INVITED PAPER

Data-Driven Security and Stability Rule in High Renewable Penetrated Power System Operation

This article discusses how to extract accurate and compatible security and stability rules in high renewable penetrated power systems based on machine-learning frameworks.

By Ning Zhang, *Senior Member IEEE*, Hongyang Jia, *Graduate Student Member IEEE*, Qingchun Hou, *Member IEEE*, Ziyang Zhang, *Graduate Student Member IEEE*, Tian Xia, *Graduate Student Member IEEE*, Xiao Cai, *Graduate Student Member IEEE*, and Jiaxin Wang, *Student Member IEEE*

ABSTRACT | Power systems around the world are experiencing an energy revolution that substitutes fossil fuels with renewable energy. Such a transition poses two significant challenges: highly variable generators that add short-term and long-term difficulties for supply–demand balance, and a high proportion of convertor-based devices that may jeopardize power system security and stability. At the same time, machine learning techniques provide more opportunities to study the complex power system security and stability problems. This article summarizes the machine learning framework to embed security rules into power system operation optimization under high renewable energy penetration. First, we explore how high penetration renewable energy impacts power system security and stability. Then, we review how the complex security and stability boundary of power systems is modeled using various machine learning techniques. Finally, we show how the machine learning model is transformed into optimization constraints that can be embedded into the power system operation model. The framework is substantiated through case studies of practical power systems.

KEYWORDS | Data-driven; high penetration of renewable energy; power system security; power system stability; rules embedding; rules extraction; security-constrained economic dispatch (ED).

I. INTRODUCTION

A. Background

The revolution of the smart grid enables real-time monitoring and active response to changes in electricity supply and demand, making the power system more adaptive to accommodate renewable energy. By taking advantage of the smart grid transition, power systems around the world are paving the way toward the carbon neutrality goal. Wind power and photovoltaics (PVs), which are denoted as variable renewable energy (VRE), are substituting fossil fuel generators and will become the major power supply of power systems. China set its carbon peaking and carbon neutrality goals in 2020 [1]. The wind power and PV in China's power system will increase from 250 and 230 GW in 2020 to approximately 2500 and 2400 GW in 2060, respectively, which will comprise 70% of the electricity supply (up from less than 10% in 2020) [1], [2]. The possibility of a 100% renewable energy supply in the United States [3], Europe [4], [5], [6], and Australia [7] has been widely discussed. It is estimated that wind power

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(Corresponding author: Ning Zhang.)

The authors are with the State Key Laboratory of Power Systems, Department of Electrical Engineering, Tsinghua University, Beijing 100084, China (e-mail: ningzhang@tsinghua.edu.cn; jhy21@mails.tsinghua.edu.cn; hqc16@tsinghua.org.cn; zy-zhang19@mails.tsinghua.edu.cn; t-xia19@mails.tsinghua.edu.cn; caix20@mails.tsinghua.edu.cn).

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and PV will account for 87.9% of the electricity supply in the United States to achieve a 100% renewable energy power system [3]. Wind power and PV will reach 57% in France when it achieves carbon neutrality [5]. This proportion would be 75% for all of Europe [6]. If the full energy system in Germany is to be decarbonized, the energy penetration of wind power and PV will need to reach 57%–82% [4].

High penetration of VRE will permanently change the structure of power systems. The most significant characteristics of VRE compared with traditional thermal or hydro generators are twofold. On the one hand, the output of VRE is driven by weather, e.g., wind or sun radiation, which makes it highly variable and difficult to control in terms of following the load. On the other hand, the VRE is connected to the power system via power electronic devices, e.g., wind power is connected to the power system through power electronic-controlled doubly fed induction generators or full-capacity power converters. PV is connected to the system using power inverters. When the energy penetration of VRE increases beyond 30% of the load (which is regarded as high penetration), the power system operation would be dominated by VRE [8]. VRE presents several challenges, including supply and demand balancing issues, stability issues, zero marginal cost issues in the power market, and flexibility issues [9]. Currently, there is no single balancing power system that can sustain more than 50% VRE penetration. Although wind supplies more than 50% of Denmark's power system, it is not a single balancing power system, as it is connected to Germany and other Nordic countries [6].

B. Motivation

Among the various challenges of high penetration VRE, security and stability issues are of the highest concern [10]. Security and stability are two basic requirements for the normal operation of power systems. According to Kundur *et al.* [11], security of a power system refers to the degree of risk in its ability to survive imminent disturbances without interruption of customer service, and power system stability is defined as the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact. The definition of power system security is from the operation management point of view, while the definition of power system stability is from the power system physics and dynamics point of view. Their connotations sometimes have overlap. The large variation in VRE output and the high penetration of power electronics in VRE generators affect power system security and stability. Large output variation would yield diverse patterns in power system operation. The security and stability of power systems under different periods, e.g., high PV output at noon and high wind power output at night, may not follow the same criteria. The power electronics brought by VRE largely complexify the stability of power systems. With a decrease in the share of synchronous generator-based thermal or hydro power generation, the synchronous inertia of the power system is reduced. The synchronous inertia of the European power grid is estimated to have fallen by 20% from 1996 to 2016 [12]. Such a reduction would increase the probability of instability faults, especially during periods when the instantaneous output of VRE is higher than 50% [13]. The stability mechanism becomes more complex due to the increasing impact of VRE. The IEEE and the International Council on Large Electric Systems (CIGRE) redefined the stability and its classifications to incorporate the effects of fast-response power electronic devices [14]. Two new categories of stability, resonance stability and converter-driven stability, are introduced. The behaviors of classic voltage stability, angle stability, and frequency stability are also changed due to the integration of VRE [15]. Therefore, power system security and stability evaluation and how to maintain security and stability during planning and operation present challenges to future power systems.

At the same time, machine learning techniques have experienced rapid development in the last decade. Data science is regarded as the fourth science paradigm after experimental science, theoretical science, and computational science and provides a new perspective on how we understand the world [16]. A power system is a typical physical system that follows physical law, e.g., Maxwell's equations. For a long time, the security and stability of power systems have been analyzed using theoretical and computational science. In recent research, an increasing number of data-driven methods have been proposed to solve the security and stability problem of power systems, showing its advantage in handling the complexity of such problems [17]. These represent a fundamental change in the paradigm of how we handle the power system security and stability problem. We no longer rely on the physical law only but start to take the problem as a statistical problem by using experiential observations. Data-driven methods open a new door through which to address the challenges of power system security and stability under the increasing penetration of VRE.

C. Framework

This article reviews the state-of-the-art data-driven method of power system security and stability analysis and optimization under high renewable energy. The framework of this article is shown in Fig. 1.

The impacts of VRE on power system security and stability are reflected in both steady-state operation and transient states. Problems that arise correlate with each other. Understanding its key principles and behavior is a prerequisite to tackling these challenges. In most practical power system operations, security and stability are not considered during the optimization, e.g., unit commitment (UC) and economic dispatch (ED). The security and stability are checked before or after the operation schedules are generated. Potential insecure and unstable operation states

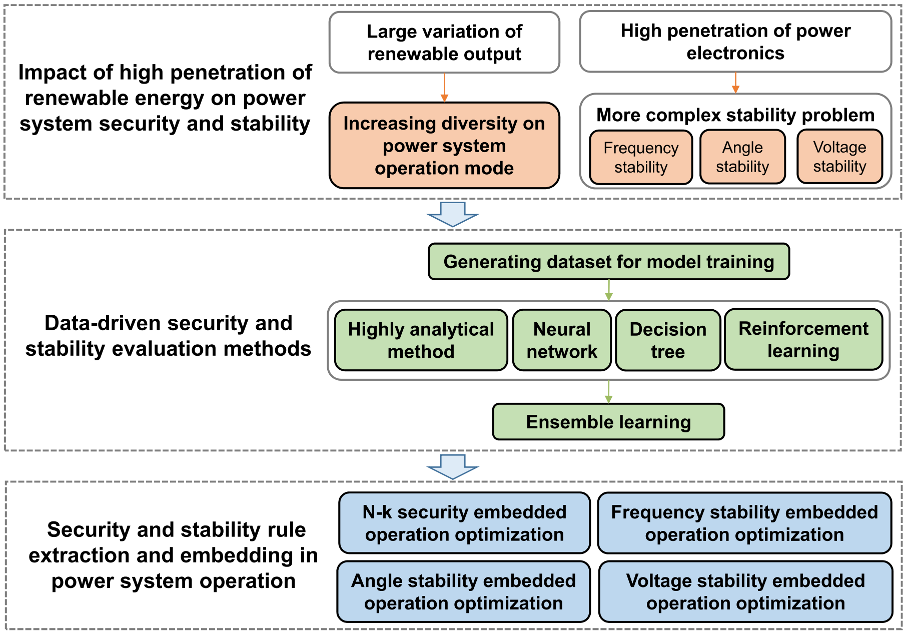

Fig. 1. *Framework of this article.*

are avoided by either precheck (setting simple operation rules beforehand, e.g., transmission line rate) or postcheck (checked and tuned iteratively using powerful simulation tools). As high penetration of renewable energy is integrated to power systems, security and stability issues are much more complex because of the large variation of VRE output and high penetration of power electronics. Beyond precheck and postcheck, power system operation needs to consider such complex security and stability issues since it is hard to identify insecure and unstable operation states in the precheck and difficult to tune in the postcheck. Before considering it in the operation optimization, a system-level understanding of what would be going on in power systems is critical. We summarize the findings of the current research in Section II.

