while the blue line represents the estimated output based on the RLC parameters identified through a least squared error minimization procedure. The parameter set after optimization leads to a much better match degree with the original data.

This procedure of data-driven parameter estimation is an example of gray-box model identification. Note that the estimation model structure has been given as a second-order transfer function with its numerator and denominator coefficients associated with the RLC parameters.

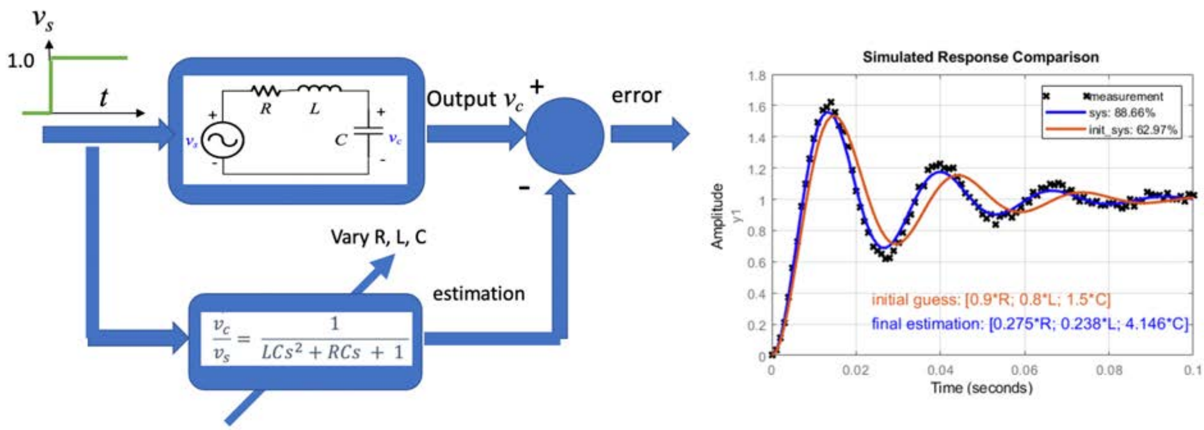


Figure 2 Estimate model parameters (R, L, C) from time-domain measurement data. This application is an example of gray-box model identification.

Figure 3 presents the procedure of extracting an input/output model represented by a Laplace transform transfer function from the frequency-domain data. First, the source voltage is perturbed with a sinusoidal signal at a frequency with a known magnitude. The capacitor voltage is measured. A Fourier transform (a technique to transform a function of time to a function of frequency) is conducted on the measurement data to extract the complex Fourier coefficient or the phasor of that frequency. The ratio of the output phasor and the input phasor is then obtained. This experiment is repeated for a varying frequency. Figure 3 also presents the resulting frequency response data. Data fitting of the frequency response measurements leads to a third-order transfer function describing the input and output relationship.

This procedure of directly fitting frequency-domain measurements to a third-order transfer function is an example of black-box model identification. The resulting transfer function does not give explicit information of the dynamic model structure. Coefficients of the numerator and the denominator of the transfer function also do not associate with physical parameters of the RLC circuit.

In summary, the measurement data used for dynamic model identification can either be in the time-domain or in the frequency-domain; the model structure can either be known (i.e., a gray-box model) or unknown (I.e., a black-box model).

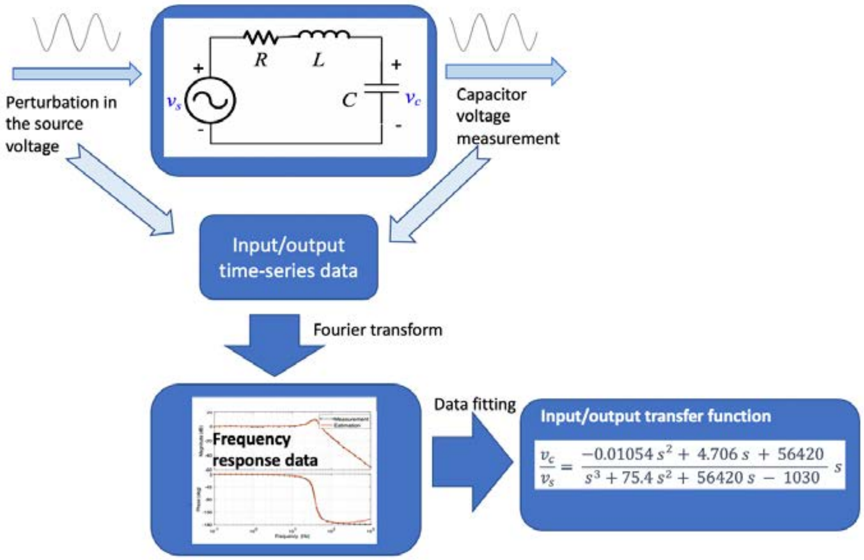


Figure 3 Procedure of extracting a transfer function from the frequency-domain measurements. This application is an example of black-box model identification.

