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Stability and Control of Power Grids

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Abstract

Power grids are critical infrastructure in modern society, and there are well-established theories for the stability and control of traditional power grids under a centralized paradigm. Driven by environmental and sustainability concerns, power grids are undergoing an unprecedented transition, with much more flexibility as well as uncertainty brought by the growing penetration of renewable energy and power electronic devices. A new paradigm for stability and control is under development that uses graph-based, data-based, and distributed analysis tools. This article surveys classic and novel results on the stability and control of power grids to provide a perspective on this both old and new subject.

1. INTRODUCTION

Bus: a conductor in a grid maintained at a specific voltage and capable of carrying a high current, making a common connection between several components (e.g., generators and loads); it is also referred to as a node in some literature

Line: a series component (e.g., a transmission line or transformer) that links two buses in a grid; it is also referred to as a branch in some literature

Power grids are giant, complex systems where the loads (power consumers) receive an electricity supply from generators (power sources) via power transfer over the underlying power networks. Instability events in power grids are unacceptable to society. The consequent blackouts can cause huge economic losses and can even threaten the security of a society. Therefore, stability and control have been issues of fundamental importance since the birth of power grids.

Stability assessment is challenging due to the nonlinearity and complexity of the dynamical behavior of power grids. Although a time domain simulation can provide details on system trajectories before, during, and after a disturbance, it is unable to explain why the system is stable or unstable under that disturbance. The stability theory of power grids was established by using mathematical tools from dynamical systems, such as Lyapunov's first and second methods for local stability and estimation of stability regions, respectively. With the decentralization of power generation driven by renewable energy, the focus of stability analysis is shifting to the role of power network structures and the development of distributed stability certificates with the help of more advanced tools from network systems theory. Section 2 surveys these classic and recent results on power system stability.

Frequency control and voltage control are two core control issues to maintain the secure and stable operation of power grids. Traditional power system control attempts to use both centralized and decentralized control and focuses on transmission systems, partly due to the properties of traditional power systems, such as centralized power generation, unidirectional power flow, and passive electricity distribution. However, the integration of renewables changes power systems from the traditional paradigm to a completely new one with distributed power generation, bidirectional power flow, and active electricity distribution (1). Furthermore, as renewable energy sources and other types of dynamical devices are connected to different voltage levels, new dynamical behaviors will appear all over the grid. Power system control is therefore facing new challenges and opportunities, which we briefly review in Section 3 from a control engineering point of view and which include frequency control, voltage control, and control of microgrids (MGs).

Essentially, conventional studies on power grid stability and control use solutions that rely heavily on mathematical models. Despite significant progress in the past few decades, these solutions may not be useful in practical grids with extremely high complexity and salient variability. Fortunately, thanks to the wide deployment of advanced information and communication technologies in today's grids, massive amounts of operational data recording system-wide dynamics in real time are available for stability analysis and control. This has helped to unlock the potential of data-based ideas and approaches, especially machine learning (ML) techniques, in tackling conventionally challenging issues encountered by model-based methods. Hence, Section 4 selects some representative research efforts to illustrate how data-based solutions effectively work on grid stability analysis and control.

2. STABILITY THEORY OF POWER GRIDS

2.1. Stability Categories and Associated Modeling

A power grid is a complex system consisting of buses and lines, where the buses may connect generators or loads and the lines link the buses and form a complex network structure. Each bus i in the grid is featured by the active power injection $P_i \in \mathbb{R}$, reactive power injection $Q_i \in \mathbb{R}$, and voltage phasor $V_i \angle \theta_i \in \mathbb{C}$, with $V_i, \theta_i \in \mathbb{R}$ being the voltage magnitude and phase angle, respectively. A line connecting bus i and bus j is represented by an admittance $y_{ij} \in \mathbb{C}$. The power network structure is represented by the so-called admittance matrix $\mathbf{Y} = [Y_{ij}] \in \mathbb{C}^{n\times n}$, where

$Y_{ij} = Y_{ji} = -y_{ij}$ if there is a line between bus i and bus j, $Y_{ij} = Y_{ji} = 0$ if there is no line between bus i and bus j, and $Y_{ii} = \sum_{j=1, j\neq i}^{n} -Y_{ij}$. Generally, power system dynamics can be described by the differential-algebraic equations

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{y}), \tag{1a}$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x}, \mathbf{y}), \tag{1b}$$

where $\mathbf{x}$ collects the state variables, such as the rotor angles and flux decays of generators and rotor slips of induction motors, and $\mathbf{y}$ collects the algebraic variables, such as the voltage magnitudes and phase angles of nodes in the grid. Equation 1a captures the dynamical behaviors of generators and loads, and Equation 1b refers mainly to the circuit equation regarding the conservation of power at buses with only static components.

Power system stability is essentially a single problem, i.e., the system-wide stability; however, treating the stability problem as such does not help to figure out the physical mechanism of the various forms of instability that a power grid may undergo. According to the main system variable in which the instability event is observed, power system stability is generally classified into rotor angle stability, voltage stability, and frequency stability (2). This classification corresponds to the concept of partial stability in stability theory (3). We can also make specific assumptions about each of the stability subcategories and obtain simplified models that capture the key factors in the respective stability issues.

2.1.1. Rotor angle stability. Rotor angle stability, or simply angle stability, refers to the ability of synchronous machines—synchronous generators (SGs) and motors—in a power system to remain in synchronism after being subjected to a disturbance (2). Angle stability is usually seen as a generator-oriented issue and depends on whether each SG in the system can maintain or restore its equilibrium between electromagnetic torque and mechanical torque. Instability occurs in the form of increasing angular swings of some generators, leading to their loss of synchronism with other generators. Angle stability is a purely short-term problem, as the time frame of interest is several seconds. According to the nature of the disturbances, it can be further classified into small-disturbance angle stability and transient stability (i.e., large-disturbance angle stability).

Angle stability problems occur mainly in high-voltage transmission systems, where there is a strong decoupling between P–θ and Q–V relations (4). Therefore, it is common in angle stability analysis to assume a constant voltage magnitude V_i for each bus and focus only on the P–θ relation. There are two major types of models for the study of angle stability: the network-reduced model and the structure-preserving model. Let $\mathcal{V}_{\mathrm{G}}$ and $\mathcal{V}_{\mathrm{L}}$ denote the set of generator buses and set of buses that are without generators and may connect loads. In the network-reduced model, all loads are assumed to be constant impedances and incorporated into the admittance matrix. Based on the bus partitioning $\mathcal{V}_{\mathrm{G}}$ and $\mathcal{V}_{\mathrm{L}}$, the admittance matrix can be accordingly partitioned into $\mathbf{Y} = \begin{bmatrix} \mathbf{Y}_{\mathrm{GG}} & \mathbf{Y}_{\mathrm{GL}} \\ \mathbf{Y}_{\mathrm{LG}} & \mathbf{Y}_{\mathrm{LL}} \end{bmatrix}$, and we obtain $\mathbf{Y}_{\mathrm{GG}}^{\mathrm{r}} = \mathbf{Y}_{\mathrm{GG}} - \mathbf{Y}_{\mathrm{GL}}\mathbf{Y}_{\mathrm{LL}}^{-1}\mathbf{Y}_{\mathrm{LG}}$ by Kron reduction. The matrix $\mathbf{Y}_{\mathrm{GG}}^{\mathrm{r}}$ represents the admittance matrix of the reduced network, where $\mathcal{V}_{\mathrm{L}}$ is eliminated and only $\mathcal{V}_{\mathrm{G}}$ remains. This then leads to the following network-reduced model:

$$M_i\ddot{\theta}_i + D_i\dot{\theta}_i = P_i - \sum_{j=1}^{g} V_iV_jG_{ij}^{\mathrm{r}}\cos(\theta_i - \theta_j) - V_iV_jB_{ij}^{\mathrm{r}}\sin(\theta_i - \theta_j), \quad i \in \mathcal{V}_{\mathrm{G}}, \tag{2}$$

where $M_i > 0$ and $D_i > 0$ denote the moment of inertia and damping coefficient of the generator, respectively, and G_{ij}^{r} and B_{ij}^{r} denote the real and imaginary parts of $[\mathbf{Y}_{\mathrm{GG}}^{\mathrm{r}}]_{ij}$, respectively. The network-reduced model greatly reduces the problem dimension and has been commonly adopted, especially in early works, which were done when powerful computers were unavailable. However, the presence of the transfer conductance G^{r}_{ij} in Equation 2 causes path-dependent terms that make the Lyapunov function not well defined (5). Although the conductance of physical lines $G_{ij} = \mathrm{Re}\{Y_{ij}\}$ is nearly zero in high-voltage transmission systems, G^{r}_{ij} is never negligible because it comes from both the lines and the loads.