There has been increasing research that evidences the potential of data-driven methods for learning power system security and stability rules. Section III provides an overview of these methods. The methods are categorized as highly analytical methods, neural networks, decision trees (DTs), and reinforcement learning (RL) methods. Data generating methods that provide training data for the above methods are reviewed. Ensemble learning methods that combine different methods are also reviewed. It should be noted that we focus more on the models that can be integrated into traditional power system operation models since we think that current machine learning methods cannot perfectly substitute UC or ED models for practical power systems.

Section IV demonstrates how the power system security and stability rules learned by the abovementioned data-driven methods can be embedded in power system operation optimization models. The methods are sorted by what types of security and stability issues are handled, including N-k security, voltage stability, angle stability, and frequency stability. Since the boundary of different security and stability issues is quite diverse, we categorize this section using the type of security and stability issues instead of data-driven methods. We do not review the converter-driven stabilities and resonance stabilities independently because these two stability issues rely more on device-level solutions, e.g., updating the setting of PSS devices' power system stabilizer, and changes in the control logic/parameters of the converters. Therefore, the solution of maintaining converter-driven stabilities and resonance stabilities would be largely decoupled with power system operation optimization, which makes it unnecessary to consider it in the power systems' operation optimization model. However, since there are indeed converter-driven stability issues that require system-level solutions, they are combined in review following the categories of stability issues caused.

Finally, existing issues are discussed, and future research directions are prospected in Section V.

II. CHALLENGES OF HIGH PENETRATION RENEWABLE ENERGY ON POWER SYSTEM SECURITY AND STABILITY

A. Diversity of Power System Operation Patterns Under High Variation in VRE Output

High variations in VRE already bring a difficulty to power system operators to maintain the supply–demand balance [18]. Currently, most power systems use flexible generators and storage to compensate for the output fluctuations of VRE. Such flexibility would run out if the VRE were to dominate the generation mix. The variations in wind power reflect both intraday and interday time horizons. Wind power does not have a very stable daily pattern, which means that wind power output could be high when the load requirements are low and vice versa, leading to a severe imbalance between generation and demand. Interconnecting different power systems to form a larger balancing area helps to smooth the variation; however, it still causes power flow fluctuations and leads to extreme operation states [19]. In extreme weather conditions, the front of the wind can move at a speed of 100 km/h, and wind power output to the entire power system can be increased in a matter of hours. Such a rapid change in wind power could strongly change the distribution of power flow.

PV output mainly increases peak and off-peak differences in the supply–demand balance [20]. The net load, which is defined as the actual power demand minus renewable energy output, becomes a duck curve in high PV penetration power systems [21]. The power flows in the systems may be fundamentally changed with the turn of day and night. Furthermore, the interday differences in PV output increase the variation of operation on different days. From a long-term point of view, power systems face a wide distribution of duck curves instead of one duck curve [22]. Finally, high penetration of wind and PV also increases the seasonal imbalance of power systems.

High VRE penetration largely diversifies the power system operation patterns and makes it hard to predict. The operation pattern is defined as a series of operation scenarios that can represent all of the operation states of power systems during the year. Since the security assessment, stability analysis, and fault calculation highly depend on operation conditions, operation rules are generally established based on several typical operation patterns to guide the operation and planning of power systems. Security rules, stability criteria, and relay settings are the guidelines for security, stability, and protection of power systems, respectively. Operation patterns in traditional power systems are determined by predicted load change or available power capacity based on empirical experience. However, the traditional empirical method may not be able to capture the variable and diversified operation of high VRE penetration power systems.

In order to understand such impact, a data-driven operation pattern identification method is proposed to analyze the influence of high renewable energy penetration on power system operation [8]. This method combines operation data (i.e., generation output, node load, and power flow) in a period of time into one vector in a high-dimensional power system operation space. Identifying the typical patterns, thus, becomes a clustering problem for such a high-dimensional vector. In this method, massive operation samples are first preprocessed by the principal component analysis (PCA) to reduce the correlated data dimensionality and remove redundant information. The compression coefficient of PCA is set as 0.99, which indicates that the data after dimensionality reduction can retain 99% of the original information. The preprocessed samples are clustered into several typical patterns by k-means++, and the cluster number is selected so that the inner group distances among operation modes in one cluster under different renewable penetrations are the same. The detailed calculation method of the optimal cluster number can be found in [8].

The operation pattern identification method enables us to understand how VRE changes the diversity and variation of power system operation patterns. We visualize operation patterns by dimension reduction into a 2-D plot. The distribution and time variation of the operation patterns under three VRE penetration scenarios (20%, 33%, and 40%) in the Qinghai power grid are shown in Fig. 2. The VRE penetration there is defined as renewable electricity penetration, which means the ratio of VRE power generation to the total load demand. Each colored point in Fig. 2(a), (c), and (e) denotes a daily operation state. Its color denotes the cluster and operation pattern to which it belongs. The daily operation state is presented by the vector composed of power system operation data in one day. Such a high-dimensional vector is transformed into a 2-D space in Fig. 2. The first and second principal features in Fig. 2 are combinations of operation data for visualization purposes, which does not have physical meanings. Fig. 2(b), (d), and (f) shows daily operation states change from one cluster to another during the year in three scenarios.

Fig. 2 shows that the space dispersion and time variation of power system operation patterns will be significantly increased with the increase in renewable energy penetration. Although empirical predefined operation patterns could represent the annual operation for traditional power systems [e.g., the three operation patterns in Fig. 2(a) and (b)], this may not always be suitable for high renewable energy penetration power systems [e.g., the ten operation patterns in Fig. 2(e) and (f)]. This result shows that more representative patterns are necessary for future power system planning. For time variation, more flexible resources should be made available to enable the more frequent operation switching seen in Fig. 2(f) than that in Fig. 2(b). Moreover, high VRE penetration also makes extreme operation states occur more frequently, which complicates the N-k security check and evaluation. Traditionally, two or three typical operation patterns based on empirical experience are sufficient for the annual power system operation and security check. However, with the growing VRE penetration, lots of N-k scenarios and operation patterns bring many permutations and combinations to the N-k security check, which presents great challenges in maintaining security and stability as the system approaches its critical limit. Security and stability constraints and preventive control should be taken into consideration in the operation optimization stage. In addition, seasonal consistency will decrease with increasing wind