Application 1: Synchronous generator model identification

This application of generator model parameter identification takes the gray-box model identification approach because the parameters identified are associated to a known model structure.

After the invention of synchronous generators in the 1880s, a synchronous generator model relying on Park's transformation (a technology developed by R.H. Park to transform variables in ABC frame to variables expressed in a rotating rotor frame) was developed in the 1920s. In this representation, a solid rotor is represented by the rotor circuits in the direct and quadrature (dq) axes. Test procedures to obtain the dq-axis circuit parameters were designed after the 1920s. As a result, IEEE published standard 115 "Test Procedures for Synchronous Machines" in 1965 and revised the standard in 1983. Both transient response measurements from short-circuit tests and frequency response measurements have been used to find reactance and time constants. For example, a procedure relying on asymptotic approximation can be used to find the parameters of a transfer function from its frequency-domain response measurements. Curve fitting of frequency-domain data also may be used to find the transfer function. The parameters of the identified transfer function may be further mapped to the parameters with physical meaning.

To generate time-domain short-circuit transient response data and frequency-domain reactance data, requires testing a generator offline. For example, to obtain frequency responses, the rotor shaft of a generator is kept standing still while the AC side is connected to a voltage source with a varying frequency. Current phasor at that frequency needs to be extracted to generate a frequency response plot of the reactance. This probing method uses frequency scans. Later, methods using online measurement data for model parameter identification have also been proposed and implemented.

Application 2: Aggregated load model identification

At a bulk power system level, load modeling deals with aggregated load modeling so that the performance of the computer model matches field measurements. This application of load model parameter identification is also normally a gray-box model identification problem. Before 1990, loads were represented by static models in computer software packages. For example, the ZIP model assumes the total real power consumption of aggregated loads is a combination of constant impedance (Z), constant current (I), and constant power components (P). Starting from the late 1980s, dynamic load models were developed to improve system modeling accuracy. Time-domain data have been used to identify load models. In 1990s, a research project carried out at the Panchiao substation in the Taiwan power system demonstrated that using the first-order representation of voltage and real power relationship cannot provide a good match to the field measurement data before/after a single-phase fault. Thus, higher-order models (second and third) were used, and the matching accuracy was significantly improved. The model identification process included three key steps:

1. determine the transfer function structure based on prior knowledge,
2. convert the transfer function to its discrete-time prediction error model, and
3. obtain measurement data and conduct curve fitting to find the model parameters.

Other load model representations are also available, e.g., an induction motor parallel with a resistor-capacitor circuit. Measurement data are then used to find the induction motor parameters and the resistor-capacitor circuit parameters.

Application 3: Reduced-order model identification for control design

Besides modeling, another category of application of measurement data is the development of a reduced-order dynamic model for control design. The control design problem could be to design a power system stabilizer for a synchronous generator's excitation system or a damping control for a flexible alternating current transmission system device. The application of reduced-order model identification normally uses the black-box model identification approach because the internal model structure is usually unknown.

For any control design problem, the plant model describing the input/output relationship is a necessity. Usually, a reduced-order plant model is desired. How do we find the plant model? The measurement-based approach is to perturb the original system's input and record the output data. From either the time-domain data or the frequency-domain data, the input/output plant model can be found.

For example, in a power system stabilizer design, the plant has an input as the reference order of the voltage regulator and the output as the generator speed. The input can be perturbed with an impulse signal and the output response will be recorded. Subspace methods, e.g., eigensystem realization algorithm, may be used to process the output data and lead to a reduced-order plant model. Based on the plant model, a controller modulating the voltage regulator's reference with the generator speed as the input can be designed and tested for the closed-loop system performance.

Subspace methods, e.g., eigensystem realization algorithm, can be traced back to the seminal state-space model realization theory established by Ho and Kalman in 1960s. The core message of the theory is that time-domain dynamic response data can be stacked properly to form a large-dimension data Hankel matrix. This data Hankel matrix is associated with the state-space model's system matrices. Factorizing the Hankel matrix via singular value decomposition leads to the system matrices. From there, a state-space model that matches the input and the output relationship can be recovered. Furthermore, with the system matrices known, the eigenvalues of the system can also be found. Subspace methods have been used in other applications, e.g., PMU data-based oscillation mode identification. They may be viewed as an inference method that relates data to a model. The methods also have the capability of differentiating noise vs. meaningful info, a feature of unsupervised clustering learning.

