



Artificial intelligence techniques for dynamic security assessments - a survey

Miguel Cuevas¹ · Ricardo Álvarez-Malebrán² · Claudia Rahmann¹ · Diego Ortiz³ · José Peña² · Rodigo Rozas-Valderrama²

Accepted: 4 October 2024 / Published online: 21 October 2024
© The Author(s) 2024

Abstract

The increasing uptake of converter-interfaced generation (CIG) is changing power system dynamics, rendering them extremely dependent on fast and complex control systems. Regularly assessing the stability of these systems across a wide range of operating conditions is thus a critical task for ensuring secure operation. However, the simultaneous simulation of both fast and slow (electromechanical) phenomena, along with an increased number of critical operating conditions, pushes traditional dynamic security assessments (DSA) to their limits. While DSA has served its purpose well, it will not be tenable in future electricity systems with thousands of power electronic devices at different voltage levels on the grid. Therefore, reducing both human and computational efforts required for stability studies is more critical than ever. In response to these challenges, several advanced simulation techniques leveraging artificial intelligence (AI) have been proposed in recent years. AI techniques can handle the increased uncertainty and complexity of power systems by capturing the non-linear relationships between the system's operational conditions and their stability without solving the set of algebraic-differential equations that model the system. Once these relationships are established, system stability can be promptly and accurately evaluated for a wide range of scenarios. While hundreds of research articles confirm that AI techniques are paving the way for fast stability assessments, many questions and issues must still be addressed, especially regarding the pertinence of studying specific types of stability with the existing AI-based methods and their application in real-world scenarios. In this context, this article presents a comprehensive review of AI-based techniques for stability assessments in power systems. Different AI technical implementations, such as learning algorithms and the generation and treatment of input data, are widely discussed and contextualized. Their practical applications, considering the type of stability, system under study, and type of applications, are also addressed. We review the ongoing research efforts and the AI-based techniques put forward thus far for DSA, contextualizing and interrelating them. We also discuss the advantages, limitations, challenges, and future trends of AI techniques for stability studies.

Keywords Artificial intelligence · Deep learning · Dynamic security assessments · Machine learning · Power system stability

1 Introduction

1.1 Motivation

Electric power systems worldwide are going through a significant energy transition in order to combat climate change. This energy transition is characterized by a massive integration of non-conventional renewable energies and, in some cases, the decommissioning of coal-fired power plants. Under this global drive, converter-interfaced generation (CIG) technologies, such as photovoltaic and wind power, appear as key pillars in future power systems. In fact, from 2012 to 2021, the total installed capacity of wind power increased from 270 GW to 825 GW, while the total installed capacity of photovoltaic power increased from 102 GW to 843 GW (IRENA, 2022). Despite its benefits, increasing the share of CIG brings several challenges to power systems, especially from a stability viewpoint. Most of these challenges arise due to some fundamental differences between conventional synchronous generators (SG) and CIGs, including limited short-circuit current capability (Jia et al., 2018), inertia-less characteristics and very fast response times of the CIG control systems (Fang et al., 2019).

Accordingly, future power systems with high shares of CIG will be extremely dependent on fast and complex control systems, rendering system dynamics faster. In these complex systems with thousands of power electronic devices at different voltage levels of the grid, dynamic security assessments (DSA) will become increasingly essential for ensuring a secure system operation.

Historically, DSAs of power systems have been performed using detailed time domain simulations (TDS) (F. Luo et al., 2015). For realistic-size power systems, these simulations require solving hundreds of thousands of non-linear differential-algebraic equations, involving high human and computational efforts (Dong et al., 2013). Consequently, these assessment are only performed for some of the most critical scenarios that may threaten stability, which are selected based on the system's historical performance and operator experience (Liu et al., 2018). Although these studies have served their purpose well, they may not remain viable in power systems with large amounts of CIG. On the one hand, the massive integration of CIG increases the uncertainty and variability of the generation feed-in, which results in an increase and shift of the critical operating conditions. In such cases, there is no guarantee that the worst-case approach will cover the most critical conditions of the system (Rahmann et al., 2017). On the other hand, DSA has traditionally focused on the time scale of the electromechanical transients, neglecting fast phenomena in the grid and other fast-response devices (Hatziaargyriou et al., 2021). However, as the number of converter-based devices increases, fast transients start to dominate the system's dynamic response, and disregarding them can lead to erroneous conclusions (Milano et al., 2018). The simultaneous simulation of both fast and slow (electromechanical) phenomena, along with the need to consider an increasing number of critical operating conditions, is pushing traditional DSA to their limits. Reducing both human and computational efforts required for stability studies is, therefore, more critical than ever.

In response to these challenges, several advanced simulation techniques leveraging artificial intelligence (AI) have been proposed in recent years. Unlike traditional analytical methods, AI techniques can capture non-linear relationships between power system operating states and stability utilizing predefined datasets. Once the AI establishes said relationships,

it can evaluate different operating conditions and contingencies without having to solve complex sets of non-linear differential-algebraic equations and, thus, significantly lowering the computational efforts. These characteristics enable intelligent systems (IS), at a research level, to produce results with high degrees of accuracy within a few hundred milliseconds to a few seconds (Dong et al., 2013), noticeably reducing the computational time required in comparison to analytical methods.

Despite the good results obtained so far, the use of AI for DSA has not yet been widely adopted by the industry. Current approaches still rely on TDS, especially for offline applications, or use stability proxies that are fast to compute but not as accurate as TDS. Stability proxies are particularly useful for real-time (online) DSA applications, given its fast-computing times. A survey of on-line DSA currently being used in real-world power system can be found in Nuthalapati (2021). On a research basis, DSAs using AI have been developed for both offline and real-time applications. While offline applications focus on maximizing accuracy (Lin, 2013), online applications aim to perform quickly and make accurate assessments so that the operator can take preventive/remedial actions (Sun et al., 2008). DSAs using AI for online applications have recently seen a significant increase due to the massification of phasor measurement units (PMUs), which allow fast, accurate and synchronized data collection (Yang et al., 2018). AI-based DSA tools are not meant to replace the use of TDS for DSA, but it should be seen as a complementary tool. For example, AI-based DSA can be used to quickly assess system stability for a wide range of situations and identify critical conditions that may jeopardize system stability. Then, detailed stability studies based on TDS can be selectively performed for the critical conditions identified. This would allow to cover a wider range of operating conditions with significantly less human and computational efforts. While hundreds of research articles confirm that AI techniques are paving the way for fast stability assessments, many questions and issues still need to be addressed. Issues like the pertinence of existing AI-based methods to study certain types of stability, as well as their application in real-world power systems are among those that still need to be further discussed and analysed.

1.2 Objective and main contributions

This article presents a comprehensive review of AI-based techniques for stability assessments in power systems. Different AI technical implementations, such as learning algorithms and the generation and treatment of input data, are widely discussed and contextualized. Their practical applications, considering the type of stability, system under study, and type of applications, are also addressed. We review the ongoing research efforts and the AI-based techniques that have been put forward thus far for DSA, contextualizing and interrelating them. We also discuss the advantages, limitations, challenges, and future trends of AI techniques for stability studies. The main contributions are the following:

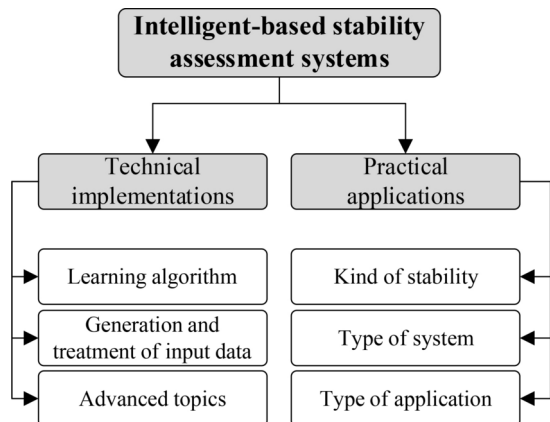
- A comprehensive review of works that have used AI, considering the revisited and extended classification of stability by the Institute of Electrical and Electronics Engineers (IEEE) Power System Dynamic Performance Committee Task Force (Hatziaargyriou et al., 2021).
- A review of the AI techniques that have been used for DSA, including works that have compared the performance of different techniques.

- The identification of the main features that have been used as input data for the AI models for each type of stability being addressed.
- The identification of gaps, challenges and limitations in the research and
- Future research opportunities regarding AI techniques, type of stability and challenges for practical applications. Even though a review of works that use AI techniques for power system security and stability assessments was already presented in (Alimi et al., 2020), this review focuses more specifically on power quality disturbance, supervisory control and data acquisition (SCADA) network vulnerabilities and threats, transient stability, and voltage stability. It does not review studies focusing on frequency stability, resonance stability and converter-driven stability. The remainder of this paper includes the following sections: Sect. 2 presents an overview of intelligent systems for power system stability assessments. Section 3 reviews technical issues related to the AI-based models used for DSA, such as the learning algorithm being explored, the generation and treatment of input data and other advanced topics. Section 4 reviews the practical applications for which the IS was developed. Finally, Sect. 5 presents the conclusions and summarizes the research gaps.

2 Intelligent-based stability assessment systems - overview

For this review, we characterized an IS for evaluating power system stability according to key definitions that must be made in two main aspects: the technical implementation and its practical application in actual power systems (see Fig. 1). On the one hand, technical implementations refer to learning algorithms, input data generation and processing, and other advanced issues, such as possible strategies for updating the models when new input data becomes available and dealing with noise, incorrect data, missing variables or communication delays. On the other hand, practical implementations refer to the purpose and the reason for developing the IS. In this regard, we include topics such as the kind of stability, the power system model used for validating the proposal, and its types of applications (online or offline stability assessment).

Fig. 1 Key issues for IS's technical implementations and practical applications in stability assessment



The database of this review comes from journal and conference papers mainly from IEEE Xplore Digital Library and Elseviers' ScienceDirect. The search criteria consisted of works that, in their abstract or their title, include one of the following keywords: "intelligent systems," "artificial intelligence," "machine learning," or "deep learning," and which bear the name of the specific AI techniques, together with stability-related terms such as "voltage stability," "resonance stability," "converter-driven stability," and "dynamic security assessment." Table 1 summarizes the total number of works included in the database. In total, 165 papers using the search criteria above were found (after filtering those unrelated to this review).