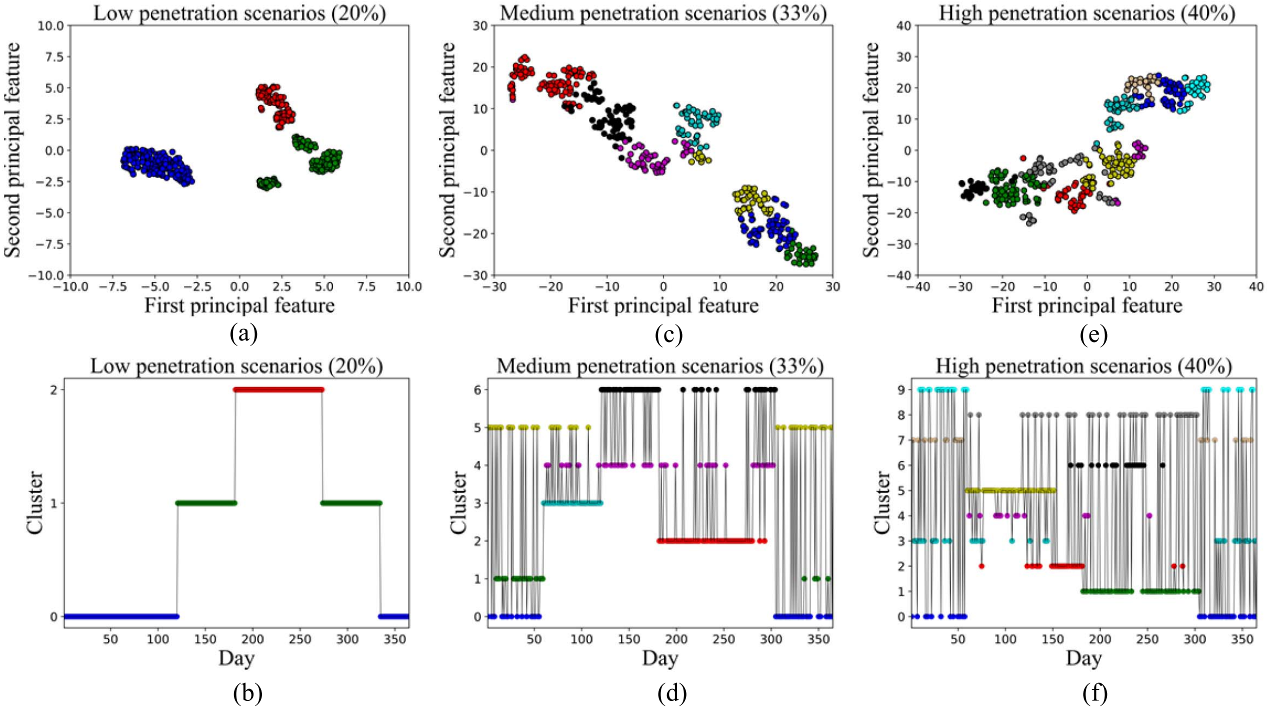

Fig. 2. ***Distribution and time variation of the Qinghai power grid in three scenarios. (a) Dispersion of the operation patterns in a low-penetration scenario (20%). (b) Time variation of the operation modes in the low-penetration scenario (20%). (c) Dispersion of the operation patterns in a medium-penetration scenario (33%). (d) Time variation of the operation modes in the medium-penetration scenario (33%). (e) Dispersion of the operation patterns in a high-penetration scenario (40%). (f) Time variation of the operation modes in the high-penetration scenario (40%).***

power and PV penetration, which drives the application of seasonal energy storage and long-term power balance in planning [23].

B. Complex Stability Problem Under Heavy Power Electronic Integration

1) Frequency Stability: Since the construction of the transmission system between Niagara Falls and Buffalo, alternating current (ac) has become the preferred choice for all power systems around the world. In a power system dominated by synchronous generators, frequency is an essential indicator of the balance between generation supply and load demand. The frequency declines when the load exceeds generation and vice versa. Frequency stability refers to the ability of a power system to maintain a steady frequency following a severe system upset, which typically results in a significant imbalance between generation and load [24]. Keeping the frequency within a specific range is a prerequisite for operating a power system [25]. Once a disturbance occurs, a series of measures will be chronologically applied to restore the frequency, including the initial inertial response from rotors of synchronous generators, the primary frequency response of generators, and load damping and automatic generation controls from regulating units [11].

In conventional power systems, the presence of a large number of synchronous units provides the system with sufficient inertia and primary frequency reserves to support frequency stability. However, the rapid integration of VRE jeopardizes the frequency response dynamics and threatens frequency stability [26]. On the one hand, the power electronic interface of VRE has no synchronous rotational mass and provides no inertia to power systems. A low-inertia power system may encounter a significant postcontingency frequency fluctuation, to the point where frequency has dropped to a very dangerous level before the activation of subsequent frequency control and protection measures [27]. For example, owing to extreme weather, South Australia suffered a serious blackout on September 28, 2016, which affected 85 000 customers. Before the contingency, the South Australian power system operates under an extremely low inertia condition with instantaneous wind penetration of up to 48% [28]. When disturbances occurred, the substantially fast rate of change of frequency (RoCoF) induced system separation in just 0.6 s and the ultimate black system [29]. On the other hand, the intermittence and uncertainty of VRE increase the difficulty of power system operation, which makes power systems with high VRE penetration more likely to operate near their stability margin. The reduced online capacity of synchronous generators and poor frequency support from VRE make frequency reserves very scarce [30]. The recovery of frequency may be a huge challenge in some cases. With the large-scale integration of VRE, frequency stability has rebecome an urgent issue for future power systems.

Another significant challenge behind the deployment of renewable energy is the secondary frequency control performance. The system should continuously balance generation and load. Power fluctuations in generation–load imbalances have increased with the replacement of conventional generators [31]. At the same time, the system frequency response capability has gradually declined [32]. These factors both lead to a decrease in the frequency control performance of power systems [33]. Haque *et al.* [34] showed that, when the proportion of wind power output increases, the flexible resources in the system will be insufficient to smooth the fluctuation of wind power. The results in [35] also show that the maximum frequency deviation of Thailand's power system will increase beyond the standard value due to the increase in VRE.

The decrease in secondary frequency control performance has led to a growing interest in frequency regulation capacity and high-accuracy, high-speed regulation resources. The high penetration rate of renewable energy requires more reserves [33]. Therefore, researchers have proposed using different resources to participate in secondary frequency regulation, such as commercial buildings [36], large industrial end-users [37], high-voltage direct current (HVdc) [38], energy storage [39], or even VRE itself. Among them, electrochemical energy storage is widely used due to its fast and accurate adjustment characteristics.

In a high renewable energy penetration power system, it is no longer sufficient to determine the reserve capacity based on experience or a fixed load ratio. Frequency regulation capacity demands change within the day with load and renewable energy output [40]. In addition, there is a nonlinear substitution effect between different resources [41]. Simulation shows that, under different renewable energy penetration rates, there is a corresponding optimal value for the ratio of energy storage in reserve [39]. In the electricity market, Pennsylvania-New Jersey-Maryland Interconnection (PJM) uses the benefit factor (BF) to approximate the rate of substitution between traditional (RegA) and dynamic (RegD) resources, which is further used to adjust the RegD resource's offer price [42].

2) Angle Stability: Angle stability refers to the ability of synchronous generators in an interconnected power system to remain in synchronism under normal operation conditions and regain synchronism after small or large disturbances [14]. In practice, two kinds of angle stability issues are most likely to occur under high VRE penetration: nonoscillatory transient instability and small disturbance oscillatory instability.

Nonoscillatory transient instability describes the phenomenon in which some of the synchronous generators exhibit a large rotor angle shift and, finally, lose synchronism after large disturbances. This is caused by an imbalance between insufficient electromagnetic torque and prime mover mechanical torque. The high penetration of converter interfaced VRE in power systems displaces large synchronous generators, thus significantly reducing system inertia. Lower system inertia makes the rotor swing process faster such that the system is more sensitive to large disturbances. However, VRE commonly has a faster response speed. With a proper control strategy, VRE can possibly help to mitigate the influence of disturbances on the torque disequilibria of synchronous generators [43]. Therefore, there is no clear consensus on whether the integration of VRE is beneficial or harmful to nonoscillatory transient stability [44].

Compared with nonoscillatory transient instability, small disturbance oscillatory instability is more likely to occur in practical power systems. Small disturbance oscillatory instability is caused by the lack of negative damping in the power system. The high penetration of converter interfaced VRE in power systems may change the system damping mode and influence the damping torque of nearby synchronous generators, inducing new modes of subsynchronous oscillation and low-frequency oscillation. The integration of VRE may change the oscillation frequency, mode, and damping, which makes the control of nonoscillatory transient stability highly challenging [45].

Currently, the impact of high penetration VRE on angle stability is complicated and case-by-case. The impact of VRE on nonoscillatory stability and small disturbance oscillatory stability is highly related to the power grid structure, power flow, penetration and location of VRE, control strategy and parameters of VRE, and synchronous generators. In addition, the performance of VRE during and after fault clearing, such as ride-through capability, is also a critical factor of nonoscillatory stability [44].