Application 4: Admittance model identification for subsynchronous resonance screening

Stability analysis via frequency-domain models has a history dating back to the 1970s in both power electronics and power systems communities. In the power electronics community, initial use of impedance models for DC circuit stability analysis started in 1976. In the power systems community, dq admittance-based subsynchronous resonance stability analysis started also in 1970s, after the Mohave power plant subsynchronous resonance events in Nevada. For these events, a synchronous generator radially connected to a series compensated line experienced oscillations in its torque shaft, causing shaft damage. The torsional oscillations were triggered by the electric network resonance due to the interaction of the series capacitor and the line inductance. When the frequency of the electric network resonance is complementary to the frequency of a torsional model, *i.e.,* the sum of the two frequencies is 60 Hz, torsional oscillations may become severe.

Compared to the DC circuit analysis dealing with a single-input and single-output system, stability analysis in power systems usually deals with three-phase systems. Modeling a three-phase system in a rotating dq-frame can greatly simplify the resulting model. Indeed, one of the most influential modeling technologies of power systems is Park's transformation, which converts variables in ABC frame to those in the rotor dq-frame. As a result, a synchronous generator model is expressed from the perspective of the rotating rotor frame. Besides generators, other components of the power systems may also be expressed in a dq frame for simplicity. Thus, dq-frame models are preferred in stability analysis.

For subsynchronous resonance analysis, a circuit of a generator with series-compensated interconnection can be interpreted as a two-input and two-output feedback system. The forward unit is the line's admittance while the feedback unit is the generator's impedance. Stability analysis can then be carried out by examining the feedback system via well- established multi-input and multi-output frequency-domain system analysis theories.

To obtain the generator and network impedance from computer simulation, frequency scans have since been popularly used in subsynchronous resonance studies. Recently, frequency scans have been used in wind farm subsynchronous resonance screening in electromagnetic transient simulation software environments by the grid operating industry. In the power electronics field, obtaining dq impedance/admittance frequency-domain measurement through hardware set up, perturbation signal injection, and measurement processing has been a research topic.

Frequency scans lead to frequency-domain measurement. A benefit of frequency-domain measurement is its use for stability analysis. Either open-loop system Bode plots or Nyquist plots can be plotted and stability prediction can be made. On the other hand, those diagrams have disadvantages compared to closed-loop system eigenvalues. They may not lead to accurate stability prediction, or they are not straightforward for interpretation.

An eigenvalue, in the form of a complex number, gives direct and accurate prediction of stability of a dynamic system. The real part of an eigenvalue must be less than zero for a system to be stable and the imaginary part of an eigenvalue implicates the oscillation frequency. Thus, eigenvalues directly tell if the system is stable or not and what the system's oscillation modes are. For subsynchronous resonance stability analysis, a generator or transmission system's frequency-domain admittance/impedance measurements must be fitted into a model in the form of a transfer function matrix. From there, eigenvalue calculation is possible. In fact, though it seems trivial to arrive at eigenvalues after obtaining the admittance measurements of subsystems, it is to be noted that the frequency-domain data fitting technology was not available in 1970s. This technology is available only after 2000. Without frequency-domain data fitting, it is difficult to identify models and compute eigenvalues.

This application of admittance model identification is to identify a black-box model describing the terminal voltage and current relationship only. The resulting model does not lead to further information on generator model structure.

Application 5: PMU data-based oscillation mode identification

PMU data have been used for oscillation mode identification where the black-box modeling approach is usually applied. In 2012, IEEE Power and Energy Task Force of Identification of Electromechanical Modes published a report, "Identification of electromechanical modes in power systems." The electromechanical modes are in the range of a fraction to several Hz. This report presents a perspective on using different identification methods for finding oscillation mode frequency, damping ratio, and mode shape based on PMU data with a sampling rate of 30-60 Hz.

If time-domain dynamic response data is viewed as the impulse responses of a dynamic system describing the entire power grid, the Laplace transform of the time-domain data represents the resulting input-output model. Oscillation modes are associated with the poles of the Laplace domain expression, or the eigenvalues. Subspace methods, e.g., eigensystem realization algorithm, may be used to form a data Hankel matrix, further extract the system matrices for eigenvalue computing. From the eigenvalues, the oscillation modes, damping ratio, and frequencies are found. PMU-based oscillation mode identification is a mature technology. For example, several utilities have real-time mode analyzers available to process PMU data.