3 Technical implementation

This section reviews the technical implementation for building AI-based models for DSA. It focuses on three main topics: the learning algorithm (section 3.1), the generation and treatment of input data (section 3.2), and other advanced topics such as model updates and dealing with noise, incorrect data, or missing variables (section 3.3).

3.1 Learning algorithm

The learning algorithm is the core of an IS (Dong et al., 2013). Machine Learning (ML) techniques are generally categorized as supervised, unsupervised and reinforcement learning algorithms (Taeho, 2021). There is also a subcategory called semi-supervised learning that combines supervised and unsupervised learning (Goodfellow et al., 2016). In total, 145 papers proposed supervised techniques, eight papers proposed both, supervised and unsupervised techniques, five papers proposed unsupervised learning, three papers with both, reinforcement and supervised learning, two papers proposed reinforcement learning and two papers semi-supervised learning techniques. Next, we briefly describe these techniques. For better readability, we first present the base techniques used for single predictors or classifiers (section 3.1.1). Then, we present ensemble techniques, which are a combination of individual predictors or classifiers to form a single high-quality one. In each case, we also provide examples to facilitate understanding.

3.1.1 Types of techniques

Supervised learning algorithms use labeled data to generate a model that predicts a targeted attribute. For example, in Zhang et al. (2019), operational variables such as wind power and load demand are used as input data to predict voltage stability. The target attribute is classified as "stable" or "unstable" in this case. Detailed TDS are needed to classify each operating condition as stable/unstable. Thus, the target attribute is known for each input data and used to train the models. Then, the trained IS can predict whether the system is

Table 1 Number of publications found

Period	Publications
≤ 2005	11
2006 - 2011	15
2012 - 2017	64
>2017	75

stable for new operational conditions. In contrast, unsupervised learning algorithms seek hidden structures in the data without using any labels. *Clustering* is a typical unsupervised learning algorithm used in DSA, which consists of breaking down a data set into groups so that the elements within one group are similar and different from the elements of the other groups. For example, in Rahmann et al. (2017), a clustering technique is used for grouping operational conditions (8760 operating points) based on operational and system-wide characteristics such as generator dispatch, Rate of Change of Frequency (ROCOF), and systemic inertia. The objective is to arrange groups so that the operational conditions within a group have similar dynamic behavior in case of disturbances. Finally, reinforcement learning is a training method to maximize a reward signal. Unlike supervised learning, it does not need labeled data or direct instructions. An example of this technique is found in Hadidi and Jeyasurya (2013), where a trained algorithm can determine the optimal limits of power system stabilizers (PSS) to improve the transient stability margin during three-phase faults. The impact of the angular deviation in the corresponding busbar is evaluated for each change in the PSS limits. If the action has a positive/negative impact, it receives a reward/penalty, which allows it to adjust the new control actions in the future iteratively.

Regarding the ML-based techniques applied to power system stability assessments, most of the proposals found in the technical literature use supervised learning. One of the most common techniques is Decision Tree (DT) because of its simplicity, accuracy, and interpretability. DTs work by sequentially splitting the data into smaller groups using an *if-then* logic and are especially suitable for classification problems. However, they can also be used for regression problems as well. The following works have used DTs as supervised learning for stability assessments: (Lin, 2013; Sun et al., 2008; Genc et al., 2010; Adewole and Tzoneva, 2017; N.G. Baltas et al., 2018; Guo and Milanović, 2014; Karapidakis, 2007; Krishnan and Thampatty, 2020; M. Mohammadi et al., 2010; M. He, Zhang, and Vittal, 2013; He et al., 2013; Mohammadi et al., 2016; Mohammadi and Dehghani, 2015; Mukherjee and De, 2020; Senroy et al., 2006; Nuqui et al., 2001; Diao et al., 2010; Rahmatian et al., 2017; Rovnyak et al., 1994; Rovnyak et al., 2000; Diao et al., 2009; Hosseini et al., 2012; Nandanwar et al., 2018; Guo and Milanović, 2013; Teeuwesen et al., 2005; Zhang et al., 2019; Yang et al., 2017; Zhang et al., 2018; Pannell et al., 2018; Zhang et al., 2012; Zheng et al., 2013; Nie et al., 2017; Zhu et al., 2017; Nandanwar and Warkad, 2016; Chang et al., 2005; Zhang et al., 2023b; Naderi et al., 2023; Ren, Yuan, et al., 2023; Y. Luo et al., 2023; Zhang et al., 2023a; Ren, Wang, et al., 2023). Another commonly used technique is Random Forest (RF) (Krishnan and Thampatty, 2020; Zhang et al., 2019; Zhang et al., 2012; Zhang et al., 2023a; Suprême et al., 2018; Kaci et al., 2014; Kamwa et al., 2010; Liu et al., 2020; Malbasa et al., 2017; Ortiz-Villalba et al., 2020; Zhang et al., 2016; Dharmapala et al., 2020), an algorithm that implements an ensemble of DTs obtained from random subsamples of the training data. Like RF, Isolation Forest (iF) (Gao et al., 2023) creates an ensemble of DTs suitable for managing outliers. Support Vector Machine (SVM) is another popular method used for binary classification in a supervised fashion (N.G. Baltas et al., 2018; Krishnan and Thampatty, 2020; Pannell et al., 2018; Zhang et al., 2012; Zhang et al., 2023b; Zhang et al., 2023a; Malbasa et al., 2017; Echeverría et al., 2017; Gomez et al., 2011; Geeganage et al., 2015; Mohammadi et al., 2018; Pérez-Londoño et al., 2017; Bo et al., 2014; M. Suganyadevi and Babulal, 2014; Tian et al., 2019; Tang et al., 2017; Yuanhang et al., 2015; Zhang et al., 2018; Zhou et al., 2016; Sajan et al., 2015a; Zhou and Zhang, 2023; Z. Zhang et al., 2023; Niu et al., 2021). SVM finds the hyperplane that separates the data while maximizing its distance

to any data point, which renders SVM useful for stable/unstable classification, provided that a hyperplane in the input space capable of separating both classes exists. If such a hyperplane does not exist, a common strategy is to employ a kernel trick technique, which transforms the input space into a higher-dimensional one where such a hyperplane does exist. In the survey works, most of them use a kernel trick, usually a Gaussian radial basis function (e.g. N.G. Baltas et al. 2018; Krishnan and Thampatty 2020; Pannell et al. 2018). The only work that employs a linear kernel is (Mohammadi et al., 2018). Support vector regression (SVR) (Alizadeh and Amraee, 2014; Cepeda et al., 2014; Suganyadevi et al., 2016), and Least-squares support vector machines (LSSVM) (Yang et al., 2018; Maihemuti et al., 2021) use the same principle as SVM. However, rather than seeking a hyperplane to classify the data, they aim to find a hyperplane (for linear relationships) or a kernel function (for non-linear relationships) that best fits the data. Hence, both techniques are employed to address regression problems. Other variations of the SVM are the Aggressive and Conservative support vector machines (ASVM and CSVM, respectively) (Hu et al., 2019), Core vector machines (CVM) (Wang et al., 2016), and Ball Vector Machines (M. Mohammadi et al., 2010). Other widely used techniques for stability studies are those based on Artificial Neural Networks (ANN). This technique implements layers of artificial neurons (also called *nodes*). An ANN comprises at least one input layer and one output layer, with any number (if any) of *hidden* layers in between the input and the output. An ANN with no hidden layers (or *perceptron*) (Z. Zhang et al., 2023) resembles a linear regression, while adding hidden layers allows the ANN to learn more complex non-linear behavior from the data. The most common ANN is the Multiple Layer Perceptron (MLP), also called Feed Forward Neural Network (FFNN), since its neurons receive information only from the previous layers. Because of the significant computation burden required for training an ANN, most MLPs use a single hidden layer (Lin, 2013; Karapidakis, 2007; Alizadeh and Amraee, 2014; Zhang et al., 2015; Bahbah and Girgis, 2004; Jensen et al., 2001; Frimpong et al., 2017; Mahdi and Genc, 2017; Jayasankar et al., 2010; Sajan et al., 2014; Sajan et al., 2015b; Sharifian and Sharifian, 2015; Nakas et al., 2023). Extreme Learning Machine (ELM) is one of the most widely used types of single hidden layer MLP, found in (Zhang et al., 2019; Zhang et al., 2018; Ren, Yuan, et al., 2023; Ren, Wang, et al., 2023; Tang et al., 2017; Zhang et al., 2018; Liu et al., 2019; Zhang et al., 2015; Li et al., 2015; Baltas et al., 2018; Li et al., 2021; Y. Li and Yang, 2017; Li and Gu, 2013; Ren and Xu, 2020; Ren and Xu, 2019; Ren et al., 2020; Zhang et al., 2015; Sulistiawati et al., 2016; Wang et al., 2019; Xu et al., 2013; Y. Xu et al., 2011; Xu et al., 2012; Zhang et al., 2017; Zhang et al., 2013; Xu et al., 2016). ELM uses fixed random weights for the input layer, allowing it to obtain the output weights analytically and substantially reducing the computational burden. However, random weights can pose a problem for the robustness of the results in prediction (Zhang et al., 2013). Thus, many works implement ELMs in ensembles. Closely related to ELMs are Random Vector Functional Link (RVFL) models (Zhang et al., 2019; Ren, Yuan, et al., 2023; Y. Luo et al., 2023; Ren, Wang, et al., 2023; Ren and Xu, 2020; Ren and Xu, 2019; Ren et al., 2020). The only difference with an ELM is that an RVFL has its output layer connected to the input layer. Another specific type of ANN is the Radial Basis Function neural network (RBFNN), in which the response of neurons is given by a radial basis function (Bahbah and Girgis, 2004; Y. Xu et al., 2011; Xu et al., 2016; Velayati et al., 2015; Siddiqui et al., 2018; Innah and Hiyama, 2011; Jain et al., 2003). There is a particular type of ML that many authors refer to as Deep Learning (DL). DL models are ANNs of multiple layers, able to capture