To bypass the difficulty caused by the network-reduced model, Bergen & Hill (6) first proposed the structure-preserving model in 1981. This model takes the following form:

$$
\begin{aligned}
M_i\ddot{\theta}_i + D_i\dot{\theta}_i &= P_i - \sum_{j=1}^{n} V_iV_jB_{ij}\sin(\theta_i - \theta_j), \quad i \in \mathcal{V}_{\mathrm{G}},\\
D_i\dot{\theta}_i &= P_i - \sum_{j=1}^{n} V_iV_jB_{ij}\sin(\theta_i - \theta_j), \quad i \in \mathcal{V}_{\mathrm{L}},
\end{aligned}
\qquad 3.
$$

where $B_{ij} = \mathrm{Re}\{Y_{ij}\}$ denotes the line susceptance. In Equation 3, the second-order equation captures the swing dynamics of the generators, while the first-order equation captures the load frequency behavior under angle oscillations. In this model, the physical network structure of the power system remains intact, and hence the physical line conductance G_{ij} is reasonably assumed to be zero. More importantly, there exist well-defined Lyapunov functions for the structure-preserving model. This model has become popular in recent network science studies of power system stability (7), and many variant models have been developed that include more detailed descriptions of system components, such as generator flux decays and excitation controllers. We direct readers to References 8 and 9 for an extensive survey of the family of structure-preserving models.

2.1.2. Frequency stability. Frequency stability refers to the ability of a power system to maintain a steady frequency following a severe system upset that results in a significant imbalance between generation and load (2). It depends mainly on the ability to maintain or restore the balance between system generation and load, with minimum unintentional loss of load. Instability occurs in the form of sustained frequency swings that lead to tripping of generating units and/or loads. Frequency stability has both short- and long-term issues. The time frame of interest spans from several seconds to several minutes, depending on the nature of the different controllers that kick in after the occurrence of a power imbalance.

Since the frequency and angle deviations will not be very large during the time frame of frequency stability analysis, linear models are commonly adopted. A typical example is the linear structure-preserving model, which is obtained by substituting the approximations $V_i = 1$ and $\sin(\theta_i - \theta_j) = \theta_i - \theta_j$ into Equation 3. Unlike Equation 3, where the sinusoid functions induce a substantial amount of nonlinearity and could cause instability, such a linear model is asymptotically stable in general. Actually, a major topic in frequency stability is the design of controllers that steer the angular frequency of each bus—say, $\dot{\theta}_i$—back to the rated value (50 or 60 Hz) as quickly as possible after the power imbalance. Note that the term frequency control is used more often than the term frequency stability; since the study of frequency stability is oriented to control techniques, we do not discuss it further in this section and instead elaborate the relevant results in Section 3.

2.1.3. Voltage stability. Voltage stability refers to the ability of a power system to maintain steady voltages close to their nominal values at all buses in the system after being subjected to a disturbance (2). It is largely a load-oriented issue and depends mainly on the ability to maintain or restore equilibrium between the load demand and the power supply that is transferred from generators via the network. The driving force for voltage instability is usually that the loads tend to restore their power consumption after the disturbance to levels that may be beyond the transfer capability of the power network. Instability occurs in the form of a progressive fall or rise of the voltages of some buses. Voltage stability has both short- and long-term issues that involve fast-acting load components (e.g., induction motors and electronically controlled loads) and slow-acting load components (e.g., tap-changing transformers and thermostatically controlled loads), respectively. The time frame of interest varies from a few seconds to tens of minutes.

In the time frame of short-term voltage stability problems, the behaviors of active powers, reactive powers, voltage magnitudes, and phase angles are all intertwined, which implies that the model cannot be simplified into the form of Equation 3. We have to resort to the general differential-algebraic equation model to study short-term voltage stability. Such a complex model inevitably makes it very hard to figure out the mechanism of short-term voltage stability, and many questions in this field remain open.

For long-term voltage stability, a topic of major concern is the condition that can guarantee the existence and proper sensitivity behavior of a long-term equilibrium. Here, the proper sensitivity behavior is indicated mainly by the voltage regularity, i.e., $\frac{\partial V_i}{\partial P_i} \geq 0$ and $\frac{\partial V_i}{\partial Q_i} \geq 0$ (10). The study of long-term equilibria can be carried out using a steady-state model obtained by letting $\dot{\mathbf{x}} = \mathbf{0}$ in Equation 1. Furthermore, with some simplifications and substitutions, the steady-state model reduces to the usual power flow equation:

$$\begin{aligned} P_i &= \sum_{j=1}^{n} V_i V_j G_{ij} \cos(\theta_i - \theta_j) + V_i V_j B_{ij} \sin(\theta_i - \theta_j), \\ Q_i &= \sum_{j=1}^{n} V_i V_j G_{ij} \sin(\theta_i - \theta_j) - V_i V_j B_{ij} \cos(\theta_i - \theta_j). \end{aligned} \qquad 4.$$

The tuple $(P_i, Q_i, V_i, \theta_i)$ satisfying the power flow equation represents a long-term operating equilibrium, which is also known as a power flow solution. Given the P_i and Q_i of each bus, power flow analysis aims to check whether there exists a voltage solution (V_i, θ_i) and how the voltage solution changes when a perturbation is applied to P_i or Q_i. Power flow analysis can provide mechanism-based explanations for some short- and long-term voltage instability phenomena; for example, the voltage stability limit is indicated by a singularity point of the power flow Jacobian (11).

2.1.4. Converter-driven stability. The above stability concepts work in conventional power grids, where the power sources are mainly fossil fuels and operate in the form of SGs that bring a large moment of inertia. Consequently, stability problems regarding angle, voltage, and frequency involve mainly electromechanical phenomena, the timescale of which is no less than 10^{-1} s. By contrast, future grids will increasingly rely on renewable generation based on converter-interfaced generators (CIGs), which have significantly different features. The dynamics of CIGs have a much wider timescale that leads to cross-couplings with both the electromechanical dynamics of SGs and the electromagnetic transients of the network (12). The CIGs may cause instability phenomena over a wide spectrum, which can be classified into fast- and slow-interaction issues. Fast-interaction instability is driven by the fast dynamic interactions of CIGs and other fast-response components (e.g., electromagnetic dynamics of lines and SG stators). The frequency of unstable oscillations can be up to several kilohertz (13). The models for fast-interaction stability problems need to include the inner (current) control loops of CIGs and network electromagnetics. Slow-interaction instability is driven by the slow dynamic interactions of CIGs and other slow-response components (e.g., the electromechanical dynamics of SGs). The models for this type of stability problems can be obtained by incorporating the outer (power and voltage) control loops or phase-locked loops of CIGs into the conventional differential-algebraic equation model (e.g., see 14, 15).

Single-machine infinite-bus (SMIB) system: a system consisting of a single generator and an infinite bus that are connected via a single line; studies of this type of system focus on how the generator is synchronized with the bus, which represents a giant system

Since CIG modeling involving electromagnetics is an emerging field, and standard models have not yet been developed, this article focuses mainly on stability and control problems related to electromechanical dynamics, which have sophisticated models.

2.2. Traditional Methods

There are two general classes of results for stability assessment: time domain simulation and stability theory. Time domain simulation refers to the numerical computation of the trajectory of a dynamical system. It applies to much-higher-order models than Equation 3 in order to include detailed descriptions of generators and loads, and it provides rich response curves during the prefault, fault-on, and postfault periods. As time domain simulation is not a theme of this article, we do not discuss it further here. In the following, we briefly review the classic results on power system stability theory, a discussion that also serves as background for the review of recent progress in stability theory in Section 2.3.

2.2.1. Angle stability. The most classic theory of angle stability is the equal-area criterion for a single-machine infinite-bus (SMIB) system. For generic systems with multiple generators, the extensions have been made mainly based on the direct method in terms of Lyapunov functions, otherwise called (transient) energy functions. The first Lyapunov function for angle stability analysis was proposed in the 1940s (16) and derived from the network-reduced model. The transfer conductances need to be dropped in order to obtain a well-defined Lyapunov function; however, as mentioned above, this operation may cause significant error in the stability assessment because it effectively ignores the real power loads.

As stated above, the structure-preserving model allowed for the construction of rigorous Lyapunov functions. A Lyapunov function is generally a sum of energies from system components; for example, the Lyapunov function for Equation 3 consists of the kinetic energy of generators and the potential energy of lines. Lyapunov functions have been established for many different power system models that contain more detailed descriptions of generator and load dynamics (9). The direct method estimates the stability region of the stable equilibrium point as a set of initial points at which the Lyapunov function values are less than a critical energy. The critical energy is usually given by the energy value at a certain unstable equilibrium point (UEP), while a different choice of UEP leads to different features of the estimated stability region. For instance, the stability region estimated by the closest UEP method is valid for checking the system stability after any kind of disturbance, but this estimation is also highly conservative. By comparison, the stability region estimated by the potential energy boundary surface method, the controlling UEP method, and the boundary of the stability region–based controlling UEP method is much less conservative but specific to the stability check after a particular disturbance. We direct readers to Reference 17 for a comprehensive study of these methods.