3) Voltage Stability: Voltage stability can be categorized into static voltage stability (for small disturbances) and transient voltage stability (for large disturbances). Static voltage stability describes whether the power system stays in an unstable equilibrium point, where the small disturbance, i.e., an increase in load, causes a collapse of voltage on any bus beyond the normal value [46]. For conventional ac power systems, static voltage stability is constrained by the active power transmitted into the load nodes and the related voltage drop through the transmission of active/reactive power through the ac transmission line. However, the mechanism of static voltage stability changes heavily for power systems with high penetration VRE. The critical change lies in the increasing penetration of power electronics introduced by renewable energy sources. On the one hand, the power supplied by VRE is injected into ac systems through electronic converters; on the other hand, the imbalances in the regional distribution of renewable energy sources call for a large amount of long-distance transmission, especially HVdc transmission. Such a transition changes the way in which we understand generators, reactive power, and the equilibrium point of power systems. Zhang *et al.* [47] proposed a definition and theoretical analysis for the general short-circuit ratio of multi-infeed direct current (dc) systems, which is derived under constant-power and constant-extinction-angle policies for line commutated converters (LCCs). The research shows that the static voltage stability of power systems with electronic converters depends not only on the load itself but also on the control strategies of converters and the power injected through the converters. Increasing dc injections would reduce the voltage stability margin of the ac system. The mechanism of static voltage stability would be changed in inverter-dominated ac systems. Although the voltage stability of LCC-based ac systems has been studied in recent years, the influence of voltage-source converters (VSCs) is still unclear. The complex and diverse controlling policy of electronic devices and the accordant new criteria for static voltage stability, thus, still need further research.

Transient voltage stability has been defined as a system's ability to restore stable voltage states following a fault. A classic criterion of transient voltage stability is transient voltage drop acceptability, which asserts that a system is unstable if the voltage drop is either too large or too long. Furthermore, Xue *et al.* [48] pointed out that transient voltage stability is interconnected with transient angle stability. Thus, the theoretical analysis becomes complex, and time-domain simulation methods are widely applied to this problem. Kawabe and Tanaka [49] studied the impact of PV power generation systems on transient voltage stability in high-penetration renewable energy scenarios and concluded that the installation of PVs severely impairs the transient voltage stability if the PVs' system shuts off after a voltage sag. However, there are two shortcomings in these methods: one is that they are time-consuming and, thus, cannot be applied to time-sensitive analysis, and the other is that their accuracy depends on device modeling, which becomes more challenging when accounting for fast responses of power electronic devices in high renewable energy penetration scenarios. Some attempts have been made to address these shortcomings of simulation methods. A series of data-driven assessment methods based on wide-area measurements was proposed by Zhu *et al.* [50], where real measurement data are used instead of simulation data. However, their performance in real systems remains unclear. Generally, modeling the intrinsic mechanism of transient voltage stability while fully considering the effects of electronic converters and assessment techniques is still an open issue.

4) Discussion: The common impact of VRE on frequency stability, angle stability, and voltage stability lies in the substitution of VRE for synchronous generators, which significantly changed the steady-state operation patterns of power systems and the corresponding dynamic system characteristics, resulting in more complicated and challenging stability issues. For frequency stability, the reduced inertia and frequency regulating capability are the major factor, while the increasing fluctuations added further burdens. For angle stability, the change brought by VRE in system dynamic characteristics induces complicated oscillation issues and transient responses, making the system operation and control parameters tuning highly challenging. For voltage stability, the reactive power injection and dynamic response mechanism of converters complicate both the steady-state operation and postfault response. The static and dynamic voltage quality constraints are getting more binding, posing higher restrictions on power system operation.

III. DATA-DRIVEN SECURITY AND STABILITY EVALUATION METHODS

A. Generating Dataset for Model Training

Data-driven security and stability evaluation and analysis require sufficient training data. However, insecure or unstable operation scenarios rarely occur in practical power system operations. Therefore, training data need to be generated rather than merely collected from historical records.

Generally, training data generation for data-driven security and stability evaluation methods consists of two steps: 1) sampling state-steady operation states and 2) labeling the security or stability states of the sampled steady-state operation states after fault based on simulation. Currently, the increasing penetration of VRE not only diversifies the steady-state operation states of power systems [8] but also induces more stability-/security-related issues that must be checked. Therefore, generating training data effectively becomes a crucial factor in the implementation of data-driven security and stability evaluation.

The power system operation state is characterized by the power system topology, power injections, bus voltage, and branch power flow. Since these variables are bounded by power flow equations, only some of the variables can be selected as independent state variables. These independent variables can be sampled randomly, while the rest of the variables are calculated using power flow equations. In most studies [51], [52], [53], active and reactive power injections are selected as the state variables to be randomly sampled. Sampling the operation states of power systems directly can cover a wide range of steady-state operation states. However, to fully capture the possible operation states, the number of sampled operation states will rise geometrically in proportion to the scale of power systems [53]. Thus, labeling all of these operation states may become intractable with a high computational burden of simulation.

In addition to sampling operation states directly, they can also be generated using optimal power flow (OPF). In OPF-based sampling, the operation boundary conditions of power systems, e.g., load level and renewable output, are modeled by a joint probability distribution function. Then, OPF is conducted for each boundary condition randomly sampled from the distribution to obtain the operation decision [54]. The commonly used sampling techniques used in boundary condition sampling include Monte Carlo sampling [55] and Latin hypercube sampling [56]. OPF-based sampling reflects the economically rational decisions made by system operators, which are most likely to occur in practice. OPF-based sampling methods have been successfully applied to studies on voltage stability [56], N-k security [57], and so on. However, the training dataset generated by OPF-based sampling only focuses on normal operation states. Some of the extreme operation states may be missed due to the limited sampling range.

Simulations need to be performed to label the postfault performance and the security or stability states of the sampled operation states. For example, eigenvalue calculation is used for small-signal stability, time-domain simulation is used for transient or frequency stability, quasi-steady-state simulation is used for mid- and long-term voltage stability issues, and continuation power flow is used for static voltage stability.

The concept of adaptive sampling or importance sampling is found to be efficient in practice to cope with the high computational burden of simulation [53]. In adaptive sampling, limited operation states are first generated and labeled. Then, the information entropy [56] or the confidence level of a discriminator [52] can be used to find the high information content region of the sampling data space, where the sampling and simulation are further biased on the high information content region. In contrast, the sampling region with low information content can also be excluded from the sampling space using critical contingency analysis to reduce unnecessary simulations [53].

The comprehensiveness of the generated dataset can be measured by the resolution of sampled points and the integrity degree of labeling, and is, finally, examined by the performance of data-driven models trained based on the dataset. The resolution of sampled points denotes the granularity of steady-state operation states, e.g., 1-MW level or 5-MW level, determined by the number of samples. In addition, enough samples need to be generated to represent the probabilistic characteristics of power system uncertainties. In terms of integrity degree of labeling, the stability or security labels of sampled steady-state operation points should be provided with high confidence guarantee, especially for the inferred or predicted labels in low information content regions without full simulation. Finally, the performance of data-driven models trained based on the dataset, e.g., accuracy or precision indices, reveals the comprehensiveness of the generated dataset. If the test results on the trained data-driven model reach the quality standard, the generated dataset is considered comprehensive. Otherwise, the dataset needs to be further enriched.

B. Evaluation Methods: Highly Analytical Methods

Considering that a power system is a high-order nonlinear dynamic system, power systems' security and stability evaluation methods are still one of the hot topics in current power system research. Traditional evaluation methods can be categorized as time-domain simulation and direct methods [24]. Time-domain simulation is the most straightforward method, which provides precise evaluation results through numerical calculations on detailed power system models. Direct methods can give the margin of power system stability through the Lyapunov function without performing numerical calculations.

With the increase in VRE, the drawbacks of traditional evaluation methods limit their application in large-scale power systems. On the one hand, time-domain simulation has difficulty adapting to the diversity of power system operation states under high variations in VRE output due to its high computational complexity and poor identification of secure boundaries [58]. On the other hand, direct methods, such as the Lyapunov function, have difficulty adapting to the complex stability problem under heavy power electronic integration. Furthermore, the acquisition and identification of parameters for large systems is also a nonnegligible challenge for the traditional methods [55].

Considering these limitations, it is promising to use data-driven methods for security and stability evaluation. Among these methods, some highly analytical methods, such as support vector machines (SVMs), logistic regression (LR), and piecewise linearization (PWL), have been researched in-depth due to their high interpretability and computational efficiency.