more complex characteristics from the data than traditional ML algorithms. DL can incorporate any of the three types of learning previously mentioned. While an ANN with no hidden layers cannot be considered a DL system, multiple connected layers of artificial neurons are the algorithms' basic architecture. DLs are adept at discovering relationships within highly complex systems (Hornik et al., 1989). Additionally, their architecture can accommodate various input and output data (such as images, time series, and continuous or discrete variables), rendering them among the most popular techniques in use today. An example of DL can be found in (Xie and Sun, 2021), which proposes a technique to predict the system's frequency evolution in real-time after the occurrence of a disturbance. DL enabled it to extract spatial and temporal features from the input data and combine local features with global ones, which ML algorithms such as SVM or simpler ANN structures could not. MLP applications with more than one hidden layer only started to become prevalent in recent years, as seen in (N.G. Baltas et al., 2018; Krishnan and Thampatty, 2020; Naderi et al., 2023; Tang et al., 2017; Zhou and Zhang, 2023; Ren and Xu, 2019; Tan and Zhao, 2023; Gurung et al., 2021; Ali et al., 2015; Bahmanyar and Karami, 2014; Sawhney and Jeyasurya, 2006; Shah and Verma, 2016; Hashiesh et al., 2012; Sepehr et al., 2022; Zhang et al., 2018; Hossain and Kumar, 2023; Abbass et al., 2023; Zhao et al., 2023a; Wang and Pal, 2023; Anderson et al., 2023; Shahzad, 2021). Some papers refer to ANNs generically without specifying the model's architecture, probably referring to single hidden layer MLP (Zhang et al., 2012; Malbasa et al., 2017; M. Suganyadevi and Babulal, 2014; Zhang et al., 2018; Zhang et al., 2013; Velayati et al., 2015; Yousefian et al., 2017; Boudour and Hellal, 2005; Goh et al., 2015; Zhao et al., 2023b). Other variations of the classic MLP are Entropy Network (Karapidakis, 2007) (which emulates a DT), Probabilistic Neural Network (Teeuwesen et al., 2005; Velayati et al., 2015) and Fuzzy Neural Network (Teeuwesen et al., 2005; M. Suganyadevi and Babulal, 2014; Sharifian and Sharifian, 2015; Liu et al., 1999). Finally, the most famous among the advanced ANNs are Convolutional neural network (CNN) (Zhang et al., 2023b; Ren, Yuan, et al., 2023; Y. Luo et al., 2023; Zhang et al., 2023a; Ren, Wang, et al., 2023; Ren and Xu, 2019; Xie and Sun, 2021; Azman et al., 2020; Arteaga et al., 2019; Tan et al., 2017; Wang et al., 2021; Bashiri Mosavi et al., 2018; Zhao et al., 2023b; Ren and Xu, 2023; An et al., 2020; Shi et al., 2020), Graph Neural Network (Zhang et al., 2023b; Y. Luo et al., 2023; Qiao et al., 2021; Huang et al., 2020), and Recurrent Neural Network (RNN) (Bahbah and Girgis, 2004; Nakas et al., 2023; Song et al., 2020). In the latter, unlike FFNN, each layer is fed by the input and its own response in a recursive way. The most famous form of an RNN is the Long short-term memory (LSTM) model (Zhang et al., 2023b; Ren, Yuan, et al., 2023; Y. Luo et al., 2023; Zhang et al., 2023a; Ren, Wang, et al., 2023; Nakas et al., 2023; Xie and Sun, 2021; Zhao et al., 2023a; Zhao et al., 2023b; Azman et al., 2020; Ren and Xu, 2023; Yu et al., 2018; Yu et al., 2017; Zhu et al., 2021; Zhu and Luo, 2021).

DTs, SVMs and ANNs (along with their respective variations) are among the most widely utilized AI techniques. Other algorithms, though less popular, include K-Nearest Neighbor (KNN) (Krishnan and Thampatty, 2020; Zhang et al., 2023a; He et al., 2016; Liu et al., 2019; Xu et al., 2010), Gaussian Process Regression (Tan and Zhao, 2023; Zhai et al., 2023), Times Series Shapelet Classification (Zhu et al., 2017; Zhu and Hill, 2022), Quantile Regression (Naderi et al., 2023), Multivariate adaptive regression splines (Rahmatian et al., 2017), Multi-Label Learning (Ren, Yuan, et al., 2023), Mahalanobis kernel regression (Liu et al., 2020), Bayesian multiple kernel learning (Gu and Li, 2013), Naïve Bayes (

Pannell et al., 2018), Logistic regression (Krishnan and Thampatty, 2020; Z. Zhang et al., 2023), Adaptive AR (Xu et al., 2005), Artificial Immune Systems (Suliman and Rahman, 2010), and eXtreme Gradient Boosting classifier (XGBoost) (Krishnan and Thampatty, 2020; Zhang et al., 2023a; Chen et al., 2019). The last AI technique found in this review is Quantum Machine Learning (QML) (Zhou and Zhang, 2023) which implements a Variational Quantum Circuit (an ordered sequence of quantum gates characterized by variable parameters that can be tuned during the training procedure) that takes advantage of the ability of quantum machines to perform complex tensor operations and utilize quantum operators (such as superposition and entanglement) to capture complex non-linear behavior. Zhou and Zhang (2023) is the first (and only work so far) that implements QML for DSA. In particular, they use QML to classify different system states into *stable* or *unstable*, obtaining degrees of accuracy higher than 96%, which is very similar to the accuracies found using MLP and SVM.

As for unsupervised, reinforcement and semi-supervised learning techniques, only a few works have used them in the context of power system stability assessments. In total, we found 14 publications that use unsupervised algorithms. The techniques used are K-means (Liu et al., 2018; Naderi et al., 2023; Pérez-Londoño et al., 2017; Wang et al., 2019), Growing Hierarchical Self-Organizing Map (GHSOM) (Boudour and Hellal, 2005), Autoencoders ((Sephehr et al., 2022; Tan et al., 2017; Mahdi and Genc, 2018; Zhang et al., 2021)), Generative Adversarial Network (GAN) (Ren and Xu, 2019), Complete Linkage Clustering (Rahmann et al., 2017; Ortiz-Villalba et al., 2020) and Bayesian Neural Network (Zhang et al., 2021; T. Liu et al., 2020). Five works that use Reinforcement Learning (RL) were found (Zhao et al., 2023a; Wang and Pal, 2023; Yousefian et al., 2017; Yousefian and Kamalasadani, 2016; Yousefian and Kamalasadani, 2018). Finally, there were only two works based on semi-supervised learning. The techniques used were Deep Belief Network (DBN) (Zhang et al., 2018) and semi-supervised SVM (S3VM) (Zhu et al., 2022). It is worth mentioning that several papers use more than one algorithm for the training structure or to compare the performance of the algorithms against another one.

Figure 2 summarizes the types of techniques that have been implemented throughout the years. This figure shows that stability assessments using AI-based techniques have increased significantly over the last few years, mainly through supervised learning techniques. Unsupervised, semi-supervised, and reinforcement learning techniques are scarce and have been proposed only in recent years.

Figure 3 presents the number of works that have used DL and ML techniques for DSA over the years. Note that single hidden layer ANN is considered an ML technique, not a DL one. This figure shows that the number of works that use an ML technique increased by 13% from 2012-2017 to 2018-2023, while the number of works using a DL technique for DSA increased by 146% in the same period. These results show growth in both techniques but highlight a greater interest in DL. The reason might be the ability of DL to employ multiple learning categories and capture more complex features compared to traditional algorithms, together with the rapid development of computational capacity.

3.1.2 Ensemble algorithms

One strategy to improve prediction capacity is to use ensemble models. An ensemble combines individual predictors (i.e., single models) to form a single high-quality predictor (Ade-

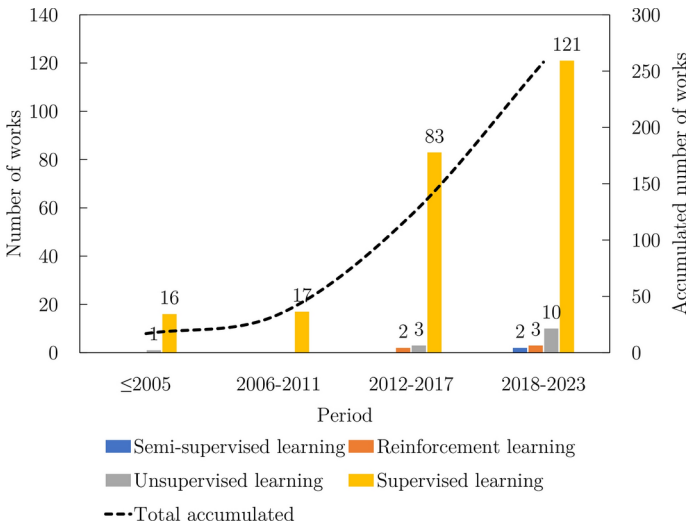


Fig. 2 Distribution of categories of Machine Learning algorithms in works over periods of years

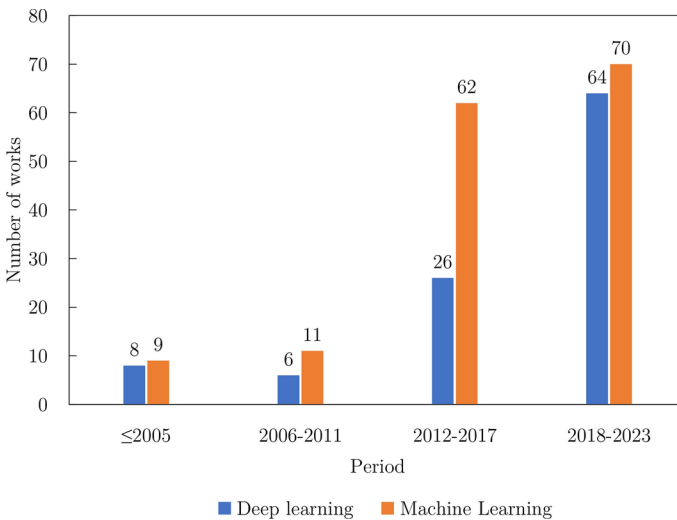


Fig. 3 Comparison of the growth of Deep Learning and traditional Machine Learning in different periods

wole and Tzoneva, 2017). Individual predictors can use the same technique and be trained using different training data and parameters, or the ensemble can consist of a mix of different techniques. Ensemble learning algorithms have benefited from several advantages, such as a decreased risk of over-fitting, avoidance of falling into a local optimum, and enlargement of the space for possible fitting hypotheses (Tang et al., 2017). The works that employ ensemble techniques for DSA are Zhang et al. (2019); Adewole and Tzoneva (2017); M. He, Zhang, and Vittal (2013); He et al. (2013); Mukherjee and De (2020); Guo and Milanović (2013); Zhang et al. (2019); Yang et al. (2017); Nie et al. (2017); Tang et al. (2017); Zhou

et al. (2016); Liu et al. (2020); Gu and Li (2013); Y. Li and Yang (2017); Ren et al. (2020); Xu et al. (2012); Zhang et al. (2013); Xu et al. (2016); Abbass et al. (2023); Yu et al. (2017); Zhu et al. (2022); An et al. (2020); Cremer and Strbac (2021); Niu et al. (2021). It is worth mentioning that in this review, RF and iF techniques were not considered ensembles.

