Data-Driven Dynamic Modeling in Power Systems

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This article is on estimation, identification, or learning dynamic models from measurement data in power systems. Dynamic models differ from static models. Static models reflect the input and output relationship regardless of evolving time. On the other hand, dynamic models associate the input and evolving time to the output.

Note that the three words, estimation, identification, and learning, describe similar notions and are interchangeable. The machine learning community prefers model *learning*, while the control community has a special name: system identification. 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 paper is not about the methodologies of the inference. Rather, it is about unique applications for deriving power system dynamic models.

Dynamic behaviors are difficult to capture, especially for the applications that are lacking analytic models. That is where data driven/machine learning techniques can play a critical role. Indeed, there is a long history of for power system engineers building dynamics model using data-driven approaches, well before machine learning is a popular term. New application of inverter-based resource (IBR) modeling adds more complexity due to underlying complex physics and strict non-disclosure requirements from original equipment manufacturers (OEM). Data driven/machine learning will play a much bigger role.

Data-driven modeling becomes an attractive option in scenarios where physical models are elusive. For example, suppose you want to represent the aggregated distributed energy resources at a transmission and distribution interface. One approach is to rely on the interface measurement data and produce a model that represents a mapping between inputs (e.g., voltage and frequency) and outputs (real and reactive power generation). Such a model may be represented using a neural network. On the other hand, neural networks are known to rely on massive data for training. What is more, these neural network representations are not useful for stability analysis. The grid industry uses the well-developed linear system analysis tools for stability analysis, for which, linear time-invariant models are preferred. Example of the analysis tools include PowerTech Labs' Small-Signal Analysis Tool: SSAT™. Many representations are indeed linear time-invariant models, e.g., a Laplace transfer function representing the current/voltage relationship, or admittance.

This article reviews data-driven dynamic modeling in power systems and lays out a forward look on an application with imminent importance for power systems with high penetrations of IBRs. Obtaining models of IBRs using measurement data is valuable because such models do not require proprietary inverter control information, which is unknown to grid operators. Acquiring IBR models from measurement data can greatly improve grid operators' capability in planning and operation.

We start with a brief introduction of measurement data and model classification, and then proceed to review the past grid industry experiences in extracting models from data. Five applications are presented:

- synchronous generator model parameter identification,
- aggregated load model parameter identification,
- reduced-order model identification for control design,

- admittance model identification for subsynchronous resonance (SSR) screening, and
- 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 none of the model structure and parameters are known, the estimation leads to ***black-box models***.

Finally, we discuss IBR model identification. The current practice of IBR model identification mainly focuses on obtaining frequency-domain admittance/impedance measurements using frequency scans. While normally admittance/impedance refers to 60 Hz impedance in power system operation, the admittance/impedance of this article refers to admittance/impedance over a frequency range. An admittance model describes the input/output relationship of voltage and current at an operating condition.

There are many ways to structure dynamic models from an input/output relation. Thus, a more challenging question is: Based on the frequency-domain measurements, can we design nonlinear dynamic models with known structures, or gray-box models? Can we figure out the parameters of the models? Readers can see that this modeling approach indeed incorporates the prior knowledge of physics and measurement data. The state-of-the-art admittance measurement technologies and the future areas for investigation will be presented.

Six applications, shown in Figure 1, will be examined in this article.