The extended equal-area criterion provides another viewpoint for critical energy. This method projects the dynamics of a generic system into an equivalent SMIB system and then determines the critical energy by applying the equal-area criterion to the SMIB system (18).

2.2.2. Voltage stability. Voltage stability theory has been established largely based on bifurcation analysis. For instance, short-term voltage collapse is closely linked to the singularity-induced bifurcation of the differential-algebraic equation model, which is also known as the impasse surface (19). In addition, saddle-node bifurcation and limit-induced bifurcation are two common indicators of a long-term voltage stability limit. A saddle-node bifurcation occurs when the maximum loadability is reached, which mathematically corresponds to a singularity point of a power flow Jacobian (11). A limit-induced bifurcation is caused by a generator hitting its reactive power limit and leads to a voltage irregular power flow solution (20). As with angle stability, there is a simple and representative system for studying voltage stability: the single-load infinite-bus (SLIB) system. The stability limit points of the SLIB system have analytical expressions. In general cases, the stability limit points are computed mainly by the continuation power flow method (21) or point of collapse method (22).

In general, the traditional methods fall into the category of node-based analysis, i.e., the role of node parameters in stability problems. Research efforts have focused mainly on including more detailed generator dynamics in energy functions (9) or quantifying the impact of generator and load parameters using sensitivity methods (e.g., see 23, 24). This appears to be mainly because the concepts of angle stability and voltage stability are connected to the behaviors of generators and loads, respectively. By contrast, the influence of the power network structure on stability has been paid much less attention. Power network parameters are simply taken as some coefficients in the respective models. The next subsection reviews some of the recent progress on stability theory, focusing in particular on the role of network structure.

Single-load infinite-bus (SLIB) system: a system consisting of a single load and an infinite bus that are connected via a single line; studies of this type of system focus on how an equilibrium can be maintained between the load demand and the power supply from the bus via the line

Algebraic connectivity: the second smallest eigenvalue of $\mathbf{L}_{\mathcal{G}}$

Laplacian matrix: $\mathbf{L}_{\mathcal{G}} = [L_{ij}] \in \mathbb{R}^{n\times n}$, where $L_{ij} = L_{ji} = -w_{ij}$ for $(i, j) \in \mathcal{E}$, $L_{ij} = L_{ji} = 0$ for $(i, j) \notin \mathcal{E}$, and $L_{ii} = -\sum_{j=1}^{n} L_{ij}$

Cut set: a set of all edges with one endpoint in $\mathcal{V}_1$ and the other endpoint in $\mathcal{V}_2$, denoted by $\mathcal{E}^{\mathrm{cut}}$, where $\mathcal{V}_1, \mathcal{V}_2 \neq \phi$ is an arbitrary partition of $\mathcal{V}$ such that $\mathcal{V}_1 \cup \mathcal{V}_2 = \mathcal{V}$ and $\mathcal{V}_1 \cap \mathcal{V}_2 = \phi$

Effective resistance: the effective resistance between two nodes $i, j \in \mathcal{V}, i \neq j$, is $r_{\mathcal{G}}^{\mathrm{eff}}(i, j) = (\mathbf{e}_i - \mathbf{e}_j)^{\mathrm{T}}\mathbf{L}_{\mathcal{G}}^{\dagger}(\mathbf{e}_i - \mathbf{e}_j)$, where $\mathbf{e}_i \in \mathbb{R}^n$ is a vector where the ith entry is one and all other entries are zero

2.3. Graph-Based Methods

The motivation of graph-based stability analysis and the obtained results on different stability problems are discussed below.

2.3.1. Power grids as dynamical networks.

Let us first introduce some basic graph notations. A weighted undirected graph is denoted by $\mathcal{G}(\mathcal{V}, \mathcal{E}, \mathbf{W})$, where $\mathcal{V}$ denotes the set of nodes and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ denotes the set of edges, with $|\mathcal{V}| = n$ and $|\mathcal{E}| = l$, and $\mathbf{W} = \mathrm{diag}\{w_{ij}\} \in \mathbb{R}^{l\times l}$ is the diagonal matrix, with w_{ij} being the weight of edge $(i, j) \in \mathcal{E}$. Signed graphs are considered here, where the edge weights can be either positive or negative.

According to these graph theory preliminaries, a power network induces a graph by treating buses as nodes and lines as edges. Furthermore, power system dynamics such as those described by Equation 3 are essentially a nonuniform multirate Kuramoto model, where the network parameters are embedded into the system dynamics. This is similar to another relevant subject, dynamical networks, which focuses on how collective behaviors are influenced by the structural properties of the underlying network. For instance, a well-known result says that network synchronization is achieved by a sufficiently large algebraic connectivity of the underlying network (25). Therefore, it is natural to push the stability theory of power grids further in the direction of exploiting the role of power network structure (26). In fact, some early works attempted to explore the impact of network structural factors on stability problems (e.g., see 27, 28), but the lack of advanced tools at that time prevented further development. Thanks to the progress on graph theory and network science (e.g., see 29–31), the past decade has witnessed the rise of graph-based stability analysis of power grids.

2.3.2. Angle stability.

Table 1 gives representative references related to the graph-based theory of angle stability. It turns out that the graph Laplacian matrices and cut sets and their associated concepts (e.g., effective resistance and algebraic connectivity) have essential importance in characterizing angle stability under small and large disturbances. Here, the graph has the same topology of the power network. Two kinds of edge weight assignments are adopted in the literature. One takes the line susceptances as edge weights, i.e., $w_{ij} = B_{ij}$; the corresponding Laplacian matrix is

Table 1 Representative references for the graph-based theory of angle stability

Stability category	Graph concepts used in the stability condition
Small-disturbance angle stability	Laplacian matrix (32, 33, 36, 38, 39) Effective resistance (35, 36, 39) Algebraic connectivity (34) Cut set (33, 38)
Transient stability	Laplacian matrix (40, 42) Effective resistance (35, 36, 43) Algebraic connectivity (40–43) Cut set (36, 37)

simply denoted as $\mathbf{L}_{\mathcal{G}}$ in the following. The other includes the angle information at an equilibrium $\theta^{\mathrm{e}} \in \mathbb{R}^n$, i.e., $w_{ij} = V_i V_j B_{ij} \cos(\theta_i^{\mathrm{e}} - \theta_j^{\mathrm{e}})$, which may be negative; the corresponding Laplacian matrix is denoted as $\mathbf{L}_{\mathcal{G}}(\theta^{\mathrm{e}})$ in the following.

The existence and local stability of equilibria, which are two fundamental issues in small-disturbance angle stability, are linked to graph concepts. Dörfler et al. (32) proposed a condition in terms of $\mathbf{L}_{\mathcal{G}}$ for the existence of a unique and stable equilibrium within the region $\{\theta_i | \, |\theta_i - \theta_j| < \frac{\pi}{2}, \forall (i,j) \in \mathcal{E}\}$. Jafarpour & Bullo (33) further established an improved version of this condition using cut set projection. A large algebraic connectivity defined over $\mathbf{L}_{\mathcal{G}}$ also guarantees the existence of stable equilibria (34). For the stability of equilibria, it has been proved that an equilibrium θ^{e} is hyperbolic and locally asymptotically stable if $\mathbf{L}_{\mathcal{G}}(\theta^{\mathrm{e}})$ is positive semidefinite and has only one zero eigenvalue (35, 36). An equilibrium is unstable if a cut set is formed by lines with $\frac{\pi}{2} < |\theta_i^{\mathrm{e}} - \theta_j^{\mathrm{e}}| < \frac{3\pi}{2}$ that induce negative weighted edges (37). The number of unstable manifolds of a UEP can be described by linear matrix inequalities with respect to $\mathbf{L}_{\mathcal{G}}(\theta^{\mathrm{e}})$ (38, 39). Moreover, the local stability of an equilibrium is indicated by positive effective resistances defined over $\mathbf{L}_{\mathcal{G}}(\theta^{\mathrm{e}})$ (35, 36, 39).