Within an ensemble algorithm, the traditional aggregation strategy for classification problems is majority voting, whereas, for regression problems, it is direct averaging. As the names suggest, with majority voting, each classifier predicts a class, and the class with the most votes is selected. For regression problems, direct averaging consists of selecting the average values delivered by each predictor. Next, we present some example proposals using ensemble models.

The work in (Mukherjee and De, 2020) proposes an ensemble of decision tree predictor models for real-time DSA of power systems. The proposed method reached a prediction accuracy of 91.44%, which is much higher than the accuracy obtained by individual classifiers such as the Method of Least Square (77.3%), ANN (78.4%), vector quantization (80.54%), and SVM (81.7%). Work in (Tang et al., 2017) proposes an online frequency prediction model using ensemble learning consisting of DT, multivariable linear regression (MLR), ANN, LSSVM, and ELM as base learners. The strategy combines individual learners by weighted averaging, using modified cross-entropy to quantify the contribution of an individual sample in the dataset. The model is tested on the IEEE 39-bus network using a limited data set (200 training and 108 test data). As a result, the relative error of the predictions ranged between 17.1% and 17.8% for individual algorithms, while the error for ensemble learning was 13.6%. These results show the potential of ensemble learning to obtain better prediction results than individual algorithms. In Adewole and Tzoneva (2017), the authors develop two ensemble methods for evaluating voltage stability for classifier and predictor problems: a boosting ensemble, and a bagging ensemble. On the one hand, the boosting ensemble uses a sequential procedure to train individual predictors. At every boosting step, the weights of the observations misclassified by a DT increase, while the weights of the correctly classified observations decrease. Then, the updated weights help train the next learner to improve the prediction accuracy of misclassified observations. On the other hand, the bagging ensemble generates bootstrap replicas of the original dataset (i.e., a set with random samples of the observations) and trains individual DTs on each of these replicas. To evaluate the performance of the ensemble methods, the authors developed a classifier and a predictor for each operating condition. The classifier's output was the system state (stable, alert, or unstable) from a voltage stability viewpoint, and the output of the predictor was the margin to the voltage collapse point. The results obtained in a case study based on the New England IEEE 39-bus showed that while the bagging ensemble method had the best performance for the classifier problem (above 99.8% accuracy), the boosting ensemble method showed the best performance for the regression problem (less than 2 mean squared error, MSE, in the predicted value of the margin to the voltage collapse point). In Zhang et al. (2019), the authors propose an ELM ensemble model with a hierarchical structure for short-term voltage stability (STVS) prediction. In the first stage, the trained model classifies the operational conditions as stable or unstable. Control actions are triggered to stabilize the system if the prediction model detects an unstable condition. A second-stage model predicts the severity of fault-induced delayed voltage recovery (FIDVR) if the condition is stable. Using a self-adaptive aggregation strategy, if the prediction's accuracy is unacceptable ("Not sure"), the STVS assessment will be postponed to the next time point,

where more information (measurements) is available. The results obtained using the New England IEEE 39-bus test system showed that the self-adaptive aggregation structure optimally balances prediction accuracy with evaluation speed. Specifically, for 1987 test samples, including 1003 stable and 984 unstable samples, in the first hierarchy (STVS), 82.39% of the samples were successfully classified within 0.2 s, while to achieve a 99.09% accuracy, the proposed method takes 0.8 s.

Figure 4 shows the number of works that have proposed single and ensemble models over the years. Sixty-six papers published from 2018 to 2023 used individual models, while only nine papers proposed ensemble models during the same period. Note that the use of ensemble models began in 2012. Even though most works still propose single models, ensemble models are gaining interest. It is important to note that most works that propose ensemble models also develop single models for comparison purposes. In the future, we anticipate a growing trend towards using ensemble models, owing to the promising results achieved in prediction accuracy. In many cases, these results surpass those obtained by their single-model counterparts.

Choosing the proper algorithm for DSA is a challenging task. In the last few years, several authors have compared the performance of different techniques. For example, in Y. Xu et al. (2011) the authors compare the performance of ELM, DT, SVM, and RBFNN for transient stability. In Zhang et al. (2018), the authors compare the performance of ANN, Regression Tree (RT), SVM, and ELM to predict STVS; in Zhang et al. (2018), the authors compared the performance of DBN, two ANNs, SVM, DT, and RF, to predict the STVS. In Xu et al. (2016), the authors compared the performance of ELM, SVM, DT, and RBFNN to assess short term voltage stability.

Regarding the training time, significant differences exist among various algorithms. In Y. Xu et al. (2011); Xu et al. (2016), and Zhang et al. (2018), the authors found that ELM is notably the fastest algorithm train, requiring between one to three orders of magnitude less than DTs, which are the second fastest algorithm to train. Training SVM is around one order of magnitude slower than DTs. Finally, various types of ANNs, such as MLPs and RBF-

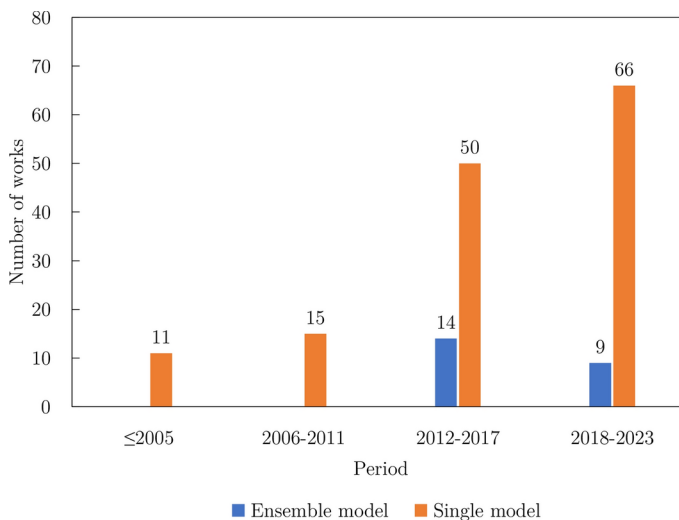


Fig. 4 Number of publications that have proposed ensemble models and single models

NNs, are as slow to train as SVM or even slower. These findings explain why ELMs and DTs (including RF) are among the most widely utilized methods. Meanwhile, despite their longer training times, ANNs have gained popularity due to their high prediction capacity.

These studies show that, while some techniques outperform others for a specific type of problem, e.g., type of stability, test system, amount, and type of input data, they may perform worse for different problems. In this regard, a research gap is to identify which type of problems and input data techniques perform better than others and why.

3.2 Generation and treatment of input data

3.2.1 Introduction

One of the basic requirements to implement an IS is to have good-quality data with a sufficiently large dataset to train and validate the models. If the database is biased, contains too few operating conditions, or lacks diversity, the extracted knowledge can be insufficient for an adequate stability classification or prediction, and the model will perform poorly (Dong et al., 2013). Hence, a key challenge is to generate enough high-quality input data for training and testing the models. Once the system's operating conditions are determined, the usual approach is to evaluate the system's dynamic performance using TDS. Then, each operating condition is either labeled (e.g., stable, unstable) for classification problems or valued by a stability index e.g., voltage stability margin (VSM), transient stability index (TSI), frequency stability margin (FSM) for regression problems.

Given the high human and computational resources involved, one of the main barriers to developing IS-based models for stability assessments in realistic-sized power systems is having to perform numerous TDS. Hence, most proposals are developed and tested in small test systems (e.g., Liu et al. 2018; Zhang et al. 2019; Adewole and Tzoneva 2017; M. Mohammadi et al. 2010; Hashiesh et al. 2012) or use only a few snapshots of the system operation. In this latter case, a usual strategy to generate a wide variety of input data is to perform minor changes in the operating conditions, for example choosing contingencies and clearing times randomly (see Zhang et al. 2019; Adewole and Tzoneva 2017; Guo and Milanović 2014; Hashiesh et al. 2012). However, this strategy may not be suitable for capturing power system dynamics during significant changes, such as the further integration of renewable energies and the resulting displacement of SGs. Only a few works use realistic-size power system models (e.g., He et al. 2013, 2016; Xie and Sun 2021; C. Liu et al. 2014). Next, we will present and discuss the literature reviewed on data preprocessing strategies for generating good-quality input data for training and testing AI-based models.

3.2.2 Class imbalance issue

The challenge of class imbalance arises when system states are unevenly distributed within the dataset. For example, if the objective is to predict voltage stability, input data should have enough cases where the system is both stable and unstable. For real-world power systems, this is challenging because the number of operating conditions where the system remains stable after a contingency is significantly larger than the cases where the power system becomes unstable. Such an imbalance can considerably deteriorate the prediction's

performance if not appropriately treated since the models could be biased toward the majority class, thus overlooking the minority class (Zhu et al., 2017).

Several authors have proposed methods for dealing with the class imbalance problem. One option is to artificially generate operating conditions where the system is unstable after a fault, thus achieving balanced classes (Zhang et al., 2019; Zhang et al., 2012; Sepehr et al., 2022; Zhao et al., 2023b; Nakas et al., 2023). However, this strategy may not be suitable for real-world power systems applications since the input data may contain unrealistic operating conditions. Another option to deal with the class imbalance problem is to introduce synthetic samples of the minority class (e.g., unstable cases) from existing data. This approach involves randomly selecting a sample from the minority class and creating new data from the same class, for example by interpolation with its close neighbors. For example, in Zhu et al. (2017), the authors mitigate the class skewness with a Forecasting-Based Nonlinear Synthetic Minority Oversampling Technique (FN-SMOTE). In addition, they employ cost-sensitive learning to impose more bias on scarce unstable instances. In this work, they also implemented other methods like Random Oversampling (ROS), Synthetic Minority Oversampling Technique (SMOTE), Borderline-SMOTE (B-SMOTE), and Adaptive Synthetic Sampling (ADASYN). As a result, they showed that the prediction accuracy improved from 80.6% (without any data treatment) to 97.8% by using FN-SMOTE and ADASYN to balance the classes. When using only the SMOTE technique, the accuracy improved to 97.2%. Finally, ROS and B-SMOTE improved the accuracy to 94.4% and 95%, respectively.