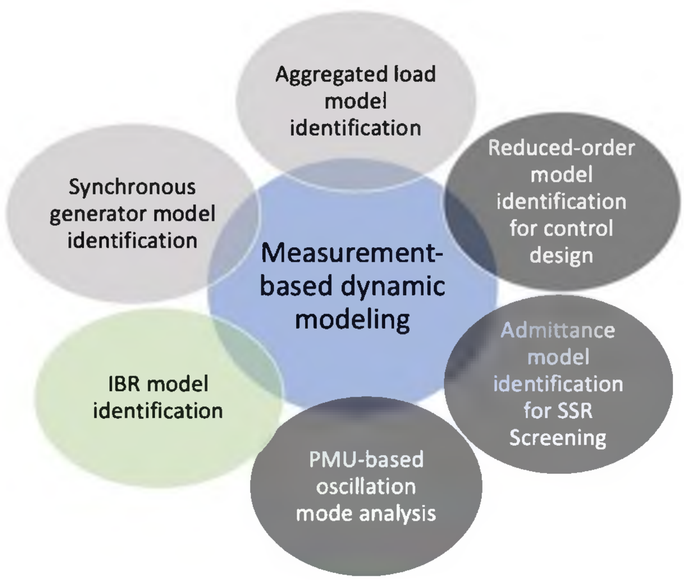


Figure 1 Measurement-based dynamic modeling: six applications. SSR stands for subsynchronous resonance. PMU stands for phasor-measurement unit.

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 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. The parameters of the model 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 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.

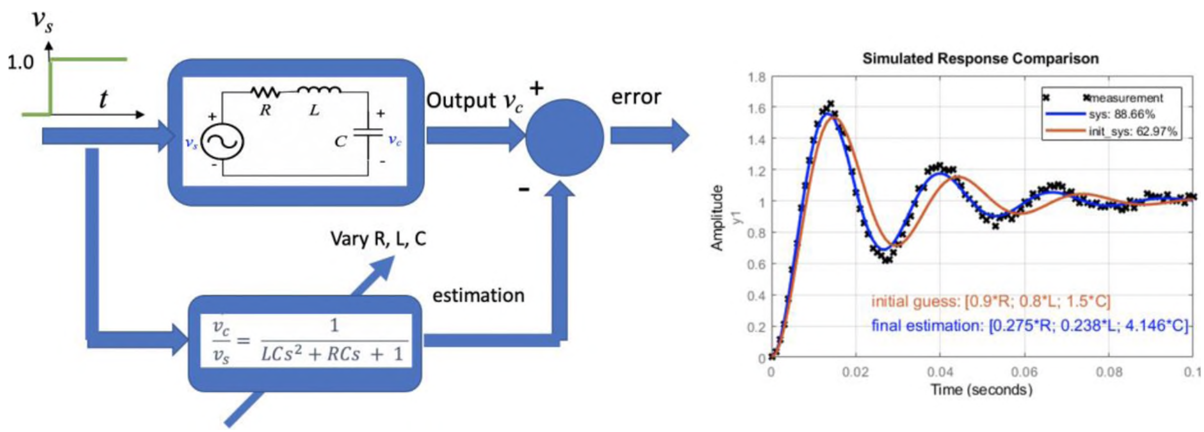


Figure 2 Estimate model parameters (R, L, C) from time-domain measurement data. This application is an example of gray-box model identification.

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 at that frequency. The ratio of the output phasor and the input phasor is then obtained for that frequency. This experiment is repeated for varying frequencies. 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 do not associate with physical parameters of the RLC circuit.

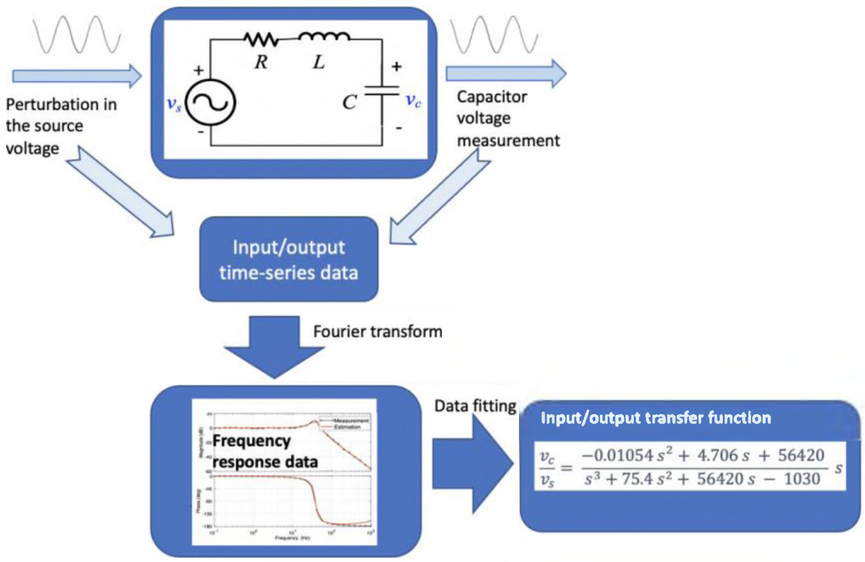


Figure 3 Procedure of extracting a transfer function from the frequency-domain measurements. This application is an example of black-box model identification.