The main idea of SVM is to produce a nonlinear boundary by finding the optimal separating hyperplanes in a large, transformed version of the feature space. As a classical pattern recognition algorithm, SVM has a clear physical meaning and mature algorithms and performs well in classification problems with high dimensionality. Given these advantages, SVM is a popular method in the security and stability evaluation of power systems and has been applied in online transient assessment [58], [59], [60], [61], voltage stability monitoring [62], [63], [64], low-frequency oscillation pattern recognition [65], and static security assessment [66]. Researchers have also made improvements to the SVM to better match the practical needs of power systems. Hu *et al.* [60] reduced the rate of false classification through an ensemble of two improved SVMs created by introducing slacking variables in the training process. Kalyani and Swarup [61] adopted the multiclass SVM to portray the degree of insecurity of power systems. Saian *et al.* [62] applied the genetic algorithm to improve the accuracy and minimize the training time of SVM. The survey in [67] reported that SVM could achieve over 95% accuracy in most power system-related security evaluation scenarios. Furthermore, support vector regression (SVR), a variant of SVM for regression, has also been applied in the estimation of some important security indicators, such as loadability margin [68], available transfer capability [69], and rotor angle of the center of inertia [70].

Unlike the deterministic classification results given by SVM, LR is a probabilistic classification algorithm that aims to regress the probability of the sample point belonging to different classes. The LR method is simple, fast, robust, and can provide relatively accurate results in a limited time and with less computational resources. The probability provided by LR can be used to reflect the degree of power system stability and security. The comparability of classification results enhances the interpretability of LR.

LR has been applied in transient stability assessment [71], islanding detection [72], outage prediction under extreme events [73], and so on.

Although the abovementioned methods have been applied in security and stability evaluation, very few studies have embedded these methods into power system operation optimization models. With high requirements on tractability, robustness, and convergence, security-constrained ED (SCED) and security-constrained UC (SCUC) are generally formulated as linear programming (LP) and mixed-integer linear programming (MILP). The nonlinearity of these methods limits their application in SCUC and SCED. PWL is the most common embeddable data-driven method. Its general procedure is to generate a series of tagged data through simulation or simplified analytical models and then use the combinations of a series of linear hyperplanes to portray the secure boundary of these tagged data. PWL is straightforward and easy to implement. Currently, PWL has been widely utilized for a variety of stability rule embedded operation optimization, including frequency security [74], [75], transient stability [76], and short-term voltage stability [77]. However, PWL usually requires a high number of piecewise segments to achieve high accuracy, which may significantly increase the computational complexity of operation optimization models.

C. Evaluation Methods: Neural Network

Methods based on neural networks have benefitted from the rapid development of neural networks in recent years and have been widely used in power system stability assessments, such as extreme learning machines (ELMs), recurrent neural networks (RNNs), convolutional neural networks (CNNs), or their combination.

ELM can be trained in a short time and, thus, can be easily updated by a new dataset. Using ELM can reduce training time and prevent the risk of overfitting. A probabilistic method based on ELM for voltage stability margin estimation is developed in [78]. Venzhe and Chatzivasileiadis [79] selected dynamic stability features and then trained ELM based on feature datasets for transient stability assessment.

RNN is suitable for processing sequence data. Since the measured values in the power grid, such as voltage and phase angle, are mostly sequence characteristics, it is very suitable to use RNN to assess power system stability. Zhu *et al.* [80] formulated spatial correlations as spatial attention factors to rectify multiple transient trajectories and then used an RNN to learn the temporal correlation in voltage stability. Arteaga *et al.* [81] utilized long short-term memory (LSTM) to form a spatial–temporal autoencoder, which is used to evaluate the voltage stability of power systems.

CNN is a neural network specially used to process data with multiple dimensions. In power systems, CNNs can extract valuable information from a large number of electrical quantities and reveal the associations between these features. A multi-CNN model was proposed in [82] to estimate the maximum voltage deviations. Azman *et al.* [83] used both CNN and LSTM to predict rotor angle stability.

Some research uses neural networks to assist in solving SCUCs, which can be divided into two categories. The first category uses a neural network to replace some or all of the optimization problems of UC, thus obtaining a higher solution speed while sacrificing accuracy. For example, Panossian *et al.* [84] use a trained ANN to provide UC solutions directly but with relatively low accuracy. To improve accuracy, researchers also use an ANN to only obtain the solution of the binary variables [85] or select a decision from candidates. However, the disadvantage of this method is that the results cannot ensure the global optimum and feasibility [85]. Furthermore, off-line training of such a neural network requires the input of a large number of optimization results, which is a very time-consuming process.

The second category uses a neural network to generate a security region and embeds this security region into the SCUC problem. Say *et al.* [86] first proposed the use of the rectified linear unit (ReLU) transfer function to fit complex systems and embed an ANN into MILP encoding. Network with ReLU as their active function is not a black box but rather a gray box. In the field of power systems, some researchers use ReLU to solve the ac OPF (ACOPF) problem [87], frequency security constraints UC [52], [88], $N-1$ security constraints UC [79], and voltage stability-constrained UC [86]. However, ReLU is inferior to the traditional nonlinear activation function in fitting ability due to its own linear characteristics. The neural network based on tanh is obviously better than the ReLU, while the neural network based on ReLU can obtain piecewise linear results. To compensate for this shortcoming, more neurons need to be used during network training, which may increase the solution time of SCUC.

D. Evaluation Methods: Decision Tree

DT methods are widely used in security evaluation and stability assessment because DTs have interpretable formulations. Current studies are mainly based on univariate DTs (UDTs) and oblique DTs (ODTs).

UDTs are easy to train and can find key features that affect security and stability, so most existing DT methods are based on UDTs, such as Iterative Dichotomiser 3, C4.5, and classification and regression tree. For example, Meng *et al.* [89] trained DTs offline using the C4.5 algorithm and used the training result for online voltage stability assessment. Sun *et al.* [90] achieved an online dynamic security assessment based on well-trained DTs for large-scale interconnected power systems. Test results on the Entergy system showed that DTs could identify key features of dynamic security [90]. Except for online security evaluation, these UDTs sometimes derive security rules that can serve as preventive and

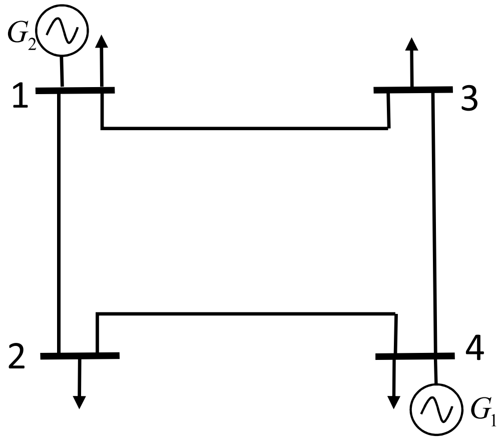

Fig. 3. *Structure of a four-bus test case.*

emergency control options. Cremer *et al.* [91] proposed a new training algorithm for DTs with small depths or intermediate depths. The proposed tree algorithm derived interpretable security rules for short-term operation actions [91]. Bernabeu *et al.* [92] proposed a security/dependability adaptive protection scheme based on DT rules. The proposed scheme turned out to be helpful for the reduction of potential cascading events on a 4000-bus system [92]. UDT methods stand out through their understandable security rules, but the learning capacity of UDTs is low because each split of UDTs is only related to one operation state feature.

ODT methods are proposed to solve such problems. They have a larger learning capacity because they split on the linear combination of all operation state features rather than splitting on a single feature. In this way, ODT can extract both accurate and understandable rules for online security evaluation. For example, Yan *et al.* [93] identified security boundaries in a high-dimensional wind power injection space utilizing ODT [93].

We compare the learning capacity between ODTs and UDTs using a four-bus example, as shown in Fig. 3. We define a 2-D state space for this small system using the two key operation features: active power output from generations G1 and G2. The security boundaries learned by a UDT and an ODT are shown in Fig. 4(a) and (b), respectively. The colored points denote the operation state in the 2-D power system state space. The results in Fig. 4 show that the ODT learns security rules by only two oblique splits with 99.1% accuracy, while the UDT learns security rules by four axis-parallel splits with just 96.2% accuracy.