Summary of the Five Applications and Recent Progress in Gray-Box Model Identification

As a summary, for the five applications, three of them, *i.e*., finding reduced-order models for control design, finding dq admittance for subsynchronous resonance stability analysis, and PMU-based electromechanical oscillation mode identification, are related to identifying black-box models from measurement data. Those models describe the input/output relationship only. The internal structure and parameters of the system under investigation are not imposed as for a gray-box model. The technology of black-box model identification is mature as we have seen real-world applications in these areas. The black-box models are all linear models.

On the other hand, gray-box model identification is actively under investigation. The first two applications-- identifying generator reactance and time constants and identifying parameters for load modeling-- belong to the category of gray-box model identification. For those applications, prior knowledge of internal physics must be combined with measurement-based learning to achieve the goal of model identification. The models can be nonlinear.

The main issue of gray-box identification is that measurement data may not contain sufficient information on parameters. This leads to ill-conditioned estimation problems. If this is the case, the estimation problem can be formulated to estimate a subset of the parameters. Algorithm-wise, convergence and local optimum are the main issues for nonlinear optimization problems. For parameter estimation, local optimum means the identified parameters may be far from the true parameters. The resulting estimated output may have a poor matching degree with the measured output. Therefore, many efforts have been devoted to refining the optimization problem formulation.

Optimization is one of the key technologies in gray-box identification. A significant achievement in recent years is the adoption of convex programming techniques into optimization problem formulation and solving. A benefit is that the solution to a convex optimization problem is the global optimum, a fact ensuring the identified parameters producing the best matching results.

IBR modeling: A forward look

The sixth application is data-driven IBR modeling. We use a 2.3-MVA inverter as an example to demonstrate the state-of-the-art technology in black-box IBR model identification, and we give our perspective on challenges to be tackled in IBR modeling.

dq Admittance Model Identification

For IBRs, dq admittance measurement technology is a mature technology. The measurement capability can be realized in software as well as hardware experiments with the availability of advanced high-power converters and medium voltage sensors.

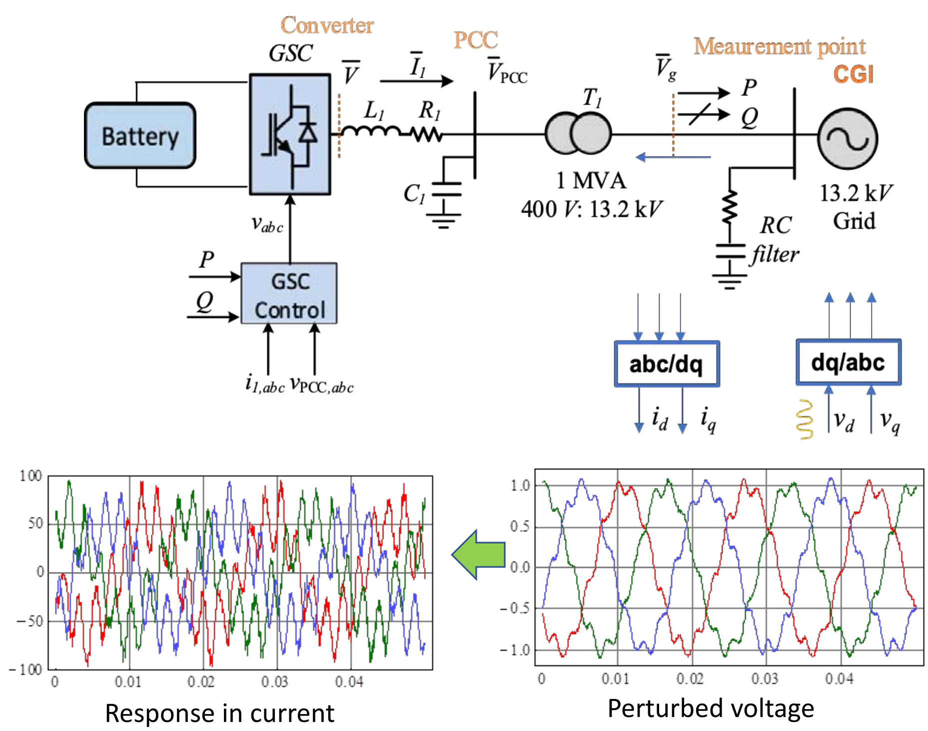


Figure 4 Measurement test bed for a 2.3-MVA inverter. PCC stands for point-of-common-coupling.