Remark: This tutorial example demonstrates two types of measurement data for model identification: time-domain vs. frequency-domain, and two types of models to be estimated: gray-box vs. black-box.

Prior Experiences: Five Applications

Indeed, even before machine learning and system identification became popular terms, power system engineers have extensively employed measurement data for various usage. There are many past instances of using measurements to identify dynamic models. Five applications are presented:

- synchronous generator model identification
- aggregated load model identification
- reduced-order plant model identification for control design
- admittance model identification for SSR screening
- PMU data-based electromechanical oscillation mode identification

Synchronous generator model identification

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 dq frame) was developed in the 1920s. In this representation, a solid rotor is represented by the rotor dq-axis circuits. Test procedures to obtain the dq-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.

This application of generator model parameter identification is gray-box model identification. The parameters identified are associated to a known model structure.

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. Organizations responsible for reliable system operation around the world have load modeling task forces.

Before 1990, loads were represented by static models in computer software package. For example, the ZIP model assumes the total real power consumption of aggregated loads is a combination of constant impedance, constant current and constant power components. 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.

A research project was carried out to model loads located at the Panchiao substation’s 69 kV level in the Taiwan power system in the 1990s. It is demonstrated that first-order representation of voltage and real power relationship cannot lead to a good match with the field measurement of 5-second data before/after a single-phase fault. Higher-order models (second and third) significantly improved the match degree. The key parts of model identification included determining transfer function structure based on prior knowledge, converting the transfer function to its discrete-time prediction error model, obtaining measurement data, and conducting curve fitting.

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

This application of load model parameter identification is also gray-box model identification. The parameters identified are associated with known model structures.

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.

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 model 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.

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 the dynamic response data can be stacked properly to form a data Hankel matrix. This data Hankel 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 are also known. This feature has been used in the fifth application: PMU data-based oscillation mode identification. This algorithm can be viewed as an inference algorithm of unsupervised learning that relates data to model and has the capability of filtering out noise using singular value decomposition.

This application of reduced-order model identification is black-box model identification. Here, the input/output relationship is identified. The internal model structure is still unknown.

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 subsynchornous 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 deal 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 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 converted to a two-input and two-output feedback system. The forward unit is the line's admittance in the dq frame while the feedback unit is the generator's impedance in the dq frame. 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. An eigenvalue, in the form of a complex number, gives direct indication 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 have to 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 from measurements.

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.

PMU data-based oscillation mode identification

PMU data is being used for oscillation mode identification. 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 dynamic system's 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.

The models identified in this application are black-box models because only the input/output relationship is used and there is no imposed structure to the model.

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 SSR 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.