However, the security rules from ODT may be too dense to be embedded in operation optimization for large-scale power systems because of high computational costs and weak convergence. To solve this problem, sparse ODT is proposed to learn sparse and embeddable security rules in [57]. Sparsity in classification rules is achieved by introducing elastic net regularization to the objective function of trees. Future work can focus on the efficiency of DT rules in high VRE power systems.

E. Evaluation Methods: Reinforcement Learning

RL is based on the Markov decision process and is further developed with the proliferation of deep neural networks (DNNs). It is widely used to enhance power system stability because it does not need to prepare labeled input–output pairs before training and is suitable to be deployed into a closed-loop controller to act following a fault. Based on whether the RL agent uses predictions of RL environment response, it is further categorized into model-based and model-free RL algorithms. Model-based algorithms take advantage of the physical knowledge of power systems, so they are successfully applied in centralized power systems. Glavic [94] proposed a model-based prioritized sweeping method and designed a resistive breaker controller based on it to enhance power system stability. Using this method, the damping of the first and the subsequent swings in the system after large disturbances are significantly improved [94]. For some situations, such as in decentralized power systems, information for the whole system is unavailable, which would enable the application of model-based algorithms. Mukherjee *et al.* [95] proposed a model-free decentralized control to enhance the stability of a decentralized power system without information pertaining to distributed renewable energy resources. This method is tested on the IEEE-64 system under multiple contingencies, and the dynamic frequency stability is largely improved [95]. Chen *et al.* [96] proposed a model-free emergency frequency control RL method, in which both multi-Q-learning and deep RL techniques are employed according to the computational resources and memory. Besides, many multiagent RL methods are proposed to tackle load frequency control for multiarea power systems [97], [98]. These methods can both nonlinearly and adaptively derive the optimal coordinated control strategies through centralized learning and decentralized implementation.

Furthermore, there are still two open issues to be studied. On the one hand, applications on the control side have shown success when tackling disturbances, but the assessment rule is the implicit knowledge behind agent policy, which cannot be extracted in an analytical form. On the other hand, with the increasing penetration of power electronics, the environment model becomes increasingly complex. How to appropriately include the dynamic process of power electronics in environment modeling remains an open question.

F. Integration Methods: Ensemble Learning

The two main ensemble learning methods used in power system security and stability evaluation are bagging and boosting. Ensemble learning algorithms can provide robust evaluation results when facing unavoidable bad inputs due to measurement errors.

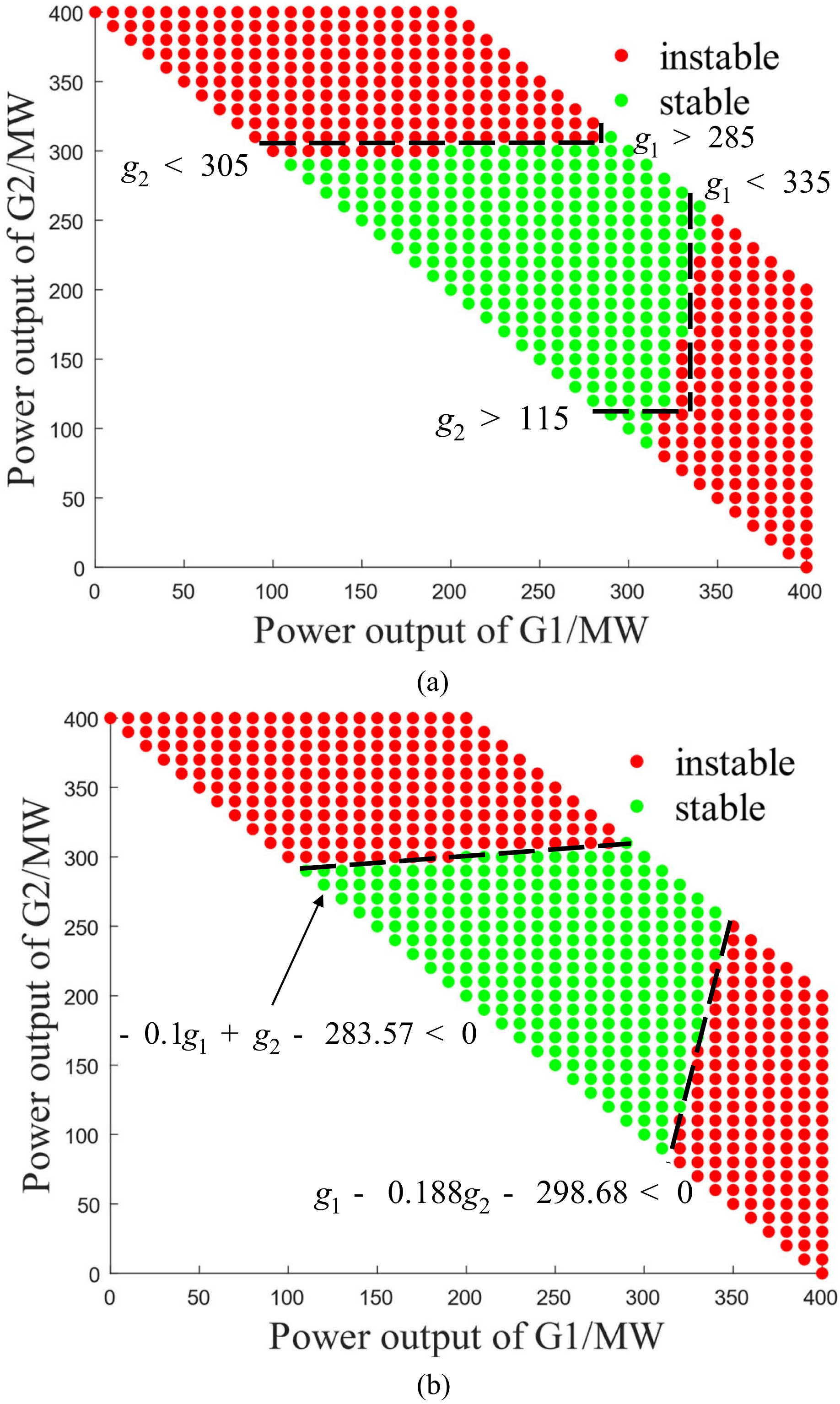

Fig. 4. ***(a) Security boundaries learned by a UDT. (b) Security boundaries learned by an ODT.***

Some authors have proposed an online security evaluation method based on the bagging technique, which trains learners in parallel based on different training data and model parameters. Bagging-based ensemble learning can still make reliable predictions although one learner in the ensemble makes mistakes. Therefore, the bagging technique is generally used for robust security evaluation. For example, Zhang *et al.* [99] built a set of classifiers to perform online voting stability assessment decision-making based on phasor measurement unit (PMU) measurements. The stability assessment decision is only made by the classifiers with available PMU inputs to tackle missing PMU measurements [99]. Kamwa *et al.* [100] proposed a fast catastrophe predictor grouping DTs into a random forest ensemble. Testing on a 783-bus system showed that the random forest is robust when facing small changes in the training data [100].

Other researchers built ensemble models based on the boosting technique, which serially trains learners. The common boosting ensemble models include Adaboost and gradient boosting. Mukherjee and De [101] compared boosting DTs with other single machine learning methods on the IEEE-118 and IEEE-300 systems. The results showed that ensemble DT classifiers have a stronger learning capacity than other classifiers [101]. Li and Liu proposed an online dynamic security assessment based on an SVM ensemble with a boosting approach. Tests on a wind-integrated power system in Shandong Province, China, verified the accuracy of the proposed method compared with linear SVM [102].

In general, ensemble learning methods are able to provide robust and accurate security assessments, but complex structures weaken the interpretability of machine learning models. Security rules from the ensemble with hundreds of DTs cannot be easily understood by operators. Moreover, time consumption hinders the online application of ensemble models. Ensemble models with complex structures are difficult to retrain with the latest PMU data in the online stage, impairing the reliability of the model in online applications [103].

G. Discussion

Comparing different methods, LR, PWL, SVM, and DT are relatively more interpretable. The physical meaning of the parameters in these models is clear. However, the accuracy of these methods will be relatively inferior to neural networks on most problems empirically. Especially for nonlinear problems, it is difficult for these methods to obtain accurate fitting results. The DNN is a type of neural network, which has a strong fitting ability but more complexity. Models with high complexity and low interpretability are often referred to as black-box models and are not preferred in power system operation. What is more, we still have to emphasize that the method needs to be selected according to the application. The accuracy of these methods is case-dependent.