Transient stability is also closely linked to these graph concepts. For a power grid with a negligible moment of inertia (i.e., $M_i/D_i = \varepsilon$), the stability region can be estimated in terms of $\mathbf{L}_{\mathcal{G}}$ and algebraic connectivity (40). These results were later extended to a general case with nonnegligible inertia (41, 42). It turns out that a greater algebraic connectivity leads to a greater estimated stability region. Song et al. (35) and Dörfler & Bullo (43) explored the relationship between transient stability and effective resistance and found that a better transient stability is indicated by a smaller positive effective resistance. In addition, the properties of graph cut sets provide a theoretical explanation for the common phenomenon that transient instability is initiated from the angle separation across a cut set in the power network (36, 37). This phenomenon is usually supposed to be related to generator behaviors, but this new finding indicates that it is attributable to the structural properties of the underlying network.

2.3.3. Voltage stability. So far, the progress on graph-based voltage stability theory has been made mainly in the existence of a power flow solution and the singularity of a power flow Jacobian, which falls into the category of long-term voltage stability. Based on fixed-point theorems such as Banach's fixed-point theorem and Brouwer's fixed-point theorem, some novel conditions for the existence of power flow solution have been established (e.g., see 44–47). The admittance matrix, which carries the structural information about the underlying power network, appears explicitly in these conditions and indicates how the parameters of the power network, generators, and loads accommodate a power flow solution as a long-term equilibrium. In addition, as a common type of voltage stability limit, the power flow Jacobian singularity is closely linked to the properties of the admittance matrix. A classic network-related result for SLIB systems says that a SLIB system reaches a singularity point of the power flow Jacobian when the equivalent admittance of the load has the same modulus as the admittance of the single line (11). Through the use of more advanced matrix analysis, this result has been extended to power grids without PV buses (e.g., distribution systems), relying on the development of a general admittance ratio of power network to loads; a generic system reaches a singularity point of the power flow Jacobian when the general admittance ratio is unity (48, 49). This extension figures out how the parameters of the power network, generators, and loads stress the system to a stability limit.

By contrast, the graph-based study of short-term voltage stability is rather preliminary because the associated differential-algebraic equation model is highly complex and hard to analyze. Alternatively, data-based methods are becoming popular in short-term voltage stability assessment, which we elaborate on in Section 4.

2.3.4. Stability in microgrids.

An MG is a low- or medium-voltage power grid consisting of distributed energy resources (DERs) (e.g., renewable CIGs and energy storage systems) and loads. It can be connected to a utility grid (i.e., the grid-connected mode) or operate autonomously to provide electricity to local consumers (i.e., the islanded mode) (50). When working in the grid-connected mode, it can manage its own power balance, either delivering power to or absorbing power from the utility grid as a generator or load. When working in the islanded mode, it can continue to supply power to local loads in case of utility grid failures and hence can increase the system resiliency.

Apart from the specific issues related to CIGs, MGs also inherit common stability issues from conventional power grids regarding angle, frequency, and voltage dynamics (51). Hence, it is natural that MG stability has also been revealed to be closely connected to graph concepts such as the algebraic connectivity of the conductance matrix (i.e., the real part of the admittance matrix). A greater algebraic connectivity indicates a better stability in MGs (52, 53). In addition, Song et al. (54) proved that an MG loses stability in the case of zero algebraic connectivity, and continuing to add CIGs into the MG using a tree-like topology makes the algebraic connectivity approach zero. This implies that the tree-like connection, which is the simplest and cheapest way to integrate CIGs, is harmful to MG stability. By contrast, adding more lines to form loops in the MG network, which helps to maintain the algebraic connectivity, is beneficial to stability.

Overall, the graph-based theory of angle stability has been established in a systematic manner, and graph-based ideas are receiving increasing attention in voltage stability and MG stability. Future results in this direction are expected not only to add to stability theory but also to facilitate new control strategies by means of grid flexibility.

2.4. Further Discussion

Apart from the aforementioned methods, some new trends are also emerging in the stability analysis of power grids, as shown below.

2.4.1. Distributed stability evaluation.

The idea that a stability evaluation is supposed to be done by centralized computation is almost never questioned. This is reasonable for a high-voltage transmission grid because the stability condition usually requires system-wide data, and a control center exists to collect all the required data and execute efficient computations. However, the proliferation of distributed generation is decentralizing power grids into a huge number of small autonomous subsystems. In this case, centralized computation is no longer adequate because it is neither effective in communicating with the numerous subsystems nor friendly to the privacy preservation of the subsystems.

In this context, distributed stability analytics become a more promising solution. So far, the distributed stability conditions have been established mainly by exploiting the structural information carried by the system Jacobian matrix or Lyapunov function. For instance, using the observability property, one can reconstruct the system Jacobian based on the data that an agent collects from the distributed communication (55). The passivity of interconnected systems (56) and separable Lyapunov functions (57–59) are applied to decompose system-wide conditions into a series of conditions with respect to each subsystem. In general, the distributed stability criteria are derived at the cost of increasing conservativeness. Sometimes special controllers are required in order to meet the criteria (56, 59). More research efforts need to be put into reducing the conservativeness of distributed stability criteria.

2.4.2. Beyond equilibrium-based analysis. Conventional stability analysis is oriented to equilibria—that is, it requires the existence of a stable equilibrium point and focuses on the system behavior after applying a disturbance to the equilibrium. Such an equilibrium-based paradigm may become less adequate for future grids using renewable energy sources (60). The uncertain nature of renewable energy means that it keeps injecting continuous disturbances into power grids, so that the system may never reach a state of equilibrium. In this case, the stability analysis needs to go beyond the existing equilibrium-based paradigm to capture this feature. Some recent works have started rethinking the paradigm, replacing equilibria with consensus and related concepts in the analysis. For instance, Zhu & Hill (41, 61) characterized the impact of continuous disturbances on stability using a positively invariant set in terms of node and network parameters. To move toward environmentally friendly power grids that use renewable energy sources, a new paradigm for stability analysis deserves more attention.

3. POWER GRID CONTROL

To enhance stability or to stabilize the system after disturbances, various types of control methods have been developed. Since angle stability is a fast, dynamic phenomenon with a timescale from milliseconds to a few seconds, only limited local fast control actions (e.g., fast valving or the use of braking resistors) have been available to prevent instability. Some more advanced exceptions are excitation control using feedback linearization, preventive control, emergency control, generation shedding, and controlled islanding against cascading events (for some examples, see 62–66), which are becoming more common in practical power system control. Thus, this section focuses on frequency control and voltage control. Of course, as more fast control devices and methods have been used and developed (e.g., energy storage system and demand response), new control methods to deal with angle instability are expected.

In addition, traditional power system control is usually developed for high-voltage networks, because dynamic devices (such as SGs) are connected mainly to these networks in a traditional power system. As more dynamic devices are connected to the grid at different voltage levels, dynamic issues will appear all over the grid. The development of the concept of MGs has brought many advantages, including the integration of renewables and improved system resilience. In fact, an MG can provide a local control platform to solve problems encountered within the MG locally. However, due to the special properties of MGs, frequency and voltage control issues in MGs are quite different from those in high-voltage networks. Therefore, this section also discusses control issues in MGs. We briefly review some aspects of frequency control and voltage control for transmission and subtransmission networks and control of MGs from a control engineering point of view. As we cannot cover everything in this field, we discuss only some aspects that we find interesting.

3.1. Frequency Control

The power system frequency, whose deviation indicates the power imbalance between generation and demand, must be maintained almost constantly at a nominal value (50 or 60 Hz) during normal conditions and must be kept within a prespecified threshold under abnormal conditions (e.g., the trip of a large SG or the loss of a transmission line). Otherwise, underfrequency protection will start load shedding to restore the frequency, and customers will be affected. If this process cannot stop further frequency drops, the protection system disconnects large generation units to protect SGs from physical damage; this in turn enlarges the power deficiency and may lead to cascading failures and blackouts (67).

3.1.1. Traditional frequency control. To maintain the system frequency, traditional power systems focus on generator-side control and make generation follow demand by including a sophisticated control mechanism with a long-term spinning reserve plan and a three-layer hierarchical control structure comprising primary, secondary, and tertiary frequency control (68). The state-of-the-art load forecast techniques provide day-ahead (in hours) and near-real-time (in minutes) demand predictions. The former help the control center to decide which units should be turned on at which generation level (i.e., the unit commitment). In close to near real time, the updated near-real-time load forecast is used in the tertiary frequency control, or economic dispatch, to periodically update set points of generators. The primary frequency control, or droop control, stabilizes the frequency to a new equilibrium point after a contingency. The secondary frequency control, or automatic generation control, then gradually drives the frequency back to the nominal value by automatically adjusting the set points of some selected generators.