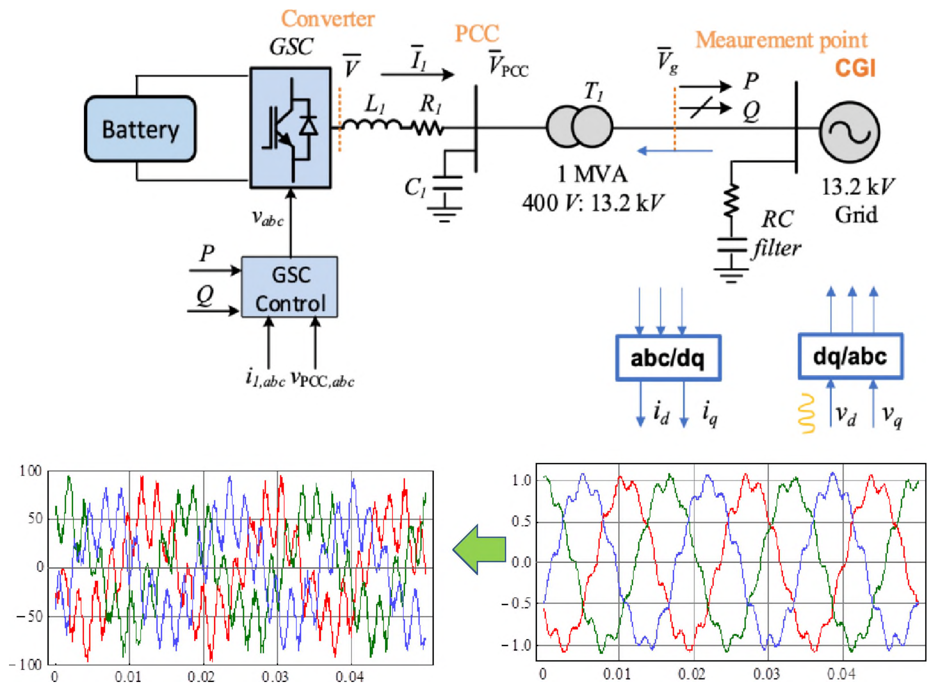
Optimization is one of the key technologies in gray-box identification. A significant achievement in recent years is the adoption of convex programming techniques into optimization problem formulation and solving. A benefit of convex optimization is that the solution to a convex optimization problem is the global optimum, i.e., the identified parameters are guaranteed to lead to the best match.

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 model identification, and we give our perspective on challenges to be tackled in IBR model identification.

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.



Response in current

Perturbed voltage

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 can 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.

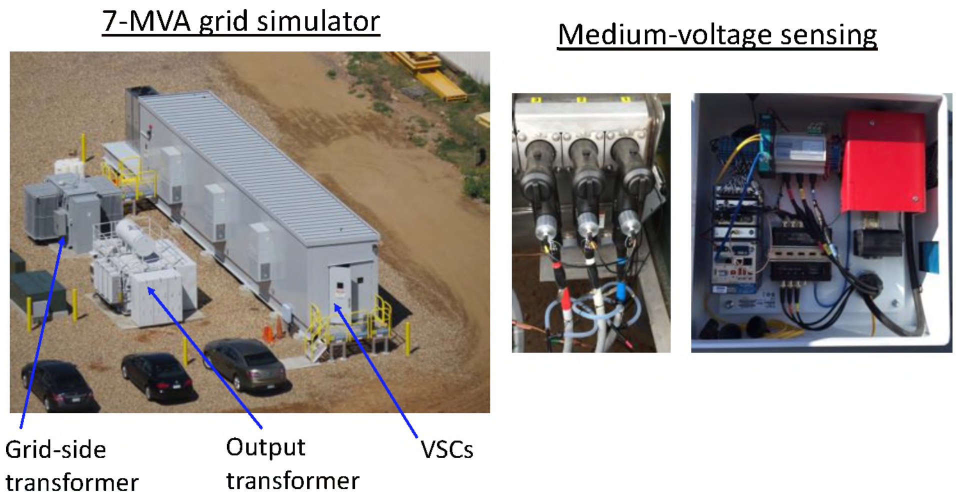


Figure 5 CGI and sensors. Source: Mark McDade, NREL.

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 in p.u. 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.

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: The frequency scan and frequency-domain data fitting are two mature technologies and can be employed to for IBR’s dq admittance model identification.