From each model itself, there is also a tradeoff between accuracy and model complexity. Researchers need to modify hyperparameters to tune the complexity of the model, such as the number of segments in a piecewise linear model, the depth of a DT model, and the number of neurons in a neural network. The choice of hyperparameters for complexity is often based on experience or a large number of trials. At the same time, it also depends on the time requirements of the application. A high-precision model can better assist decision-making and avoid misidentification. However, a higher model complexity will make training time longer and may even make the rule embedded optimization problem difficult to solve.

IV. SECURITY AND STABILITY RULE EXTRACTION AND EMBEDDING IN POWER SYSTEM OPERATION

A. Embedding N-k Security Rules Into Operation Optimization

The SCUC for $N-1$ security traditionally uses line outage distribution factors (LODFs) to generate constraints. However, consider that all of the line outages will make the problem computationally intractable. An SCUC implementing transmission security on the IEEE 118-bus system [104] was found to have 99.3% of its constraints to be unnecessary.

When analyzing the N-k contingencies in the SCUC, researchers can only use a reduced set of contingencies as a set of scenarios. This process often requires heuristic algorithms. However, the reduced scenarios cannot always ensure the security of the results.

Data-driven methods have also been proposed to solve the N-k security-constrained operation optimization problem. For example, the DT method mentioned in [105] and the convex relaxation method in [53] decouple the processes of N-k security assessment and UC optimization. Therefore, the assessment of N-k security is able to consider outages of any k lines.

Hou *et al.* [57] proposed a sparse weighted ODT (SWODT) method. Through regularization, this method can extract understandable and embeddable security rules from a high-dimensional and highly correlated power system dataset. The security rules studied by SWODT with G secure leaves can be formulated as linear constraints using the Big-M method

$$\begin{aligned}
\mathbf{R}_1\mathbf{p} &\geq -M\left(1-I_1\right)\\
\mathbf{R}_2\mathbf{p} &\geq -M\left(1-I_2\right)\\
&\vdots\\
\mathbf{R}_G\mathbf{p} &\geq -M\left(1-I_G\right)\\
\sum_{i=1}^{G} I_i &= 1.
\end{aligned}$$

To illustrate the effectiveness of [57], taking the IEEE-30 system as an example, 50-MW solar units and 50-MW wind farms are added to nodes #10, #24, and #28 to increase the uncertainty of the system. A total of 8000 valid samples are generated by a two-stage sampling method. After that, with the power flow data of all lines as features, a DT with a depth of three is generated. Fig. 5 visualizes the rules learned from the IEEE-30 dataset for illustration. For the IEEE-30 system, the proportion of the secure states is only

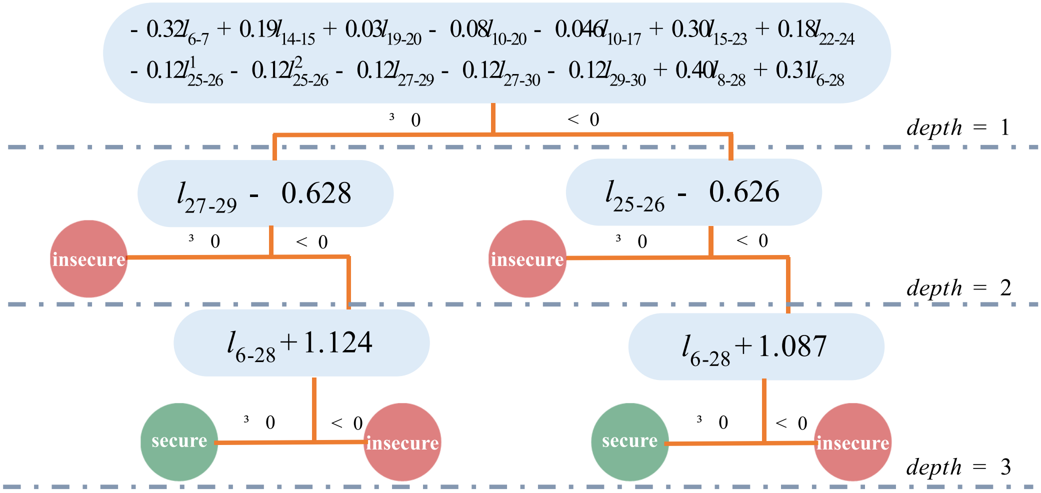

Fig. 5. ***N-k security rules learned from the IEEE-30 system.***

62.2% if the ED problem is solved directly. After embedding the rules into economics dispatch, the percentage of secure states produced by the ED improved to over 95.0%.

B. Embedding Frequency Stability Rules Into Operation Optimization

In traditional operation models, frequency security is generally ensured by imposing reserve rate constraints since the inertia of conventional power systems is sufficient. However, with a high share of VRE, inertia has a significant influence on frequency dynamics. It is, thus, necessary to incorporate frequency dynamics in power system scheduling [106].

The frequency dynamics of power systems are generally described with swing equation (1) [24]

$$2H\frac{d\Delta f}{dt} + D\Delta f = \Delta P_m - \Delta P_L \tag{1}$$

where Δf is the frequency deviation, H is the system inertia, D denotes the load damping, ΔP_m is the adjustment power of frequency regulation resources, and ΔP_L is the postcontingency power imbalance.

Rather than embedding the whole trajectory of frequency dynamics, power system operation models mainly focus on the security rules on three indices, namely, frequency nadir, maximum RoCoF, and quasi-steady frequency. Among them, obtaining the frequency nadir requires solving the ODE, which is not easy to embed in optimization models. Currently, such studies can be broadly classified into three categories. The first is to simplify the frequency response model to obtain a frequency nadir approximation with low nonlinearity [107], [108]. The second is to approximate the frequency nadir through PWL [74], [109]. The third is the application of machine learning methods to formulate frequency security rules, such as DT [110]. Each of these methods has its own advantages and disadvantages. The former two methods are more dependent on frequency dynamics models. They perform better in generalizability and interpretability, while their accuracy is limited. Machine learning models have the potential to achieve fairly high accuracy, while their adaptability to scenarios outside their training set has yet to be tested. In addition, the extra computational complexity due to security rule embedding is a common problem for the latter two problems.

C. Embedding Angle Stability Rules Into Operation Optimization

The transient angle stability of power systems is described by a large set of differential-algebraic equations, which is difficult to embed in the operation optimization. Therefore, transferring the implicit transient stability constraints into analytical constraints on power system operation decision variables is an effective way to mitigate this difficulty.

Specifically, there are two kinds of methods used to construct the transient stability constraints: DT-based stability rule extraction methods and trajectory-based sensitivity calculation methods. Cremeer *et al.* [91] proposed using DTs to extract transient stability rules. The utilization of DTs exhibits several advantages, including their high accuracy, rule interpretability, and relatively low requirements on the training data size. The features of each training sample consist of normalized active and reactive power injections, voltage, and phase angle of buses. The case study in the IEEE 68-bus system shows that employing a DT in transient stability rule extraction has a prediction accuracy of more than 90% with a maximum depth of 5. These results indicate that the tradeoff between the precision and interpretability of transient stability rules can be realized with the DT algorithm.

In the trajectory-based sensitivity method, Yuan *et al.* [76] and Xia *et al.* [111] utilized the trajectory sensitivity method to approximate the transient stability margin as a function of operation decision variables. In [76], a perturbation is created for the decision variables, and the change in the transient stability margin is calculated using the extended equal area criterion (EEAC) method to derive the sensitivity coefficients. Finally, the linearized transient margin stability constraint is embedded in the operation optimization model. In [111], the energy-based stability margin constraint is constructed using a similar sensitivity-based method. The constraint is embedded in the ACOPF problem, and the parameters are updated in each iteration. Compared with DT-based stability rule extraction, the sensitivity-based method can approximate the transient stability constraints in the neighborhood of an operation point with higher accuracy. However, the linear formulation of extracted constraints represents local stability rules, making it difficult to depict the global nonlinear transient stability constraints.

D. Embedding Voltage Stability Rules Into Operation Optimization

Operation optimization with voltage stability constraints has been investigated for high VRE penetration power systems. The methods involved can be divided into two steps: extracting voltage stability constraints and embedding these rule constraints into an operation optimization model.