Figure 4 shows a measurement test bed set up at the National Renewable Energy Laboratory's Flatiron campus in Colorado, United States. A critical component of the test bed is the 7 MVA-13.2 kV controllable grid interface (CGI). CGI essentially works as a grid-forming converter. It draws electricity from a utility grid and acts as a controllable voltage source. When an IBR is connected through a step-up transformer to a CGI, it can be configured to operate at a certain operating condition. The CGI can produce a harmonic voltage source superimposed to its 60 Hz voltage source. This harmonic voltage source's frequency may vary. Thus, frequency scans can be conducted using CGI.

For this test bed, the model to be identified describes the relationship between the two inputs (the dq-axis voltages) and the two outputs (the dq-axis currents), as shown in Figure 4. This model is called dq admittance and it is a two-by-two matrix in Laplace domain. The four components of the dq admittance matrix are*:* Y_{dd}*,* Y_{dq}*,* Y_{qd}*,* and Y_{qq}.

Figure 5 presents the photos of the CGI and medium-voltage sensing equipment at National Renewable Energy Laboratory.

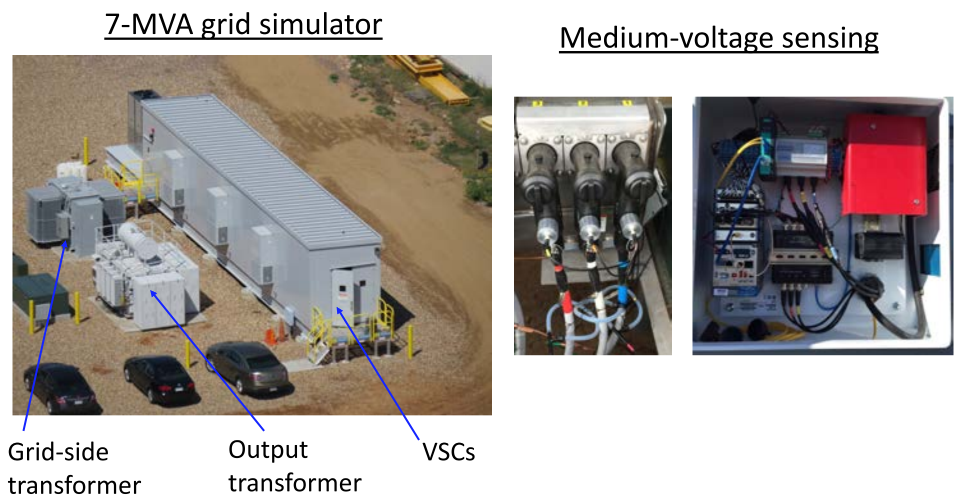


Figure 5 CGI and sensors. Source: Mark McDade, NREL.

The resulting dq admittance of the IBR viewed at the measurement point is shown in Figure 6. The measurement test bed is configured so that the IBR works in four operating conditions expressed by real power and reactive power. For per unit values, the base power is 1 MVA.
Case 1: real power at 0 MW and reactive power at 0 MVAr
Case 2: real power at 500 kW or 0.5 p.u. (-6 dB), reactive power at 0 MVAr
Case 3: real power at 0 MW and reactive power at 500 kVAr or 0.5 p.u. (-6 dB)
Case 4: real power at 1 MW (0 dB) and reactive power at 0 MVAr.

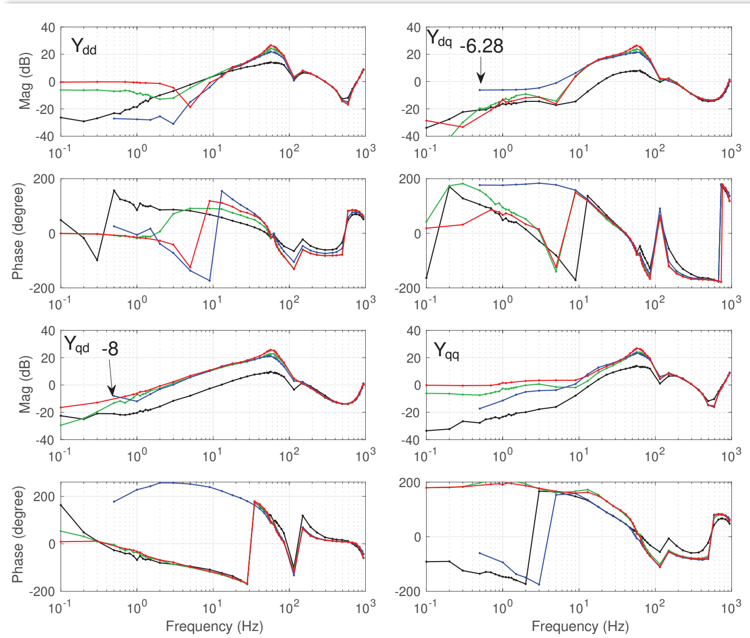


Figure 6 dq admittance of a 2.3-MVA inverter under four operating conditions. Black: Case 1; Blue: Case 2; Green: Case 3; Red: Case 4. Case 1: real power at 0 MW and reactive power at 0 MVAr. Case 2: real power at 500 kW or 0.5 p.u. (-6 dB), reactive power at 0 MVAr. Case 3: real power at 0 MW and reactive power at 500 kVAr or 0.5 p.u. (-6 dB). Case 4: real power at 1 MW (0 dB) and reactive power at 0 MVAr.