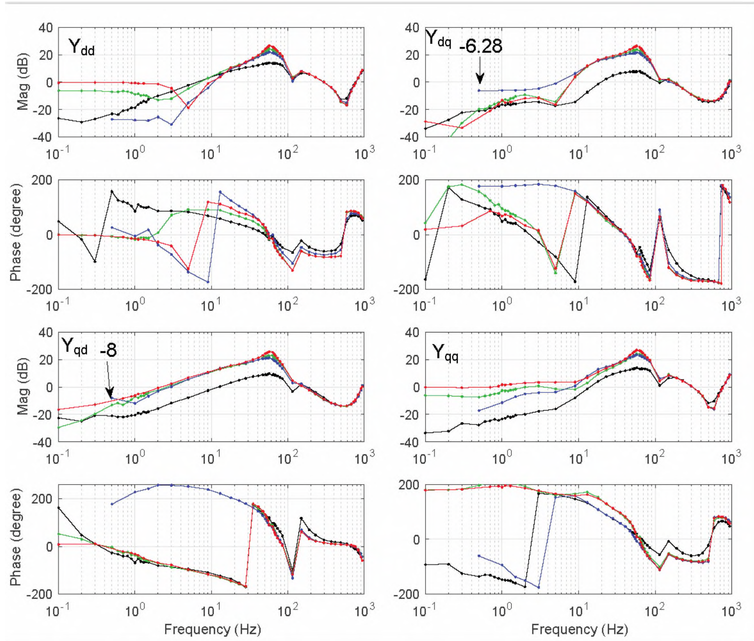


Figure 6 Dq admittance of a 2.3-MVA inverter under four operating conditions. Black: Case 1; Blue: Case 2; Green: Case 3; Red: Case 4. Case 1: real power at 0 MW and reactive power at 0 MVAr. Case 2: real power at 500 kW or 0.5 p.u. (-6 dB), reactive power at 0 MVAr. Case 3: real power at 0 MW and reactive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

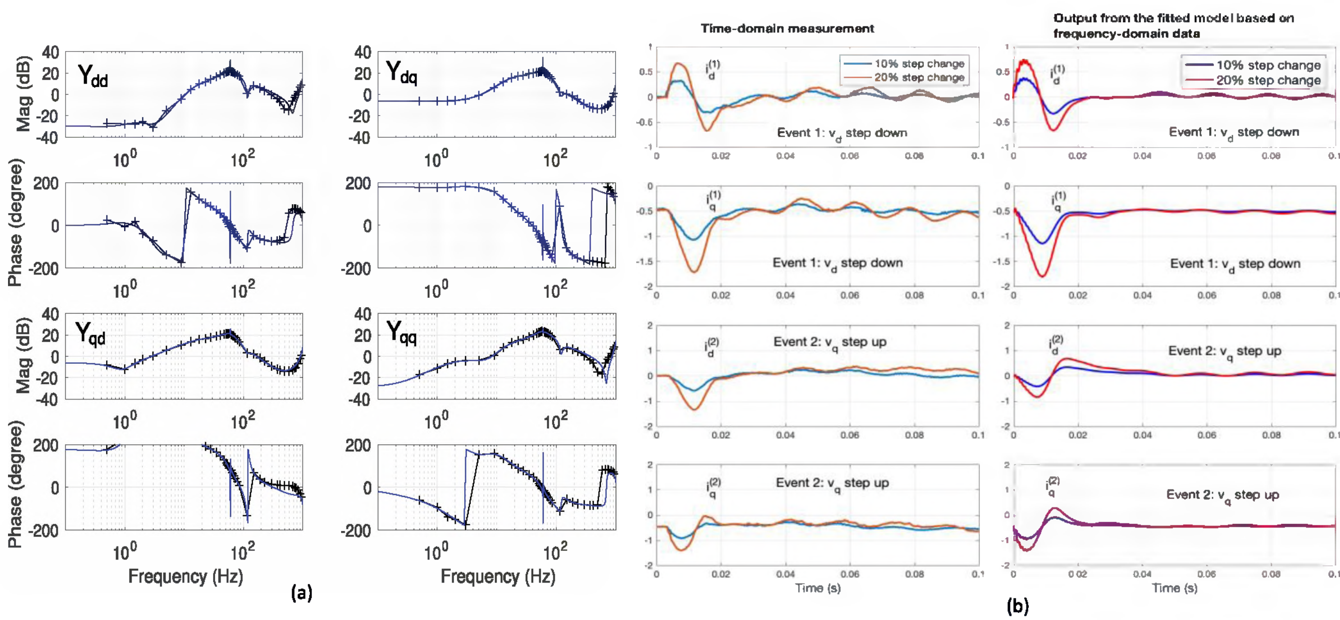


Figure 7 (a) Frequency-domain data fitting results. Solid blue line: model. Black crosses: measurements. Operating condition: case 3 where P =0 MW, Q =500 kVar. (b) Comparison of the step response of the identified black-box model versus the time-domain measurements

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 principle 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 in both IBR dynamic model building perspective and mathematic optimization problem solving perspective.