3.1.2. New issues. With the high penetration of renewables, the traditional generation-following-demand control paradigm may be inadequate to regulate frequency due to the high intertemporal variation and limited predictability of renewables (69). Under this circumstance, the system uncertainties come from both demand and generation, neither of which can be predicted without errors. Moreover, because renewable generators are usually connected to the grid via power converters, which usually do not provide inertia to the system, high use of renewables may also reduce the total system inertia and make a system more sensitive to contingencies. As more SGs are replaced by CIGs, the system inertia will be reduced significantly and may even vary with respect to time. Ulbig et al. (70) showed that the inertia of a system with high use of renewables decreases significantly and that the frequency with traditional generator-side control will exceed the acceptable region during the transient response after a contingency, which can be handled by the same control method for the system with no renewables. We refer readers to References 60 and 71 for surveys of new issues caused by renewables.

3.1.3. New methods. To address these issues, new control methods and devices have been developed. First, for the generator side, new control methods have been developed for SGs, such as event-triggered control to replace the traditional periodic sampling mechanism of automatic generation control (72) and consensus-based control to replace automatic generation control (73). Recently, wind turbines have also been used to help frequency regulation by optimally controlling their rotor speeds and pitch angles (e.g., 74). Different control methods have also been designed for CIGs, such as droop control, the virtual synchronous machine strategy, and virtual oscillator control. More details on CIG control are provided in References 60 and 71 and references therein.

Energy storage devices have a high ramping capability and thus can help to eliminate fast frequency deviations caused by renewables. For primary frequency control, energy storage devices can provide droop control service and synthetic inertia (75). They can also participate in secondary frequency control, where the key problem is how to fully consider different characteristics of SGs and storage devices. Usually, the load signal is decomposed into a slow-moving but possibly biased component and a fast-moving but energy-limited one, and SGs and storage devices are used to track these two components, respectively. In addition, how to consider different characteristics of different storage devices (e.g., energy-to-power ratios) is an issue that deserves attention. Mégel et al. (76) obtained some preliminary results in this direction, formulating the problem as an optimization problem and then solving it in a distributed way.

Due to properties such as instantaneous response, economic efficiency, and distributed availability throughout the grid, load-side control (demand response) has received an increasing amount of attention (77). Smart loads, such as loads with electric springs (78), have the ability to adjust their active power continuously to follow the change in generation, leading to a new control paradigm in which demand follows generation. Various types of load-shedding methods have been successfully used in practice to restore the frequency in extreme situations (79); the difference between load shedding and load-side control is that the latter aims to secure the system's operation while minimizing the impact on end users. Two goals must therefore be considered simultaneously: One is to be fully responsive, with high-resolution system-level control across multiple timescales, and the other is to be nondisruptive, with an imperceptible effect on end-use performance (77). Liu et al. (80) proposed a novel distributed switching control method to balance the two conflicting targets, where the designed load-side controller can work in either a frequency restoration mode or a load restoration mode determined by a well-designed switching signal.

Power systems traditionally have a hierarchical structure consisting of transmission, subtransmission, and distribution systems. Frequency control problems are usually considered at the transmission level, with loads that can be the aggregation of loads in a subtransmission network. Similarly, a load in a subtransmission network can be the aggregation of all loads in the related distribution systems. How the control signal obtained in transmission systems can be split down to the subtransmission systems and then to the distribution systems needs to be carefully investigated. Addressing this issue may require using the idea of granular control, where all controllable devices need to work together and behave exactly as required by the higher-level controllers. However, due to the higher resistance/reactance ratio in these networks, active power changes may also cause voltage problems, and thus both frequency and voltage must be considered simultaneously. Zhang et al. (81) have reported some preliminary results along these lines, using a distributed leader–follower consensus algorithm for frequency control and decentralized voltage control to guarantee bus voltages.

A related issue is the dynamical model for each aggregate load. Loads are dynamical systems. With CIGs, storage devices, and a load-side controller involved, the aggregate load dynamics will be enhanced and may change quickly (82). Therefore, they will play an increasingly important role in frequency control, and how to build an accurate load model deserves attention.

3.2. Voltage Control

The primary target of voltage control is to maintain bus voltages in a power system within expected ranges under diverse operating conditions. Various control actions can achieve this result, such as generation rescheduling, excitation adjustment, reactive power compensation, on-load tap changer regulation, and emergency load shedding (11).

3.2.1. Traditional voltage control. Traditional voltage control schemes can be categorized into two classes based on the system status: voltage stability control, which is used in stressed or risky situations (11, 83), and automatic voltage control, which is used in normal conditions (84, 85). Voltage stability control aims to address the aforementioned voltage stability problems. During online operation, if a system is predicted to be insecure with respect to potential contingencies, preventive control strategies such as generation rescheduling can be used to regain sufficient security margins. Since it may be impossible to preventively stabilize the system against all contingencies, corrective control is used as a complementary countermeasure and is expected to be automatically executed quickly after an emergency situation occurs. For example, although load shedding can significantly affect the power supply, this type of action can effectively save the system from voltage collapse induced by either small or large disturbances (86).

Automatic voltage control is devoted to optimally regulating system-wide bus voltages during normal operation. Similar to traditional frequency control, automatic voltage control can be implemented in a three-layer hierarchical control structure that includes primary control, secondary control, and tertiary control (84). When automatic voltage control is used, the system is far from an emergency situation and thus can be gradually governed toward optimized voltage profiles via mild actions such as generation rescheduling, on-load tap changer adjustment, and voltage or reactive power control (87).

3.2.2. New issues. Renewables also cause new voltage issues for power systems. In particular, variable renewable generation may cause fast and dramatic voltage changes. In subtransmission and distribution systems, such changes may be larger than those in transmission systems due to their higher resistance/reactance ratios (88). Moreover, the reverse power caused by renewables may lead to voltage rise issues and cause incorrect actions of protective devices and disconnection of equipment. This subsection therefore focuses on voltage control in subtransmission and distribution systems.

Traditional voltage control in these networks uses on-load tap changers and capacitors that have discrete steps (89) but may be inadequate for new voltage issues. First, on-load tap changers and capacitors may not be fast enough for voltage regulation under the new circumstances (90) due to their discrete control nature. Second, they may undergo excessive numbers of operations, which may reduce their lifetimes significantly (91). Thus, new control methods are needed to deal with these new issues.

3.2.3. New methods. As in frequency control, CIGs, storage devices, and flexible loads can all participate in voltage control. In fact, these three types of devices, known as DERs, can provide fast active and reactive power support for voltage regulation through the control of electronics that interface them with the grid. Problems in this area include how to coordinate DERs scattered in a network and how to cooperate with the existing voltage control devices (e.g., on-load tap changers and capacitors). Load-side control provides an example. The two goals of load-side control discussed above in relation to frequency issues also apply here. On the one hand, traditional voltage control devices have slow control actions; on the other hand, load-side control needs to minimize the impact on end users. To deal with these issues, Tang et al. (92) proposed a novel coordinated control framework to handle negative voltage impacts in a weak subtransmission system, where traditional voltage controllers are used to regulate voltage deviations in the system all the time and the load-side controller is activated only when needed—for example, when the traditional voltage controllers cannot keep voltages within the expected ranges.

Another issue with using DERs for voltage control relates to the hierarchical structure of power systems, where a subtransmission system may have many different DERs scattered in different distribution systems. It may be hard to control these DERs directly using the subtransmission voltage controller. Again, the idea of granular control may help. For example, Tang et al. (93) treated distribution systems with DERs as clusters that serve as intermediaries between small DERs and the subtransmission voltage controller. Due to the high resistance/reactance ratio, the active power changes of DERs can also cause serious voltage issues in distribution systems. To address this issue, the authors developed a novel two-module distributed control framework where a command-following module is used to track the active power change command from the subtransmission voltage controller by coordinating the active power of the DERs, and a power quality management module is used to improve the power quality by coordinating both the active and reactive power of the DERs.

Voltage issues in distribution systems can also be handled by network reconfiguration. For example, Song et al. (94) formulated a new reconfiguration model that minimizes the network loss and restricts the voltage volatility indices with the coordination of switched capacitor banks, which provides some new insights regarding voltage issues in distribution systems with high renewable penetration.

3.3. Control of Microgrids and Networked Microgrids

The concepts of MGs and networked MGs refer to key modules for future power grids where distribution systems with distributed generators can be clustered into connected MGs. By controlling a huge number of connected MGs properly, keeping a local power balance within each MG, and making them help each other, we may solve all problems locally. The key problem then becomes how to operate a stable MG and a networked MG.

3.3.1. Control of microgrids. To safely operate an MG, we need instantaneous control to stabilize the MG when it is subjected to disturbances (i.e., controller design). To economically operate an MG, we need to optimally manage its controllable devices within a certain time period (i.e., energy management system design). We must also integrate these ideas to form an automatic control system that includes an upper-layer energy management system and a lower-layer instantaneous control system. When operating an MG, a hierarchical control structure is usually adopted that combines centralized and decentralized methods—that is, controlling the MG requires a control center (95). This control method was originally developed for high-voltage power systems and may reduce control performance or even jeopardize stability if the distinctive characteristics of MGs are not properly considered.