Sensitivity analysis and machine learning methods are employed to extract understandable and accurate voltage stability rules. Sensitivity approaches implement the sensitivities of voltage stability indices into power system operation optimization as constraints. These sensitivities are created as optimization options for preventive controls and voltage stability improvement. The voltage stability indices used in the existing literature include the loading margin from the power flow equation [112] and the singularity of the Jacobian matrix [113]. Voltage stability indices and their constraints are easy to understand and can be directly used in operation optimization. However, existing sensitivity approaches often suffer from approximation error and computational issues. Voltage stability rules can also be learned by machine learning methods. Rules from black-box models tend to be difficult to understand. Some researchers introduce model interpretation tools, such as the Shapley additive explanation (SHAP) and sensitivity analysis, to black-box voltage stability assessment models for model interpretation. For instance, SHAP can determine the importance of controllable features from trained deep learning models. Voltage stability preventive control can be performed in a timely manner based on the most effective control objects explained by SHAP.

Machine learning methods learn voltage stability rules for voltage stability assessment and constraint extraction. The machine learning models used in the existing literature can be divided into interpretable models and black-box models. Interpretable models, such as DTs, can be directly used to extract understandable voltage stability constraints, while black-box models, such as neural networks, often define complex voltage stability rules [114], which are difficult to transform into reliable voltage stability constraints.

Voltage stability can be improved through voltage stability-constrained operation optimization. In addition to being used as preventative control options, voltage stability constraints can be embedded into power system operation optimization models, such as OPF models. Unlike other stability or security problems, voltage stability is strongly driven by the voltage level. Therefore, the dc OPF (DCOPF) model, which ignores the voltage, can hardly be used for rule embedding. Voltage stability-constrained OPF models often suffer from high computational cost and low convergence. To solve this problem, some works focus on the convexity of OPFs: formulating voltage stability-constrained operation optimization as semidefinite programming by relaxation or utilizing a linear OPF model [115]. Other work is devoted to finding new tight voltage stability indices and their sensitivities. In [116], a new voltage stability index named clustered effective reactive reserve (CEQR) was proposed to identify the risk of dynamic voltage stability. The CEQR value is utilized as an operation criterion of emergency control actions to secure dynamic voltage stability. The results show that the operational blocking tap charger scheme based on CEQR can prevent dynamic voltage collapse in the Korean electric power system.

V. CONCLUSION AND FUTURE WORK PROSPECTIVE

The abovementioned data-driven methods share similar logics and goals: to use data-driven models to act as the proxy of power system security and stability constraints in the optimization of power systems. The advantage of such a methodology framework is twofold. On the one hand, it is highly flexible in terms of the types of security and stability problems, the data-driven model chosen, and the way of embedding the rule into power system operation optimization. On the other hand, it does not affect the mathematical form of traditional power system optimization models, e.g., security-constrained UC, ED, OPF models, or even market-based models. Therefore, such data-driven methods can smoothly integrate into the current power system operation framework without overthrowing any current models. Furthermore, the technique that is used to accelerate the optimization of large-scale power systems' operation problems can still be used. Therefore, the framework has a good potential for stability and generalizability to be used in practical power systems.

Although many methods under such a framework have been proposed and have shown promising results, more research and development are required before they can be applied to practical power systems. At least four challenges need to be addressed.

A. Interpretability of Machine Learning Models

Machine learning models are essentially statistical models. However, their generalization performance, i.e., their accuracy on the samples outside of the training dataset, is determined by how well they capture the physical laws of power systems. Aside from training error, it is critical to evaluate how much "knowledge" of the power system it can learn from the training data. Such a requirement is unique to power systems since it largely determines whether the model is robust enough for applications in power systems. However, few machine learning models have a closed form. Most of them have black-box parts that are hard to interpret. It is extremely hard to identify whether the model is overfitting with respect to the physical model. To make the model learn the physical law of power systems instead of the external appearance of the training data, special skills and strategies for training and feature selection are required. Recently, a new trend of interpretable machine learning methods has raised increasing attention that may help to improve the interpretability of machine learning models in power system applications.

B. Cooperation Between the Data- and Model-Driven Methods

Although data-driven methods have become more acceptable than before, power system applications cannot throw model-driven methods. In contrast, data-driven methods need to cooperate with model-driven methods to achieve more efficient analysis and smarter decision-making. The major challenge is how to embed physical models into data-driven models. Some attempts have been made in power system studies. In the admittance matrix estimation problem, power flow equations are added as constraints in the training model. The sparsity of the admittance matrix is used through the regularization of the model. Another way of combining data- and model-driven methods is to embed the data-driven models in the model-driven framework. In the power flow linearization study, the linearization parameters are determined using the historical power flow data, thus making the model self-adaptive to different power systems. For the more complex power system security and stability models, it is much harder to directly combine physical and data-driven models.

C. Assisting the Optimization of the Power System

The ultimate goal of using a data-driven method in power system security and stability analysis is to make it to be able to assist the optimization of power systems, i.e., security-constrained UC, ED, voltage control, and generation and transmission planning. However, such an optimization problem itself already suffers from calculation tractability problems. Although some machine learning models, such as RL models, are able to conduct the optimization themselves, power systems still need classic optimization models and engines. Therefore, the data-driven method should help to improve the efficiency of power system optimization instead of slowing it down. Recently, machine learning-driven optimization has become a new hot topic in machine learning research. However, it is still far from being mature enough to be used in power systems.

D. Generalization of Security and Stability Rules in Optimization

Generalization is one of the main challenges in the real-world application of machine learning models. For well-studied security and stability evaluation models, the generalization only cares about the model's performance on the out-of-distribution dataset, which can be measured by testing error. Transfer learning [117] and metalearning [118] are two general techniques to improve this kind of generalization. However, for security and stability-constrained optimization tasks in power systems, the learned security rules are transformed as constraints in the optimization. According to the optimization theory, the optimal operation states usually lie in the extremes or boundaries of the feasible region, which are determined by the constraints. Therefore, we not only care about the rule's generalizability on normal power system states but also about the boundary of the feasible region and its impact on the optimization results to keep the optimized operation states economic and secure. To the best of our knowledge, both the techniques and the theory for improving this kind of generalization in optimization are seldom studied in the power system and machine learning fields, which we think deserve more attention. ■

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ABOUT THE AUTHORS

Ning Zhang (Senior Member, IEEE) received the B.S. and Ph.D. degrees from the Department of Electrical Engineering, Tsinghua University, Beijing, China, in 2007 and 2012, respectively.

He is currently a Tenure Associate Professor with Tsinghua University. His research interests include power system planning and operation, multiple energy systems' integration, and renewable energy.

Hongyang Jia (Graduate Student Member, IEEE) received the B.S. degree in electrical engineering from Tsinghua University, Beijing, China, in 2021, where he is currently working toward the Ph.D. degree.

His research interests include renewable energy, power system operation and optimization, and data-driven power system analysis.

Qingchun Hou (Member, IEEE) received the B.S. degree from the Huazhong University of Science and Technology, Wuhan, China, in 2016, and the Ph.D. degree from the Department of Electrical Engineering, Tsinghua University, Beijing, China, in 2021.

His research interests include power system operation and planning with high renewable energy penetration, data-driven analytics, power system optimization, machine learning, combinatorial optimization, and digital supply chain.

Dr. Hou was a recipient of the Advanced Technology Talent Program "AliStar" of Alibaba.

Ziyang Zhang (Graduate Student Member, IEEE) received the B.S. degree from the Department of Electrical Engineering, Tsinghua University, Beijing, China, in 2019, where he is currently working toward the Ph.D. degree.

His research interests include renewable energy, power system operation, and power system planning.

Tian Xia (Graduate Student Member, IEEE) received the B.S. degree from the Department of Electrical Engineering, Huazhong University of Science and Technology, Wuhan, China, in 2019. He is currently working toward the Ph.D. degree at Tsinghua University, Beijing, China.

His research interests include power system operation and planning with high renewable penetration and integrated energy systems.

Xiao Cai (Graduate Student Member, IEEE) received the B.S. degree from the Department of Electrical Engineering, Tsinghua University, Beijing, China, in 2020, where he is currently working toward the Ph.D. degree.

His research interests include power system operation and planning with high renewable penetration, data-driven analytics, and system frequency regulation.

Jiaxin Wang (Student Member, IEEE) received the B.S. degree from the Department of Electrical Engineering, Tsinghua University, Beijing, China, in 2022, where he is currently pursuing the Ph.D. degree.

His research interests include security-constrained system scheduling and planning considering the influence of power electronic converters.