Challenges in gray-box model identification

Using the 2.3-MVA inverter as an example, we will further demonstrate how to use the black-box model 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 structure. 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 achieving zero inputs at steady sate. Therefore, they can force 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 v.s. 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 pretty 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.

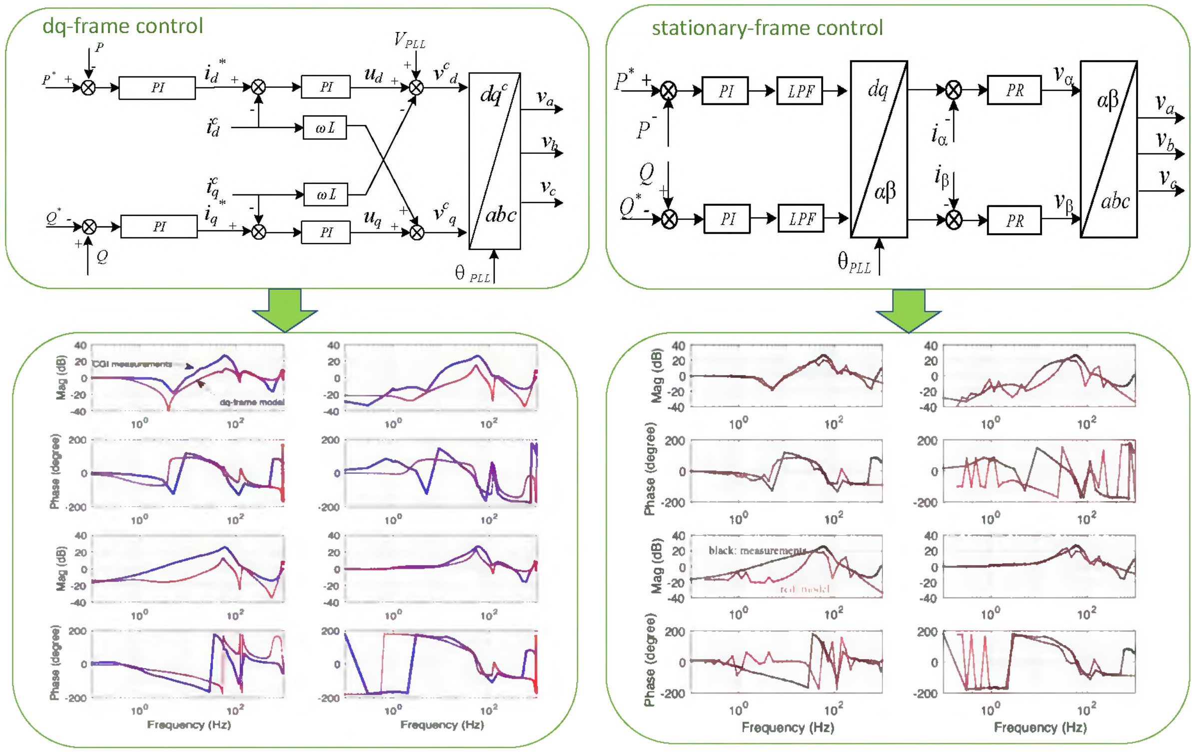


Figure 8 Upper row: Two types of control structures differ in current controls. Left: dq-based current control. Right: stationary-frame-based current control. Bottom row: Comparison of frequency responses and measurements. Left: dq-frame control. Right: stationary-frame control.

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 the grid industry, this is an ongoing research and development area. 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 as they are suitable for small-signal analysis. Therefore, modeling efforts are required to convert a model in ABC frame to a model with its state variables constant at steady state. This type of nonlinear models can be easily linearized via numerical methods for linear time-invariant model extraction.

Besides the aforementioned 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 aiming 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. We may leverage many recent advancements in computing for the purpose of IBR model parameter estimation. In this area, many optimization solvers and platforms have been developed and for free use, e.g., nonlinear optimization solvers such as IPOPT, optimization problem formulation interfaces such as 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

The authors wish to recognize the support of the United States Department of Energy and National Science Foundation for some of the material reported.

For Further Reading

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