The authors in Kamwa et al. (2012) propose another strategy: replicating as many non-secure cases as needed to balance the unsafe/safe ratio. The original data set of 60836 operational conditions only included 22.5% unstable cases. To balance the unsafe/safe ratio, the authors increased the number of unstable operating conditions by replicating the unstable cases three times, bringing the dataset to 98800 cases. However, this strategy introduces too many conditions overlapping each other, thus leading to overfitting problems (Zhu et al., 2017).

3.2.3 Amount of input data

To address the challenge of acquiring many TDS to train an IS, a sound strategy is to develop models that require fewer input data. This strategy can be crucial in reducing the barriers when developing AI-based stability assessments for real-world power system applications. Unfortunately, this issue remains unresolved. In this regard, reference Malbasa et al. (2017) is the only work that attempts to reduce the number of TDS for training an IS. The authors propose an active learning approach for a multi-class problem. The training dataset is built iteratively, starting from a single operating condition for each class. Using TDS, new operating conditions are selected and labeled in each iteration. Then, the IS is re-calibrated with this newly acquired information. Three approaches were proposed for choosing the new operating conditions for each iteration: 1) random selection, 2) uncertainty sampling, and 3) margin sampling. As a result, they show that the IS can accurately classify operating conditions in terms of voltage stability with only a few operating conditions. For example, when using only 100 operating conditions, the prediction accuracy reached 85%, whereas using 1000 operating conditions resulted in a maximum accuracy of around 90%. While the margin sampling strategy exhibited the highest performance among the three, the random sampling strategy achieved the worst results. The main drawbacks of this work are: 1) it

does not consider contingencies, and 2) in the case study, the classes were well-balanced, which is unrealistic. However, the good results suggest that choosing the operating conditions for performing TDS strategically based on a stability criterion rather than randomly may render benefits for improving the IS accuracy when there is limited availability of TDS.

3.2.4 Dimensionality reduction

Dimensionality reduction is a data pre-processing step aiming at transforming the input data into an effective domain, eliminating data redundancy while maintaining most of the information. Feature extraction and feature selection are two methods that can achieve dimensionality reductions. While feature extraction transforms the input data into a reduced set of new features, feature selection finds a subset of the original variables. Applying a dimensionality reduction technique reduces the training data size, which results in faster learning and, in many cases, may even lead to better prediction accuracy (Zhang et al., 2012; Geeganaige et al., 2015; Jensen et al., 2001; Y. Li and Yang, 2017; Y. Xu et al., 2011; Sawhney and Jeyasurya, 2006; Zhang et al., 2016). Examples of techniques used for dimensionality reduction are Relevant Interaction Evaluation Features (RELIEF) (Liu et al., 2018; Zhang et al., 2019; Liu et al., 2020; Liu et al., 2019; Xu et al., 2010; Xu et al., 2012; Xu et al., 2016), Principal Component Analysis (PCA) (Mohammadi et al., 2016; Sawhney and Jeyasurya, 2006), divergence analysis (Voumvoulakis et al., 2006), Fischer discrimination (Jensen et al., 2001; Jain et al., 2003), Gram-Schmidt orthogonalization (Bahmanyar and Karami, 2014), and Wrapper models (Wang et al., 2008). In addition, in M. Mohammadi et al. (2010), DTs are also used to select relevant features. Metaheuristic algorithms can also be utilized to identify relevant features in other research areas (see, for example, Ameen et al. 2023 for classifying electrocardiograms). However, in the field of DSA, their use is relatively scarce: in Zheng et al. (2013) and Sajan et al. (2015a), GAs are used to identify relevant features, and in Zhang et al. (2015), PSO is used for feature selection and for tuning the input weights and the activation function of ELM.

In Zhang et al. (2012), the performance of eight feature selection approaches, which are various combinations of evaluation criteria and search methods, were tested for a transient stability assessment problem. Concretely, the techniques explored were RELIEF, Chi-square, k-NN, Fisher, and Divergence. The search methods were Genetic algorithm, Back-track search, Forward, and Select-by-rank. For a case study using the IEEE 145-bus 50-generator test system, they obtained that, although applying a feature selection reduced the training time significantly, it only achieved marginal accuracy improvements. Without any treatment of the input data, the prediction accuracy using ANN, SVM, and DT was 93.0%, 97.1%, and 95.9%, respectively, with training times of 586.6 s, 1369.4 s, and 58.7 s. When applying the best feature selection techniques (RELIEF, Select-by-rank, and Genetic algorithm), the prediction accuracy increased marginally to 94.7%, 97.4%, and 96.4%. However, the training time decreased to 61.2 s, 75.5 s, and 9.4 s, respectively. In contrast, when applying the worst techniques (Divergence and back-tracking search), a slight increase in accuracy was observed for ANN (93.7%) with a training time of 55.8 s. However, for SVM and DT, the accuracy decreased to 95.3% and 95.9%, respectively, with 72.1 s and 9.8 s training times. The results of this work reinforce that implementing a dimensionality reduction technique allows for reducing the training times, but it does not necessarily lead to better performance in prediction accuracy.

3.3 Advanced topics

3.3.1 Model update

Power systems are constantly changing. New components such as lines, substations and generating units are added to the system every year. In addition, renewable energies may exhibit different power feed-in patterns throughout the year. This results in changes in the operating conditions and the system's dynamics after a contingency. Because of the changing conditions in real-world applications, prediction models must be updated periodically, which usually requires generating new training samples (Liu et al., 2019). However, incorporating them efficiently to update the models is an active research area.

Among the techniques used for model updating are active learning (Malbasa et al., 2017), transfer learning (Zhang et al., 2023b; Zhang et al., 2023a; Xie and Sun, 2021), and confidence-based models (Zhang et al., 2021). Active learning consists of creating new training samples or enhancing the existing ones iteratively, upon demand, instead of collecting and labeling new data in chunks, which is computationally costly. An example of this technique is presented in Malbasa et al. (2017) for a voltage stability prediction problem. In this work, the proposed approach actively searches for operating conditions, in which inaccurate predictions occur. It then performs dynamic simulations around these identified conditions and adds them to the existing pool of training datasets. On the other hand, transfer learning consists of utilizing the characteristics of an already developed model as a starting point for developing another one. In neural network-based models, transfer learning is usually implemented by freezing some layers of neurons from the source model (i.e., the model trained initially) and then re-training a subset of its layers (typically the last ones) using new data, which is also known as fine-tuning. This way, models can be updated with new data without having to train the model from scratch, which helps reduce the amount of data sampling and training time. The same strategy was used in Xie and Sun (2021) for an online frequency stability assessment problem. First, a CNN LSTM model was trained on an IEEE 118-bus test system using around 2000 samples. Then, the model was successfully transferred and applied to the New England 39-bus system and the South Carolina 500-bus system using only 300 samples. In Zhu and Luo (2021), this strategy was implemented for a voltage stability prediction problem to update the model to adjust it to unexpected topological changes and changes in the load and generation dispatch. In a case study on the 77-bus Nordic test system, the original model was trained with 54000 samples and then adjusted to new operating conditions using 1500 samples. Lastly, confidence awareness refers to the ability of a machine learning model to quantify how confident the model is in its prediction of a given dataset (Zhang et al., 2021). If the likelihood that the output is correct does not satisfy minimum requirements, then the model is updated. In Zhang et al. (2021), the authors propose a Conditional Bayesian Deep Auto-Encoder (CBDAC) based security assessment framework to compute a confidence metric of the prediction, which allows the operator to judge whether the model needs updating.

Another strategy for developing an IS that can adjust to changing operating conditions is to identify and group similar operating conditions, for example, using a clustering technique, and then train specific models for each group. Once the models are built, it is possible to assess new operating conditions with the model trained with the data that best matches the operating condition under evaluation. Such a strategy was implemented in Xu et al. (2012)

for a real-time dynamic security assessment problem and in Liu et al. (2020) for a transient stability assessment problem, where the authors propose a similar strategy that addresses changes in the network topology. Here, the proposed model is a weighted sum of several models, each trained using data collected from a specific topology. The topological similarity and the numerical similarity between the samples determined the weights.

Other works that re-train a model to adjust to new data are He et al. (2013); Diao et al. (2010); Zhu et al. (2017); Naderi et al. (2023); Zhai et al. (2023); Li and Gu (2013); Zhang et al. (2015); Xu et al. (2012); Zhu and Luo (2021); Zhao et al. (2023b); Nakas et al. (2023).