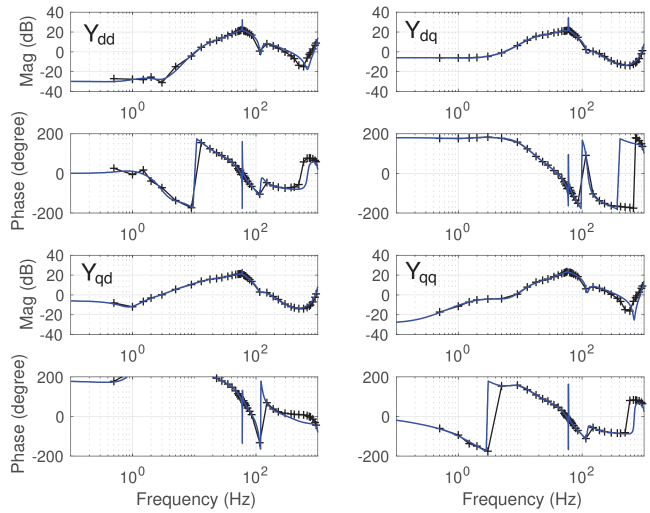
At each operating condition, about 40 sinusoidal injection experiments are conducted. For each sinusoidal injection experiment, injection in the d-axis voltage is first conducted and the resulting dq-axis current measurements are collected. Fourier transform is then applied to the steady-state time-domain data to find the phasors. From there, the first column admittance components $Y_{dd}(f)$ and $Y_{qd}(f)$ are found. Next, injection in the q-axis voltage is conducted and the second column admittance $Y_{dq}(f)$ and $Y_{qq}(f)$ are found. From the frequency-domain measurement, we may apply frequency-domain data fitting methods and obtain a black-box model. This step is necessary if we aim to have an s-domain admittance for eigenvalue analysis, which can lead to an overall picture of the system modes.

The data in Figure 6 have been fitted using a frequency-domain data fitting package, and the comparison of the frequency responses of the model vs. the measurements are shown in Figure 7(a). The figure shows that data fitting leads to a high matching degree in the studied frequency spectrum. One more comparison can be made: the step responses of the physical device vs. the model. Figure 7(b) presents the comparison under two step changes in dq-axis voltages: 10% or 20%. The physical device and the model have very similar step responses.

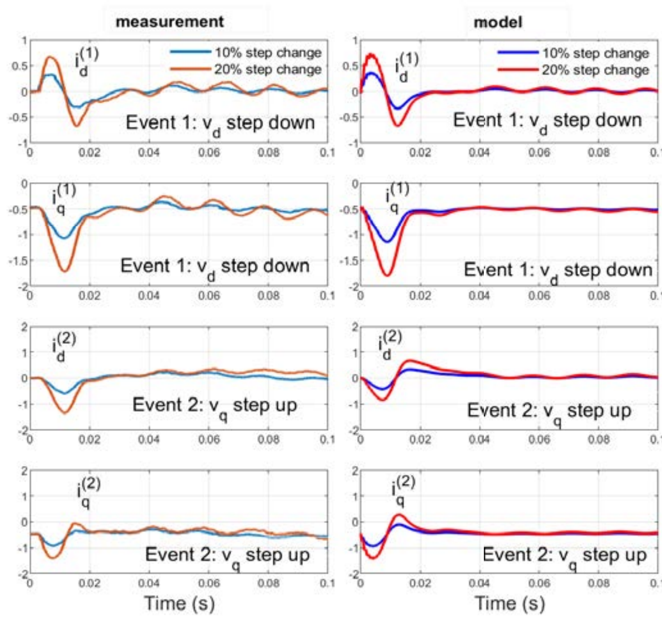
Another admittance model identification technology is to use time-domain step responses. Converting the step responses into s-domain expressions and assembling lead to an s-domain dq admittance model directly. In real-world applications, step response data are polluted with noises. The resulting model may not be accurate in the high-frequency range or when the measurement data have small values.