Frequency and voltage are the two core interacting issues in ensuring stable MG operation. Many works have focused on the controller design of CIGs. If used alone, this generation-type control may have some limitations. First, CIGs such as wind and solar plants are usually connected to the system via electronic devices that do not provide any system inertia. To overcome this issue, droop control [e.g., P–f and Q–V droop control (96, 97)] is designed to maintain an instantaneous power balance. Achieving better transient performance requires high droop gains, which may jeopardize stability (98). Second, distributed renewable sources have a limited control capacity, which limits the MG's ability to survive large disturbances (99).

Load-side control and ancillary devices (e.g., energy storage and reactive power compensators) offer possible ways to address these issues. In particular, controllable loads [e.g., voltage-dependent loads (100) and loads with electric springs (78)] are used to regulate frequency by adjusting load bus voltages within certain ranges. These ideas create a new way to regulate frequency and voltage simultaneously by using load-side control. However, Lee et al. (78) showed that a cooperative control method using a group of smart loads may have positive effects on system performance, whereas a decentralized control method may lead to negative impacts and even instability. This issue may also apply to the control of the other types of controllable devices in MGs. Therefore, a cooperative control method is needed to make controllable devices work properly in a coordinated way.

In contrast to large-scale power systems, it is difficult to implement a supervisory control center in MGs due to issues such as the high cost of communication lines (101). The plug-and-play nature of MGs (102) also limits applications of centralized algorithms that are sensitive to changes. To meet these new requirements, distributed algorithms have been extensively used to address issues in MGs (for examples, see 55, 103, 104). Combining the hierarchical control idea with distributed algorithms should enable the development of an automatic control system under which MGs can operate stably and economically.

3.3.2. Control of networked microgrids. A single MG usually has limited operational flexibility (105), which may limit its ability to tolerate large disturbances. A feasible way to solve this problem is to connect nearby MGs and form a larger system (99); the key problem is then how to make these MGs help each other without introducing new problems.

Different aspects of the concept of networked MG systems have begun to attract attention, including self-healing (106), energy trading (107), and load sharing (108). However, most works in these areas have focused on energy management issues. Liu et al. (109) studied the frequency control problem in a two-MG system using voltage-dependent loads. The results showed that the control performance of the networked MGs is significantly better than the performance of each individual MG when they are subjected to the same disturbance, and the networked MGs could survive a larger disturbance by helping each other maintain frequency and bus voltages within the allowable ranges. However, important control issues remain open—for example, how to optimally manage power trading between MGs and regulate the tie-line power between connected MGs for stable operations. Again, the integration of hierarchical control and distributed algorithms may provide a way to solve these problems.

3.4. Further Discussion

Most of the traditional control methods are model based. Strictly speaking, every model is wrong to some extent because of the complexity and many types of uncertainties involved, including both structured and unstructured uncertainties, which may influence model-based control performance.

Economic mechanisms have also led to an increase in stresses on the grid. For example, the growing use of renewables increases the complexity of power balance control, and the use of rooftop solar power and batteries in the distribution systems changes customers from pure power consumers to prosumers who can also supply power to the grid. Solving these problems requires new concepts, such as transactive energy—a system of economic and control mechanisms that use value as the key operational factor and allow a dynamic balance between generation and demand across the whole power system (110). All of these developments call for new ideas and methods, which may lead to approaches such as combining big data with traditional control and game theory.

4. DATA-BASED STABILITY ANALYSIS AND CONTROL

In today's power grids, with the availability of huge volumes of operational data acquired by advanced sensors such as phasor measurement units (PMUs) (111), data-driven solutions for power grid stability analysis and control hold great promise. In particular, the advancement of ML technologies, especially the emerging deep learning (DL) approaches (112), has made such data-driven solutions more tractable and powerful than ever before. In the following, we focus on how ML approaches are leveraged to address various problems of power grid stability analysis and control from a data-driven perspective. While other data-based methods that do not include explicit learning (e.g., time series analysis, signal processing, and data-enabled model predictive control) have also been developed in recent years, they fall outside the scope of this section. Unlike the sections above that reviewed existing studies on model-based power grid stability and control based on specific stability issues and the mathematical models adopted therein, here we group data-based solutions into different classes for detailed review according to the inherent nature of the different ML methods. As shown below, ML methods of the same class can be exploited to address different stability issues once they are appropriately designed.

Environment: for power grids, the actual operational context of the grid or the virtual context specified by the grid's numerical simulation model

Dynamic stability/security assessment (DSA): a method of quickly and reliably performing power grid stability or security analysis, especially for online monitoring contexts, to enhance the grid's awareness of risky situations

4.1. Overview of Machine Learning–Based Solutions in Power Grids

The ML field comprises two basic classes of methods: supervised learning and unsupervised learning (113). While the former tries to learn a mapping from input–output pairs (e.g., classification and regression), the latter aims to uncover the inherent data distribution and characteristics of the inputs in the absence of outputs (e.g., clustering). If some learning instances are labeled with explicit outputs, semisupervised learning can be performed to learn knowledge from both labeled and unlabeled data. In addition to these ML approaches, there exists another special class of ML methods called reinforcement learning (RL) (114). In general, RL strives to train an agent by iteratively exploring and interacting with a given environment.

Here, we further classify all of these methods into two major categories according to their learning data flows: feedforward learning (which includes supervised, unsupervised, and semisupervised learning) and interactive learning (which includes RL). **Figure 1** illustrates how these categories work in the context of power grids. As can be seen in the figure, both of them involve two basic phases: offline learning and online application. Because most of the computational burdens are concentrated on offline learning, the online application phases incur almost negligible computational costs, which often enables ML-based solutions in power grids to achieve extremely high online efficiency. This is a significant advantage over conventional model-based methods, especially when the latter involve complicated optimization. In addition, with no limitations on system scale or complexity, ML-based solutions are more applicable in practical contexts and can therefore be extensively deployed in various grids. For detailed applications, although feedforward ML can be widely applied to both grid dynamic stability/security assessment (DSA) and control, interactive RL is generally more suitable for control issues, as shown below.

4.2. Data-Driven Power Grid Dynamic Stability/Security Assessment

Given a specific system (grid) with n major buses, data-driven DSA generally aims to quickly predict its stability/security status and/or margin after encountering a certain fault. Specifically, the prediction is carried out by inferring the input–output mapping $\mathcal{F}: \mathbf{x} \rightarrow y$ for $\mathbf{x} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$. Here, $\mathbf{x}$ denotes the initial system states observed in prefault or early postfault stages, and y represents the eventual stability/security status or margin of the dynamic process induced by the fault. For the state observed at bus i ($1 \leq i \leq n$), i.e., $\mathbf{x}_i$, it can be either measured/featured data points obtained from specific snapshots of the system dynamics or time series trajectories sequentially acquired from a given time window. To comprehensively capture the system dynamics, multiple variables at bus i, such as the bus voltage magnitude, phase angle, frequency deviation, active power, and reactive power (V, θ, Δf, P, and Q, respectively), can be gathered into $\mathbf{x}_i$. The output y can be either a binary label indicating the stability/security status or a continuous value quantifying the stability/security margin. Based on the means of feature extraction or learning from $\mathbf{x}$, we divide the reviewed data-driven DSA studies into three groups, as presented in **Table 2**.