3.3.2 Dealing with noise and bad data

Many AI-based proposals for DSA are developed to be implemented in real-world power systems. However, in these cases, the quality of the data collected by measurement units may not always meet the requirements for developing or using AI-based models. Bad data can come in many forms and refer to noise, bias, or inconsistencies, such as a measurement unit failure. In particular, noise from local, fast, or random load changes can cause measurement peaks (Liu et al., 2020). Hence, an important research line is how to deal with noise and bad data. Works that have dealt with these issues are Naderi et al. (2023); Zhang et al. (2023a); Ren, Wang, et al. (2023); Gao et al. (2023); Zhang et al. (2018); Zhou and Zhang (2023); Liu et al. (2019); Zhai et al. (2023); Sharifian and Sharifian (2015); Nakas et al. (2023); Wang and Pal (2023); Zhao et al. (2023b); Ren and Xu (2023); Yu et al. (2018, 2017); Shi et al. (2020). For example, in Sharifian and Sharifian (2015), for estimating the critical clearing time (CCT) of a fault, the authors propose a Type-2 fuzzy neural network-based method to address the uncertainty and noisy nature of the measured data. The Type-2 fuzzy layer converts uncertain and noisy inputs into more reliable linguistic variables that become useful inputs in an MLP ANN layer. As a result, the proposed strategy could estimate the CCT with higher precision and at a lower computational cost than the MLP ANN method without treatment of the input data. In Yu et al. (2018), to study the influence of noise on PMU samples in a transient stability assessment problem, a random noisy signal was added to the measured voltages in the data set for training and testing. The results obtained from a case study on the IEEE 39-bus New England system with 5000 samples showed that adding noisy data to the measurements decreased the average response time from 1,466 cycles to 1,448 cycles and the accuracy decreased from 100% to 99.92%, in comparison to the test data without noise. These results indicate that, for real-world applications, noise in the input data can reduce the model's prediction accuracy. Cyber-attacks are another source of bad data, as they introduce malicious data without being detected by human observation (Z. Zhang et al., 2023). Recent works, such as Z. Zhang et al. (2023); Wang and Pal (2023); Zhao et al. (2023b); Ren and Xu (2023), developed AI systems resilient to these attacks. In Z. Zhang et al. (2023), the authors present a method for evaluating the robustness of an AI-based DSA model against cyber-attacks. The proposed method, called physics-constrained robustness evaluation, computes the minimum perturbation required to reverse the label (stable/unstable) of the AI-based DSA model, from which it creates a robustness metric. This metric then guides the selection of AI-based models and/or model parameters, resulting in the development of more robust models against cyber-attacks. In Wang and Pal (2023), the authors present a deep deterministic policy gradient (TD3) algorithm to determine the least effort attack path on the droop control gains of inverter-based renewable energies and

to obtain the corresponding robust defense strategy. In Zhao et al. (2023b), the authors present an ML-based robust online stability assessment using lightweight mitigation to enhance the prediction accuracy of the ML model against cyber-attacks. Adversarial samples from cyber-attacks are purified using label-independent self-supervised learning. In Ren and Xu (2023), the authors design a universal defense strategy against cyber-attacks for AI-based DSA models. This strategy first uses attack-free data to build a base classifier. Then, it uses a randomized smoothing algorithm to construct a new (smoothed) classifier, which assigns the most likely output the base classifier returns with the noise perturbations that the cyber-attack caused to the input data.

3.3.3 Dealing with missing variables

Another important issue for implementing AI-based models for DSA in real-world power systems is to deal with missing variables. Most AI-based data-driven stability assessments proposals assume that input data is fully available. However, in practice, some PMUs may be unavailable due to failure, which may either deteriorate the stability assessment's performance or invalidate it. Studies that consider the unavailability of some input data are Adewole and Tzoneva (2017); He et al. (2013); Guo and Milanović (2013); Zhang et al. (2019, 2018); Ren and Xu (2019); Y. Xu et al. (2011); Zhang et al. (2018); Mahdi and Genc (2018). For example, Ren and Xu (2019) develops a GAN model that can generate samples of the missing data by using the Adam algorithm. On the other hand, for real-time STVS assessments the authors in Zhang et al. (2019) designed an ensemble learning method to adjust its structure so it uses only the available inputs. Under scenarios of a PMU loss or topology changes, the proposal strategically selects the observable buses in the system to maintain a high level of network observability. As seen, even though there are methods proposed to deal with missing variables, they are still scarce, which is a gap that needs solutions for real-world applications.

3.3.4 Dealing with communication delays

For real-world applications, when PMUs transmit the measurements collected from remote locations to monitoring centers, the signal experiences a delay that may impact the performance of the AI-based predictions and, if applicable, the triggered control actions. The impacts of communication delays in DSA is investigated in Naderi et al. (2023); Ren et al. (2020); Gurung et al. (2021); Yousefian et al. (2017); Yu et al. (2018); Zhu and Luo (2021); Yousefian and Kamalasadani (2018). In Zhu and Luo (2021), a method based on LSTM for Undervoltage Load Shedding (UVLS) considers a delay of 360 ms. In this case, the results show that the delay does not severely affect the proposed scheme's capability for short-term voltage stability enhancement. However, it leads to larger voltage sags before the execution of UVLS actions. In Ren et al. (2020), two different communication delays are considered for UVLS: 140 ms and 400 ms. The results indicate that the earlier the load is shed, the less load shedding is needed. The main reason is that when it considers a delay of 140 ms, the load can be shed based on the predictions of voltage stability, thus resulting in less amount of load shed and earlier voltage stability recovery. On the other hand, when considering a delay of 400 ms, the load is mainly shed due to low voltages, without the possibility of shedding load beforehand, based on voltage predictions. In Yousefian et al. (2017), the authors

investigated the robustness of an RL-based Wide Area Control (WAC) system against communication delays. To this end, they considered delays of 100 ms and 200 ms for all PMU signals. The results demonstrate that while the proposed RL-based WAC dampens oscillations faster, delays negatively impact its performance. In Yousefian and Kamalasadani (2018), the authors investigated the impact of data delay on sending and receiving signals in a damping controller for transient stability improvement based on a WAC system using RL. Their findings indicate that oscillations between areas increase with delays, thereby deteriorating the performance of the proposed controller.

4 Practical applications

This section reviews the works in terms of the practical application for which the AI-based models for DSA were conceived. This review focuses on three main topics: the kind of stability it addresses, the type of system where proposals were developed and validated, and the type of targeted applications. The latter differentiates between offline and online applications.

4.1 Kind of stability

Power system stability is defined in Kundur et al. (2004) 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.*”. Recently, Hatziargyriou et al. (2021) proposed an extended stability classification, covering the effects of fast-response power electronic devices up to electromagnetic transients. The new proposal classifies the stability phenomena as 1) rotor angle stability, 2) voltage stability, 3) frequency stability, 4) resonance stability, and 5) converter-driven stability. However, power system stability is essentially a single problem Kundur et al. (2004). Indeed, in many situations, one form of instability will probably not occur in its pure form, particularly in stressed systems with high levels of CIG, in which one form of instability may ultimately lead to another form. Accordingly, while the classification of system stability is an effective and convenient means to deal with the high dimensionality and complexity of stability problems, overall system stability should always be kept in mind.

Regarding the kind of stability addressed, most works in the technical literature focus on short-term transient stability and short-term large-disturbance voltage stability. Only a few works focus on short-term small-disturbance rotor-angle stability, long-term small-disturbance voltage stability, and frequency stability (both short and long-term). Only one work focused on resonance stability and two on converter-driven stability (fast and slow interaction).

It is worth mentioning that some works claim that their proposal is general enough to be used for any type of stability (see, for example, Zhang et al. 2023a; Liu et al. 2019; Zhu and Hill 2022; Y. Xu et al. 2011; Zhao et al. 2023b; Zhang et al. 2021). However, the following review only considers the kind of stability addressed within the case studies. The main reason is that even though a model for stability assessment can be developed to consider a wide range of stability issues, different kinds of stability issues may have different challenges for

their prediction. Therefore, the only way to demonstrate the prediction capability is through specific case studies.

4.1.1 Rotor angle stability

Rotor angle stability refers to the ability of synchronous machines of an interconnected power system to remain in synchronism after being subjected to a disturbance (Kundur et al., 2004). Rotor angle stability can be subcategorized into small-disturbance angle stability and transient stability. These kinds of stabilities are both considered short-term phenomena.

IS-based proposals for evaluating transient stability are F. Luo et al. (2015); Lin (2013); Sun et al. (2008); Genc et al. (2010); N.G. Baltas et al. (2018); Guo and Milanović (2014); M. He, Zhang, and Vittal (2013); He et al. (2013); Mukherjee and De (2020); Senroy et al. (2006); Rahmatian et al. (2017); Rovnyak et al. (1994, 2000); Guo and Milanović (2013); Yang et al. (2017); Zhang et al. (2018); Pannell et al. (2018); Zhang et al. (2012, 2023b); Naderi et al. (2023); Ren, Yuan, et al. (2023); Zhang et al. (2023a); Ren, Wang, et al. (2023); Suprême et al. (2018); Kaci et al. (2014); Liu et al. (2020); Echeverría et al. (2017); Gomez et al. (2011); Geeganage et al. (2015); Tian et al. (2019); Yuanhang et al. (2015); Zhou et al. (2016); Zhou and Zhang (2023); Cepeda et al. (2014); Maihemuti et al. (2021); Hu et al. (2019); Wang et al. (2016); He et al. (2016); Liu et al. (2019); Xu et al. (2010); Zhu and Hill (2022); Tan and Zhao (2023); Liu et al. (2020); Gu and Li (2013); Chen et al. (2019); Zhang et al. (2015); Bahbah and Girgis (2004); Jensen et al. (2001); Frimpong et al. (2017); Mahdi and Genc (2017); Sharifian and Sharifian (2015); Nakas et al. (2023); Li et al. (2015); Baltas et al. (2018); Li et al. (2021); Y. Li and Yang (2017); Li and Gu (2013); Ren and Xu (2020, 2019); Zhang et al. (2015); Sulistiawati et al. (2016); Y. Xu et al. (2011); Xu et al. (2012); Zhang et al. (2017); Siddiqui et al. (2018); Sawhney and Jeyasurya (2006); Hashiesh et al. (2012); Zhang et al. (2018); Zhao et al. (2023a); Anderson et al. (2023); Yousefian et al. (2017); Boudour and Hellal (2005); Zhao et al. (2023b); Liu et al. (1999); Azman et al. (2020); Tan et al. (2017); Bashiri Mosavi et al. (2018); Yu et al. (2018, 2017); Mahdi and Genc (2018); T. Liu et al. (2020); Yousefian and Kamalasadani (2016, 2018); Zhu et al. (2022); An et al. (2020); Niu et al. (2021); Zhang et al. (2016); Wang et al. (2008); Zhang et al. (2021); Shi et al. (2020); Dharmapala et al. (2020); Glavic (2019); Shahzad (2022c, 2022a, 2021); Qiao et al. (2021); Huang et al. (2020); Liu et al. (2021); Shahzad (2022b). Most of these works were developed for online-transient stability assessments, except a few developed for offline applications (e.g., Lin 2013; Zhang et al. 2012; Yuanhang et al. 2015; He et al. 2016; Liu et al. 2020; Jensen et al. 2001; Li et al. 2015; Baltas et al. 2018; Arteaga et al. 2019; Zhang et al. 2016). The main purpose of the works focusing on online transient stability assessment is to reach a prediction as fast as possible to trigger corrective measures. The capabilities of IS in this regard have been widely demonstrated. For example, the average computation time for the transient stability assessments in Yu et al. (2018) was around two cycles with a 99.98% accuracy. In Zhang et al. (2015), also for transient stability assessment, their proposal took 2.5 cycles to reach a prediction, with an accuracy of above 99.4%.