Remark: Frequency scans and frequency-domain data fitting are two mature technologies and can be employed to for IBR's dq admittance model identification.

The admittance model identified is a linear model associated with an operating condition. An IBR may have a variety of operating conditions. Thus, one challenge is how to find any admittance model associated with a random operating condition. A straightforward solution is to build a nonlinear model that can reflect the operating condition. This approach is the gray-box modeling approach: building the model structure based on the first principles and prior knowledge while estimating the model parameters using measurement data. On the other hand, IBR gray-box model identification is a more challenging problem from both the IBR dynamic model building perspective and mathematic optimization problem solving perspective.



(a)



(b)

Figure 7 (a) Frequency-domain data fitting results. Solid blue line: model. Black crosses: measurements. Operating condition: Case 3 where P =0 MW, Q =500 kVar. (b) Comparison of the step response of the identified black-box model versus the time-domain measurements

Challenges in gray-box model identification

Using the 2.3-MVA inverter as an example, we will further demonstrate how to use dq admittance measurement data to speculate the inverter control structure and parameters. As the first step, the control structure needs to be specified. In this case, two types of popular control structures are examined. Figure 8 presents the converter control structures and a comparison of the frequency responses of the two models vs. the measurements.

In both models, the converter controls have the same goal of real power and reactive power following. Both employ a cascaded control structure: outer controls to track real and reactive power, while the inner controls to track current orders. The two models differ in the inner current control implementation frames. The dq-frame control has its inner current control implemented in a dq frame. That is, the phase current measurements are first converted to a dq frame. This dq frame has a rotating speed of the nominal frequency at steady state. When projected to the dq frame, periodic signals with the nominal frequency become dc signals.

The proportional integral (PI) control units are known for their capability of tracking dc signals. They can enforce the dq-axis current measurements to follow the current orders generated by the outer controls. The stationary-frame control has its inner current control implemented in a stationary frame. In this frame, currents are still periodic. To track a current order, proportional resonant (PR) control units are employed to ensure the error between the measurement and the order achieving zero at the nominal frequency.

Comparison of the dq admittance of the 2.3-MW inverter vs. the two models shows that the second model results in better matching for the diagonal components Y_{dd} and Y_{qq}. Specifically, for the dd component, a large mismatch is observed in the range of 1-100 Hz if the dq-frame control is assumed. On the other hand, the 2.3-MW inverter and the model match well in the range of 0.1-100 Hz, if the stationary-frame control is assumed.

Refining the model structure and parameter tuning are the next steps. Specifically, parameter tuning can be achieved using an automatic procedure instead of manual tuning. To achieve automatic tuning, optimization problem formulation and solving becomes an immediate task.

From this 2.3-MW inverter example, we may see that mainly there are two challenges: model design and customized model parameter estimation algorithm design.