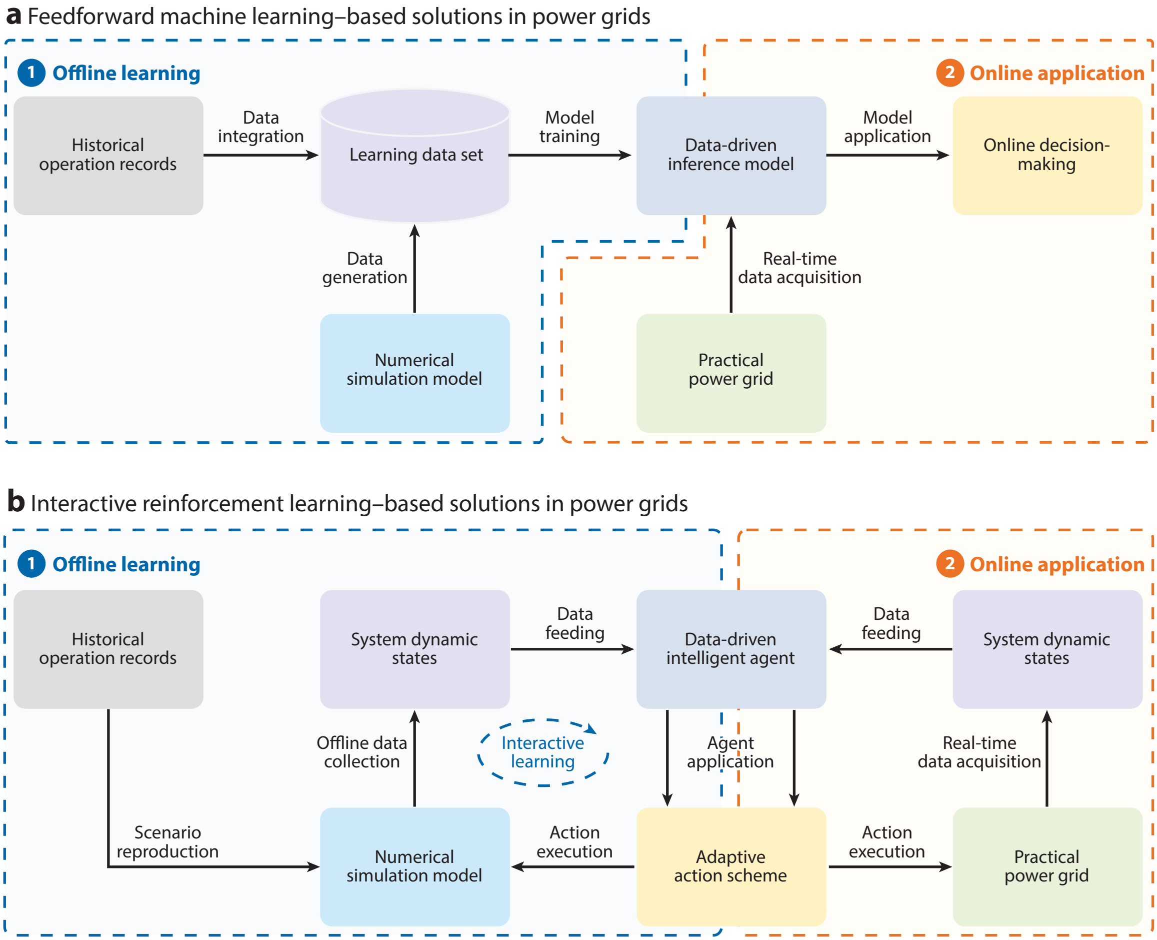

Figure 1

(*a*) Feedforward machine learning–based and (*b*) interactive reinforcement learning–based solutions in power grids.

Table 2 Representative references for data-driven power grid dynamic stability/security assessment

Means	Stability issues	Learning methods
Snapshotted feature engineering	Transient stability (115, 116) Short-term voltage stability (117, 118) Long-term voltage stability (119, 120) Frequency stability (121)	Decision tree (115) Random forest (119) Support vector machine (116, 119) Multiple linear regression (120) Artificial neural network (119) Extreme learning machine (117, 121) Random vector functional link (118)
Temporal dependency learning	Transient stability (122, 123) Short-term voltage stability (124, 125) Long-term voltage stability (126)	Convolutional neural network (122) Recurrent neural network (123) Shapelet learning (124–126)
Spatial–temporal correlation learning	Transient stability (128) Short-term voltage stability (129–131)	Graph convolutional network (128, 129) Recurrent neural network (130) Shapelet learning (131)

4.2.1. Snapshotted feature engineering for dynamic stability/security assessment. This line of work generally takes system states acquired from single snapshots or handcrafted feature values calculated from specific snapshots as inputs to learn system stability patterns. Following this basic idea, data-driven DSA has been carried out for various stability issues, including transient stability (115, 116), short-term voltage stability (117, 118), long-term voltage stability (119, 120), and frequency stability (121). With individual dimensions of inputs presented in the form of single values, a wide variety of classic ML algorithms can be employed to derive DSA models, including decision trees, random forests, support vector machines, multiple linear regression, multilayer perceptron–based artificial neural networks, and randomized artificial neural networks such as extreme learning machines and random vector functional links. These methods generally have shallow learning structures, which fit well with snapshotted inputs involving flat data structures. As these efforts merely take data points or featured values obtained from individual snapshots of system dynamics as independent inputs for learning, they could fail to capture the inherent evolution features hidden behind system dynamic trajectories. Without sufficient feature learning, it may be difficult for the obtained DSA models to generalize to online application contexts, where various unforeseen operation scenarios with complicated system dynamics constantly occur.

4.2.2. Temporal dependency learning for dynamic stability/security assessment. In contrast to the above data-driven DSA efforts, which learn information from certain snapshots independently, approaches based on temporal dependency learning take temporal dependencies or correlations within the system dynamics into sufficient account for stability feature learning. In particular, assuming that the intrinsic temporal dependencies are well preserved in system time series trajectories, they take multidimensional time series data acquired from individual buses as the raw inputs to derive DSA models. To learn from such consecutive time series inputs, they generally employ emerging DL techniques with a stronger capability in feature learning and representation, such as convolutional neural networks (122) and recurrent neural networks (123). Due to their advantage in uncovering stability features from large-disturbance-induced system dynamics, these DL-based methods have been widely applied to address stability issues on transient timescales. However, we would like to note that, as the DSA models derived from DL are essentially black boxes with no interpretability, it would be difficult for system operators to comprehend how they work effectively in practical DSA.

Given the need for both temporal dependency learning and interpretable model derivation, a new explainable learning approach called shapelet learning has been introduced in power system online DSA in recent years (124–126). Similar to the well-known wavelet concept, shapelets are local subshapes (subsequences) of time series that are discriminative enough to clearly distinguish different classes of time series instances (127). The shapelets are first extensively searched from all the time series instances and then taken as critical features to measure the differences between individual time series instances via distance values. Doing this transforms the raw time series data into flat distance data, which can be compatibly handled by various standard ML algorithms for DSA model derivation. As the shapelets are essentially representative time series subsequences, they are quite interpretable and can help provide intuitive insights into the critical evolution patterns of system stability.

4.2.3. Spatial–temporal correlation learning for dynamic stability/security assessment. In addition to paying special attention to temporal dependencies, efforts on spatial–temporal correlation learning further take the inherent correlations between buses in the grid into explicit account. Specifically, considering the irregular graph-like structure of the power grid, some of them apply a promising DL method called graph convolutional networks to tackle the online DSA issue

(128, 129). With the help of such a network, the irregular power grid structure is embedded into the learning procedure to account for networked spatial correlations between individual buses; conventional convolutional neural network or recurrent neural network modules are further added to enable temporal dependency learning. Recently, Zhu et al. (130) made a different attempt by formulating spatial correlations as attention factors to govern recurrent neural network–based temporal dependency learning.

On the basis of the shapelet learning approach, Zhu et al. (131) developed an interpretable spatial–temporal feature learning scheme. By quantifying spatial correlations with geospatial information on practical substations (buses), this scheme constructed wide-area voltage animations to incorporate system spatial information with temporal dynamics. The obtained DSA model can interpret system voltage stability characteristics from a wide-area spatial–temporal perspective. However, its reliability depends greatly on the precision of the geospatial information, which may not always be guaranteed in practice.

4.3. Data-Driven Power Grid Control

When a data-driven DSA model identifies system instability or insecurity, corrective or preventive control actions should be taken as soon as possible to restore stable or secure operation. In addition, in normal operating conditions without large disturbances, proper control measures should be used to maintain variables such as bus voltages and frequencies within desired ranges. Similar to the above data-driven DSA task, these control problems can be addressed from a data-driven perspective. **Table 3** summarizes representative studies involving data-driven power grid control in three classes.

4.3.1. Feedforward machine learning–based solutions. Feedforward ML-based solutions resemble the data-driven DSA efforts reviewed above, with the potential of ML methods in mapping inference sufficiently explored to figure out adaptive online control strategies. These solutions have been implemented to tackle diverse control issues, including transient stability control (132, 133), voltage stability control (134, 135), and frequency control (121). Among them, various ML algorithms have been employed to help derive data-driven control schemes, including decision trees, support vector machines, artificial neural networks, extreme learning machines, and recurrent neural networks. The most straightforward way to implement these schemes is to directly learn the mapping between system dynamic states and the optimal control actions (121, 134).