References Liu et al. (2018); M. Mohammadi et al. (2010); Teeuwssen et al. (2005); Gao et al. (2023); Zhai et al. (2023) propose small-disturbance rotor-angle stability assessment using IS techniques. In Liu et al. (2018), the authors propose a self-adaptive approach combining K-means (a traditional clustering technique) with Particle Swarm Optimization (PSO) to identify representative operating conditions for a fast small-signal stability exploration

and voltage evaluation. In a case study performed on the 59-bus IEEE test system with data from the Australian National Electricity Market, the authors state that the proposed model overcomes two critical drawbacks of K-means, which are that the results depend on the results on the initial centroids and the risk of getting trapped in local optima due to the use of gradient descent. The proposed method reduced the number of operating conditions from 8760 to 555 representative ones, reaching a dimensionality reduction of 95.2%. Compared to K-Means, the average error of the proposed clustering decreased from 4.5% to 3.2%, meaning that the computational burden of performing dynamic simulations can significantly decrease for practical applications since dynamic simulations must only take place in representative operating conditions. Work in M. Mohammadi et al. (2010) presents another online small-disturbance rotor-angle stability assessment model. The proposal uses a Ball Vector Machine to classify operating conditions into four classes according to their small-signal stability margin: normal, alert, correctable emergency, and uncorrectable emergency. As a result, operating conditions were classified with an accuracy of over 97%.

One option to evaluate small-signal rotor-angle stability without performing TDS is using modal analysis. In this case, the damping ratio is the most widely used variable as a stability index, for example in Teeuwsen et al. (2005) which evaluated small signal rotor angle stability. Here, the IS: i) classifies the states of the system according to its damping; ii) estimates the minimum damping; iii) predicts the positions of the dominant eigenvalues; iv) classifies the eigenvalue regions where the dominant eigenvalues typically occur; and v) predicts the eigenvalue regions, which is a combination of eigenvalue prediction and eigenvalue region classification.

Regarding the features utilized for characterizing operating conditions, the most common ones for transient stability are voltage magnitudes and angles (e.g. He et al. 2013; Yang et al. 2017; Zhang et al. 2018; Pannell et al. 2018; Zhang et al. 2012; Suprême et al. 2018; Xu et al. 2010; Chen et al. 2019; Sawhney and Jeyasurya 2006), as well as the active and reactive power of generating units (e.g. Li et al. 2021; Y. Xu et al. 2011; Xu et al. 2012) and lines (e.g. Jensen et al. 2001; M. He, Zhang, and Vittal 2013). Other features for transient stability assessment include rotor angle (e.g. Siddiqui et al. 2018; Zhang et al. 2021), rotor speed (e.g. Guo and Milanović 2014; Bahbah and Girgis 2004), rotor acceleration (e.g. Tan et al. 2017), and the apparent resistance of the rotor, and its change (Rdot) (Rovnyak et al., 2000). For small-signal rotor-angle stability, the most common features are voltage magnitudes and angles, as well as the active and reactive power of lines, generation, and loads (e.g. M. Mohammadi et al. 2010; Arteaga et al. 2019). As for the stability index, the most common index utilized is the maximum angle deviation between two generators in the transient period (target output for prediction) (Rahmatian et al., 2017). This index is also utilized for calculating the TSI (Genc et al., 2010; M. He, Zhang, and Vittal, 2013; Senroy et al., 2006; Gomez et al., 2011; Cepeda et al., 2014; Liu et al., 2020; Baltas et al., 2018; Li et al., 2021; Zhang et al., 2015; Zhang et al., 2017). If the TSI is positive, the system is stable; otherwise, it is unstable. Another index utilized for assessing small-signal angular stability assessment is the damping ratio (Liu et al., 2018; M. Mohammadi et al., 2010; Teeuwsen et al., 2005).

4.1.2 Voltage stability

Voltage stability refers to the ability of a power system to maintain steady voltages throughout its buses after being subjected to a disturbance (Kundur et al., 2004). Depending on how long it takes for the disturbance to cause a system collapse, voltage stability issues can be short-term or long-term.

As for short-term large-disturbance voltage stability assessments, several IS have been proposed in recent years (see, for example Yang et al. 2018; Zhang et al. 2019; Nuqui et al. 2001; Hosseini et al. 2012; Zhang et al. 2019; Zhu et al. 2017; Zhang et al. 2023b; Y. Luo et al. 2023; Zhang et al. 2023a, 2018; Sajan et al. 2015a; Nakas et al. 2023; Xu et al. 2016; Ali et al. 2015; Hossain and Kumar 2023; Abbass et al. 2023; Zhao et al. 2023b; Ren and Xu 2023; Dharmapala et al. 2020). All these methods were proposed to detect fast (online) instabilities after a contingency, where prediction speed is crucial. In Zhang et al. (2019), the authors proposed a hierarchical self-adaptive method using ELM for assessing voltage stability. They used the Root-Mean-Squared Voltage-Dip Severity Index (RVSI) as a stability index. With the proposal, instabilities were identified within 0.17 s after the fault with an accuracy of 99.1%. The model also determines the FIDVR index when the system remains stable. The model in these cases predicted the FIDVR index within 0.39 s with an accuracy of 97.6%. Transient Voltage Collapse Index (TVCI) is another commonly used index for assessing short-term voltage stability (Adewole and Tzoneva, 2017; Zhu et al., 2017; Xu et al., 2016) and voltage control area real-time voltage stability assessment index (vcaRVSA) (Adewole and Tzoneva, 2017) and the Transient Voltage Severity Index (TVSI) (Xu et al., 2016) are other indices. While the vcaRVSA index predicts the margin to collapse from the maximum available reactive power of the generators, the TVSI quantifies the magnitude of the voltage violation and the associated duration time.

IS for evaluating long-term (small-disturbance) voltage stability are proposed in Adewole and Tzoneva (2017); Mohammadi et al. (2016); Diao et al. (2009); Nandanwar et al. (2018); Zheng et al. (2013); Nie et al. (2017); Nandanwar and Warkad (2016); Malbasa et al. (2017); Suganyadevi et al. (2016); Xu et al. (2005); Ren et al. (2020); Zhang et al. (2013); Innah and Hiyama (2011); Jain et al. (2003); Shah and Verma (2016); Zhu et al. (2021); Zhu and Luo (2021). In Malbasa et al. (2017), the proposed model classifies the system operating conditions as stable, alert or critical, depending on the VSM index. Their results showed a prediction accuracy between 86% and 90% out of 1000 operating conditions of each class. In Zheng et al. (2013), the authors proposed a Regression Tree model to estimate the Oscillatory Stability Margin (OSM) and the VSM index. The OSM index was estimated with 12572 records, and the VSM index with 15303. Their results showed that the model could predict the OSM index with an accuracy of 48.6%, 79.6%, and 92.3% for 2%, 10%, and 100% of the training database, respectively. For predicting the VSM index, the model reached an accuracy of 75.9%, 86.9%, and 93.2% for the 2%, 10%, and 100% of the training database, respectively.

Regarding the input features, the most common ones for short- and long-term voltage stability assessments are voltage magnitudes (e.g. Yang et al. 2018; Malbasa et al. 2017; Suganyadevi et al. 2016), voltage angles (e.g. Nuqui et al. 2001; Hosseini et al. 2012; Ali et al. 2015), active and reactive power of lines (e.g. Mohammadi et al. 2016; Diao et al. 2009; Jain et al. 2003), active and reactive power of generating units (e.g. Adewole and Tzoneva 2017; Zhang et al. 2019; Zhu et al. 2017), and loads (e.g. Zhu and Luo 2021).

Real-time measurements from PMU have also been used as input data for online stability assessments in real-world applications, as in (Yang et al., 2018; Zheng et al., 2013; Malbasa et al., 2017).

4.1.3 Frequency stability

Frequency stability refers to the ability of a power system to maintain a steady frequency following a disturbance that results in imbalances between generation and load (Kundur et al., 2004). Models for evaluating frequency stability were proposed in Karapidakis (2007); Chang et al. (2005); Ortiz-Villalba et al. (2020); Bo et al. (2014); Tang et al. (2017); Z. Zhang et al. (2023); Alizadeh and Amraee (2014); Nakas et al. (2023); Wang et al. (2019); Xie and Sun (2021); Wang et al. (2021); Song et al. (2020). For example, in Xu et al. (2013), the authors proposed an ELM-based model that uses the generators feed-in, the load demand, and the total power generation and demand as input data for predicting the system's FSM in a given set of contingencies. Their results showed that for 360 operating conditions, the training time is 0.156s, and the accuracy calculated through the mean average percentage error (MAPE) is 0.63%. In Tang et al. (2017), the authors proposed a cross-entropy ensemble algorithm that uses PMU measurements as input data for predicting the system's frequency nadir. The prediction error of the ensemble algorithm is 13.6%, which is better than the accuracy reached by individual base learners (ANN, LSSVM, and ELM), which reached prediction errors between 17.1% and 17.8%. In Wang et al. (2019), the proposal combines a model for system frequency response (SFR) with an ELM-based data-driven one for fast online frequency stability assessment. The ELM-based model is used to fit and correct the error of the SFR model. Their results showed that integrating both models improves the accuracy of the predictions. For example, the MAPE obtained by SFR, ELM, and the integrated model for the maximum frequency deviation is 43.2%, 9.6%, and 5.8%, respectively. In general, input features utilized for frequency stability assessments include the frequencies at some busbars (e.g. Tang et al. 2017; Alizadeh and Amraee 2014), the generators' feed-in (e.g. Bo et al. 2014; Xu et al. 2013; Xie and Sun 2021) the demand at each busbar (e.g. Bo et al. 2014; Xu et al. 2013; Xie and Sun 2021), the total generation and demand (e.g. Chang et al. 2005; Wang et al. 2021), and the spinning reserves of the generators (e.g. Karapidakis 2007; Bo et al. 2014). In Karapidakis 2007, the spinning reserves are differ according to the type of generating unit (combined cycle, diesel, steam, and gas).