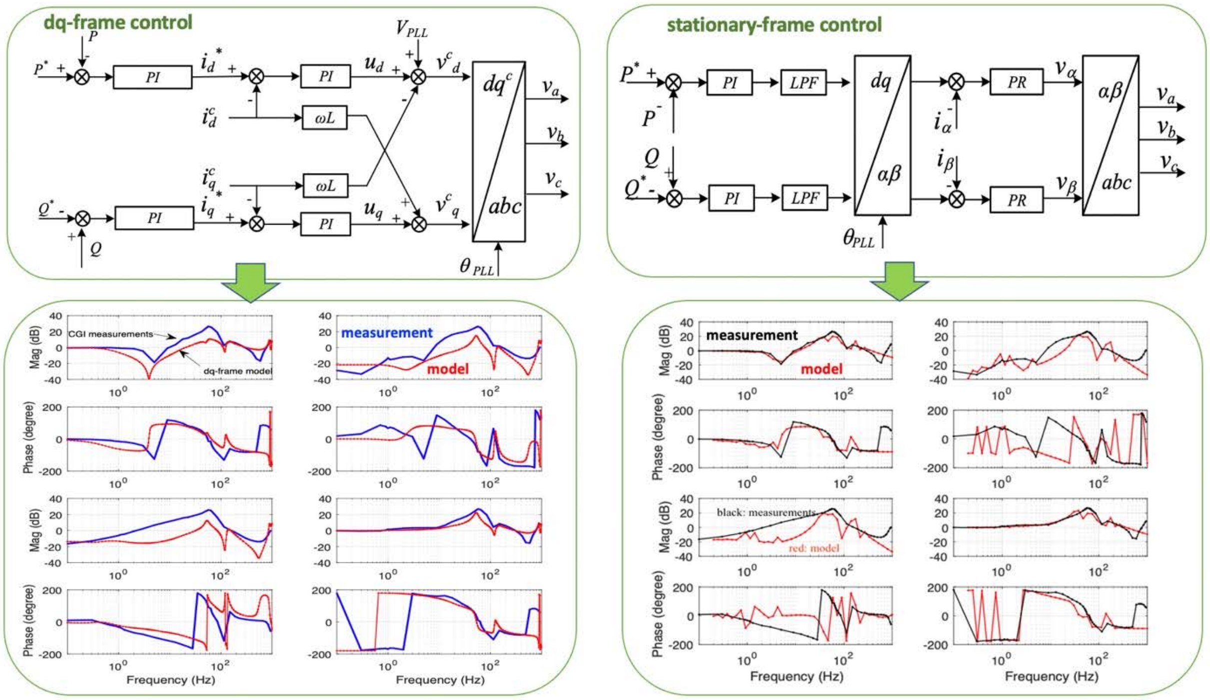


Figure 8 Upper row: Two types of control structures differ in current controls. Left: dq-based current control. Right: stationary-frame-based current control. Bottom row: Comparison of frequency responses and measurements. Left: dq-frame control. Right: stationary-frame control.

Challenge 1: IBR model structure design

In the past decade, a set of generic models for IBRs have been developed by Western Electricity Coordinating Council's model validation subcommittee for grid dynamic assessment. These models are suitable for power system transient simulation studies with numerical integration time steps in the range of 1 to 5 milli-seconds. Such models are based on quasi-steady-state positive-sequence phasors and usually do not include fast electromagnetic transient dynamics and fast inverter current controls.

To have models accommodating for a wide range of operating conditions, including unbalance, fast dynamics, and weak grid conditions, IBR models including electromagnetic transients and fast controls are desired. For power industry, this is an ongoing effort. For example, CIGRE C4.60 working group aims to design generic electromagnetic transient models of IBRs with transparent IBR control structures.

Because state variables are time-varying at the fundamental frequency in the ABC domain, it is very difficult to derive linear models in ABC frame. Linear time-invariant models are preferred since they are suitable for small-signal analysis. Therefore, modeling efforts are required to convert a model in ABC frame to a model in different coordinates so that its state variables are constant at steady state. The resulting nonlinear models can be easily linearized via numerical methods for linear time-invariant model extraction.

Besides the technical challenges in modeling, another significant technical gap of designing transparent models is that the IBR controls are proprietary information of OEM. Strict nondisclosure requirements are imposed by OEMs, which makes any model design a challenging task. Thus, efforts must be made to standardize IBR control to better define their dynamics and support gray-box modeling. Currently, there are ongoing efforts in the grid industry, e.g., IEEE P2800 working group aims to set up the minimum technical requirements for IBRs.

Challenge 2: Customized model parameter estimation algorithm design

The second challenge lies in model parameter estimation algorithm design. This requires familiarity with the domain knowledge of IBR power electronic converter control and various mathematical methods relying on linear algebra and optimization. To this end, power system engineers can leverage many recent advancements in computing and leverage those free optimization solvers and platforms such as the nonlinear optimization solvers (e.g., IPOPT) and optimization problem formulation interfaces (e.g., YALMIP and CVX for MATLAB and JuMP for Julia).

Conclusion

In summary, data-driven dynamic model building has a long history of applications in power systems. As early as in the 1960s, measurements have been used to identify a synchronous generators' dq reactance and time constants. For the current power grids with high penetrations of IBRs, the power system community once again is examining data-driven dynamic modeling for IBRs. Compared to the previous century, we now have better hardware equipment to conduct experiments, thanks to the advancements in power electronics. We also have better computing tools, thanks to the advancements in operations research, system identification, and machine learning.

Acknowledgement

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For Further Reading

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Biographies

Lingling Fan (linglingfan@usf.edu) is with the University of South Florida, Tampa FL 33620, USA.
Zhixin Miao (zmiao@usf.edu) is with the University of South Florida, Tampa FL 33620, USA.
Shahil Shah (shahil.shah@nrel.gov) is with the National Renewable Energy Laboratory, Golden, Colorado, 80401, USA.
Przemyslaw Koralewicz (przemyslaw.koralewicz@nrel.gov) is with the National Renewable Energy Laboratory, Golden, Colorado, 80401, USA.
Vahan Gevorgian (vahan.gevorgian@nrel.gov) is with the National Renewable Energy Laboratory, Golden, Colorado, 80401, USA.
Jian Fu(jian.fu@ee.doe.gov) is with the Wind Energy Technology Office, Department of Energy, Washington DC, USA.