Table 3 Representative references for data-driven power grid control

Category	Control problems	Learning methods
Feedforward machine learning–based approaches	Transient stability control (132, 133) Voltage stability control (134, 135) Frequency control (121)	Decision tree (132) Support vector machine (133) Artificial neural network (134) Extreme learning machine (121) Recurrent neural network (135)
Interactive reinforcement learning–based approaches	Transient stability control (136) Voltage stability control (136) Automatic voltage control (137) Frequency control (138) Wide-area damping control (139)	Q-learning (139) Deep Q-network (136) Soft actor–critic (137) Deep deterministic policy gradient (138)
Other learning approaches	Automatic voltage control (141, 142) Wide-area damping control (143)	Approximate dynamic programming (143) Knowledge search (141, 142)

Alternatively, by constructing a stability/security space with decision variables, a risky case can be moved to the stable/secure region by properly adjusting the decision variables, which implicitly yields the control strategy (132, 133). Zhu & Luo (135) recently developed a promising recurrent neural network learning approach that incorporates the basic idea of model predictive control into ML. By predicting system voltage changes after taking potential control actions, it can efficiently minimize the cost of control actions while satisfying voltage recovery requirements for voltage stability control. However, we should mention that these solutions either rely heavily on the preparation of a high-quality case base with optimal control experiences (121, 134) or depend largely on the precision of system dynamics prediction for control strategy derivation (132, 133, 135).

4.3.2. Interactive reinforcement learning–based solutions. As illustrated in **Figure 1*b***, interactive RL is well suited to adaptive control in power grids. Let a system trajectory obtained from the interactive procedure shown in **Figure 1*b*** be described as $\tau = \{s_0, a_0, s_1, r_1, a_1, \ldots, s_{T-1}, r_{T-1}, a_{T-1}, s_T, r_T\}$, where s_i and a_i are the observed system state and executed control action at the ith ($0 \leq i \leq T$) time step, and r_{i+1} ($0 \leq i \leq T-1$) is the reward obtained by executing action a_i after observing system state s_i (with the system state changed to s_{i+1}). The aim of RL is to derive an optimized decision strategy $\pi^*(a|s)$ that can maximize the accumulated rewards—i.e., $R(\tau) = \sum_{i=0}^{T-1} \gamma^i r_{i+1}$, where $\gamma \in [0, 1]$ is a discount factor that determines how important future rewards are with respect to the current state. In power grids, relating the rewards $R(\tau)$ to different electrical variables for control performance optimization enables various control problems to be handled, including transient stability control (136), voltage stability control (136), automatic voltage control (137), frequency control (138), and wide-area low-frequency oscillation damping control (139).

Classical RL algorithms such as Q-learning (114) generally define system states and actions in discrete spaces, which would limit their applications in practical grids with diverse continuous variables. In recent years, by systematically combining DL with RL, an advanced RL paradigm called deep reinforcement learning (DRL) with a stronger capability in learning representation and generalization has exhibited great potential in many complex control and decision-making problems, including the game Go (140). Given the significant advantages of DRL, some typical algorithms (e.g., deep Q-networks, the soft actor–critic algorithm, and the deep deterministic policy gradient method) have been recently introduced into power grids and provided excellent performance on various control tasks (136–138). However, RL/DRL approaches generally must learn the optimized control strategies via numerous trial-and-error interactions, which makes them computationally costly. For practical large-scale grids involving tens of thousands of buses and transmission lines, high-performance computing platforms would be needed.

4.3.3. Other learning approaches. Following the basic learning idea in ML-based solutions, some related learning schemes have been developed for power grid control in recent decades (141–143). Among them, a popular approach called approximate dynamic programming has been employed to address typical control tasks such as low-frequency oscillation suppression (143). In fact, approximate dynamic programming works in the same manner of interactive learning as RL does but from a stochastic decision and programming perspective. Ma & Hill (141, 142) reported a class of automatic coordinated voltage control schemes based on knowledge search. In this scheme, a knowledge base consisting of representative optimally controlled cases is prepared and then applied to online voltage control via knowledge search. Concretely, the case that best matches the current online operation scenario is picked out from the knowledge base for application. Although no ML algorithm is explicitly involved, this method adopts the basic idea of nearest-neighbor-based learning (113).

4.4. Further Discussion

In the above subsections, instead of exhaustively introducing all the related ML applications, we have selected some representative studies to categorize and review. For more extensive summaries of ML/DL applications to power grid stability and control, we refer interested readers to several recent surveys (144–146). Although ML-based solutions have shown great potential in power grid stability and control, they still face many significant challenges in practice, and they still have a long way to go before they will be widely applicable in practical grids. In the following, we briefly discuss relevant challenging yet crucial issues that deserve more systematic research efforts in the future:

- Incorporating model-based and data-based methods: Although the use of data-based solutions assisted by advanced ML techniques to address various stability and control issues in power grids is highly promising, their performance could be further boosted if the conventional model-based methods were systematically incorporated with them. Doing so would take advantage of the strengths of both model-based and data-based methods, helping create more powerful solutions.
- Reducing the reality gap between simulation models and practical contexts: Existing ML-based solutions generally assume that offline numerical simulation models can effectively mimic practical grids. However, due to unavoidable system modeling and simulation errors, there are nonnegligible reality gaps between them, meaning that the obtained data-driven solutions deviate from practical contexts. In this respect, it is necessary to improve the fidelity of offline learning data to mitigate the drift of offline ML procedures.
- Improving the interpretability of data-driven solutions: Unlike model-based methods, which usually involve explicit physical significance, data-driven solutions—especially DL-based alternatives—often make decisions in black-box form. In practice, it would be difficult for system practitioners on the industrial side to accept such nontransparent decisions and believe that they can reliably work all the time. Hence, there is an imperative need to develop more interpretable ML schemes without sacrificing learning performance. In fact, this can not only promote the acceptance of ML solutions in the electric power industry but also provide interpretable knowledge uncovered from data to help practitioners better understand the complicated characteristics of practical grids.
- Addressing the rarity of unstable or unsafe scenarios: In spite of the high risk of encountering various faults, practical power grids can maintain stability in most cases and are unstable or unsafe in only a few situations, which tend to be rare in practice. It can therefore be hard to rigorously validate the reliability of a data-driven solution in practical contexts, especially when simulation models are not precise enough to mimic practical conditions. To address this issue, realistic data augmentation should be carefully carried out. In addition, the rarity of unstable or unsafe scenarios may distort learning cases, but this can be mitigated by specific tricks, such as over- or subsampling and cost-sensitive learning.
- Enhancing the robustness to practical defective environments: Because data-driven solutions are built on system operational data, the data quality acts as a cornerstone for their reliable implementation in practice. In practical contexts, however, due to the inevitability of defective measurement and communication conditions, PMU data errors or dropouts and wide-area communication delays or failures reduce the quality of online PMU data. Moreover, considering possible cyberattacks in modern power grids, the PMU data quality issue may be more severe. In this regard, more robust ML schemes need to be designed

against various defective conditions. In recent years, some efforts have been made to tackle specific types of defective data issues (118), yet more powerful solutions are still needed to comprehensively address diverse low-quality data conditions.

- Adapting to online changing conditions: Due to the uncertainty and variability introduced by various renewable energy sources and loads, the operating conditions of practical grids generally change over time, meaning that data-driven models that were initially learned from limited offline scenarios are constantly encountering unforeseen scenarios. To enhance a model's adaptability to online changing conditions, it must be periodically updated via online continuous learning. To this end, lifelong or incremental learning strategies (112) can be carefully designed to help it closely follow changing conditions and enable new knowledge discovery.
- Transferring knowledge between related power grids: For existing ML-based solutions in power grids, data-driven models are often devoted to specific systems. For new systems, or even expanded existing systems, they are often learned from scratch, which incurs heavy offline computational burdens, especially in practical large-scale systems. Although this does not influence online efficiency, it could impede the efficient implementation of the online model updates described above. In fact, if a practical large system shares some similarities with a small one, a new data-driven model can be efficiently derived for the former by strategically transferring knowledge first learned from the small one. In addition, instead of learning from scratch, this knowledge transfer may provide a better starting point to accelerate offline learning in a large system.
- Implementing ML-based schemes in a distributed manner: The majority of existing ML-based solutions in power grids are assumed to be deployed in a centralized way, where system-wide data such as PMU measurements are uploaded to the control center for ML implementation. This could create a high risk of data leaks as well as heavy communication burdens. If these problems become major concerns in practice (e.g., networked MGs being sensitive to data privacy and communication flexibility), then distributed ML implementations such as federated learning (147) would be a necessity.

5. CONCLUDING REMARKS

This survey has provided a brief overview of power grid stability and control. In addition to summarizing classical model-based analysis and control approaches, we have highlighted some new trends, including stability issues induced by renewable energy sources, graph-based methods, distributed stability analysis and control, and networked MG control. Given the potential of data-based methods in tackling some conventionally challenging issues in practical grids, we have also discussed recent progress in data-driven power grid DSA and control as well as some unsolved problems. We hope this survey can inspire more innovative ideas, methods, and technologies to further develop new solutions for secure yet sustainable operation and control of future power grids.

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Errata

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