4.1.4 Resonance stability

Resonance generally occurs when energy exchanges between devices and components of a power system oscillate. Particularly for sub-synchronous resonance (SSR), it can manifest in two possible forms: due to a resonance occurring between the series compensation and the mechanical torsional frequencies of the turbine-generator shaft or due to a resonance between the series compensation and the electrical characteristics of the generator. When these oscillations grow because of insufficient energy dissipation in the flow path and manifest as amplified voltage, current, or torque magnitudes exceeding the specified thresholds, a resonance instability is said to have occurred. Hence, resonance stability can be torsional resonance (effect of High Voltage Direct Current links, HVDC and flexible AC transmission systems, FACTS) or electrical resonance (effect of Doubly-fed induction generators, DFIG)

(Hatziaargyriou et al., 2021). Because resonance stability is a relatively new phenomenon, only one work addresses this type of stability using IS (Krishnan and Thampatty, 2020), in which the authors trained different techniques to predict unstable SSR oscillations. The techniques explored were Logistic Regression, ANN, KNN, DT, SVM, XGBoost, and RF. As a result, RF achieved the highest accuracy (96.18%) in a case study based on the IEEE First Benchmark Model. As input features, this work utilizes the change in the torque angle at each shaft section, the deviation of angular speed of the generator, and the deviation of load angle.

4.1.5 Converter-driven stability

Converter-driven stability refers to stability issues associated with the CIG's cross-couplings with the electromechanical dynamics of SGs and the network's electromagnetic transients. This interaction may lead to unstable power system oscillations over a wide frequency range (Hatziaargyriou et al., 2021). This phenomenon can be a fast or slow interaction (Hatziaargyriou et al., 2021). Since this phenomenon has gained importance recently, only two works address this issue with AI techniques, Sepehr et al. (2022) and Wang and Pal (2023). In Sepehr et al. (2022), the authors proposed an ANN model composed of stacked autoencoders (SAE) for the early detection of Power Synchronization Control (PSC) instability in a system with a weak grid. In an unstable condition, determined by the predicted voltage limits at the Point of Common Coupling (PCC), a phase freeze mode is activated in the converter synchronization loop, allowing other grid-following converters to stay connected to the PCC and back up the grid during contingencies. Input features of this model include pre-fault active power, voltage sag severity, duration of the voltage sag, and the SCR and X/R ratio. In a case study based on a power system with renewable-based CIGs connected to a weak AC grid through two transmission lines, the SAE algorithm obtained an accuracy of 99.5%, slightly higher than the 98.9% accuracy obtained with a simpler ANN. The authors in Wang and Pal (2023) analyze the impact of cyber-attacks on the control gains of CIGs. The attack and defense problems are formulated as a Markov Decision Process (MDP) and an adversarial MDP. A deterministic policy Deep RL method determines the least-effort attack and a corresponding defense strategy. Input features of this model include frequency and voltage droop gains. In a case study based on the 123-bus IEEE system with 10 CIGs, it shows that the proposed defense method manages to keep the systems's eigenvalues in the stable region.

4.1.6 Summary

Figure 5 presents the number of papers using AI by kind of stability. This figure shows that most papers focus on rotor angle stability (97 papers in total) and, secondly, on voltage stability (43 papers in total). Only 13 papers focus on frequency stability, one on converter stability and only one on resonance stability. Only the following limited number of papers focus on more than one type of stability: Liu et al. (2018); Diao et al. (2010); Zhang et al. (2023b); Kamwa et al. (2010); Nakas et al. (2023); Zhao et al. (2023b); Wang et al. (2019); Cremer and Strbac (2021).

Figure 5 also reveals a significant growth in the number of works addressing stability issues with AI techniques over time, especially after 2012. Before that year, there were

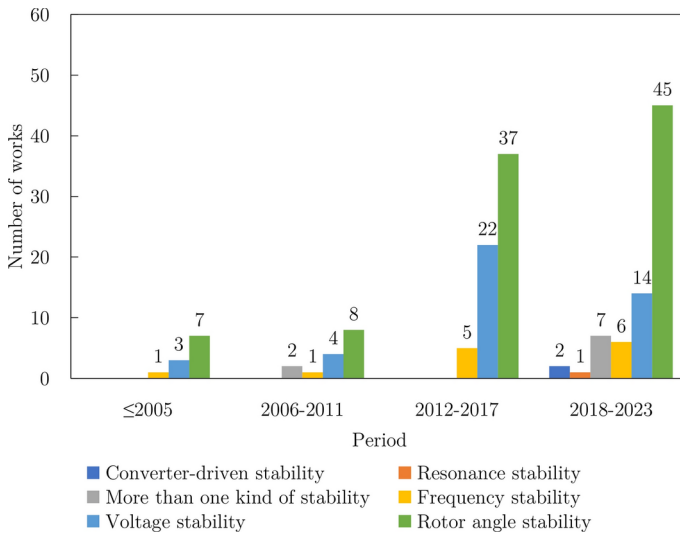


Fig. 5 Number of works by kind of stability

only 15 papers addressing rotor angle stability, 7 addressing voltage stability, and only 1 addressing frequency stability. In the period 2012 - 2017, the scientific production in this field almost doubled the total production before that year (with 64 papers in total), mainly because of works focusing on rotor angle stability (37 papers) and voltage stability (22 papers). There were only five papers focusing on frequency stability in this period. In 2018 - 2023, the number of works in this field remained about the same, compared to the 2012 - 2017 period (65 papers in total). Even though works focusing on rotor angle stability continued to grow with 45 papers during this last surveyed period, the number of papers focusing on voltage stability decreased to 14. The number of works focusing on frequency stability remained the same, with six papers. Finally, in the last five years, the first works focusing on converter-driven stability appeared (in 2022 and 2023), as well as works focusing on resonance stability (in 2020), which may be due to the growing evidence of the impact of high levels of CIG on those types of stability issues. Interestingly, during this last period, there was a significant growth in works focusing on more than one kind of stability (7 in total).

In summary, rotor angle stability has always been the main kind of stability addressed by AI techniques. Given the growing concern about the negative impact of high levels of CIGs on rotor-angle stability, we expect this trend to continue in the following years. In the next years, more works focusing on converter-driven stability and resonance stability should appear, given the growing concerns about these stability issues due to the further incorporation of CIGs into power systems.

4.2 Type of system

The database generation that the models use can come from synthetic or real test systems. A common research practice is to test the model’s performance on small test systems and then evaluate its performance on more realistic ones. However, many works are only validated using small test systems, in which the proposed models may exhibit different performances

than if tested in realistic-sized power systems. This section reviews test systems used to validate the proposals found in the technical literature, which readers can use to select test systems for developing and testing their proposals.

4.2.1 Synthetic systems

Synthetic systems are characteristically test networks developed by IEEE, Western Electricity Coordinating Council (WECC), and other institutions. Based on the number of buses considered, these systems can be classified as small (less than 50 busbars), medium (between 50 and 500 busbars), or large (greater than 500 busbars). Small test systems used in the literature are the IEEE 4-bus test system (Abbass et al., 2023), the IEEE 9-bus test system (N.G. Baltas et al., 2018; Xu et al., 2005; Bahbah and Girgis, 2004; Baltas et al., 2018; Boudour and Hellal, 2005; Goh et al., 2015; Liu et al., 1999; Hossain and Kumar, 2023), the IEEE 14-bus power system (Zhang et al., 2019; Pannell et al., 2018; Ortiz-Villalba et al., 2020; Pérez-Londoño et al., 2017; Z. Zhang et al., 2023; Jayasankar et al., 2010; Innah and Hiyama, 2011; Ali et al., 2015; Goh et al., 2015; Dharmapala et al., 2020; Adewuyi et al., 2019), the IEEE 24-bus power system (Zhang et al., 2019), the IEEE 30-bus power system (Mukherjee and De, 2020; Nandanwar et al., 2018; Zhang et al., 2019; Pérez-Londoño et al., 2017; Suganyadevi et al., 2016; Suliman and Rahman, 2010; Jain et al., 2003; Ali et al., 2015), the IEEE 39-bus New England (Zhang et al., 2019; Yu et al., 2018; Xu et al., 2016; Xu et al., 2013; Bo et al., 2014; M. He, Zhang, and Vittal, 2013; Yang et al., 2018; Adewole and Tzoneva, 2017; Echeverría et al., 2017; Tan et al., 2017; Rovnyak et al., 1994; Geeganage et al., 2015; Zhang et al., 2015; Y. Xu et al., 2011; Cepeda et al., 2014; Hashiesh et al., 2012; Gomez et al., 2011; Liu et al., 1999; Sawhney and Jeyasurya, 2006; Liu et al., 2019; Siddiqui et al., 2018; Chen et al., 2019; Zhang et al., 2018; He et al., 2013; Wang et al., 2019; Zhang et al., 2018; Shah and Verma, 2016; Hosseini et al., 2012; Hu et al., 2019; T. Liu et al., 2020; Ren and Xu, 2020; Zhang et al., 2017; Ren and Xu, 2019; Azman et al., 2020; Li et al., 2021; Zhu and Hill, 2022; Liu et al., 2020; Sharifian and Sharifian, 2015; Yu et al., 2017; Bahmanyar and Karami, 2014; Wang et al., 2016; Zhang et al., 2018; Y. Li and Yang, 2017; Gu and Li, 2013; Yang et al., 2017; Zhang et al., 2016; Li et al., 2015; Frimpong et al., 2017; Zhang et al., 2015; Li and Gu, 2013; Yuanhang et al., 2015; Velayati et al., 2015; Sajan et al., 2015b; Sajan et al., 2014; Mohammadi and Dehghani, 2015; Mohammadi et al., 2018; Sajan et al., 2015a; M. Suganyadevi and Babulal, 2014; Shahzad, 2021; Shi et al., 2020; An et al., 2020; Huang et al., 2020; Zhu et al., 2022; Zhao et al., 2023b; Tan and Zhao, 2023; Naderi et al., 2023; Zhai et al., 2023; Ren, Yuan, et al., 2023; Y. Luo et al., 2023; Nakas et al., 2023; Ren, Wang, et al., 2023; Ren and Xu, 2023; Tang et al., 2017; M. Mohammadi et al., 2010; Suprême et al., 2018; Liu et al., 2020; Ren et al., 2020; Xie and Sun, 2021; Hossain and Kumar, 2023; Wang et al., 2019; Zhang et al., 2019), the 9-bus WSCC dynamic test system (Tang et al., 2017; Alizadeh and Amraee, 2014; Wang et al., 2019), the 9-bus WECC system (Tian et al., 2019), the 11-bus Two-area system (Zhou and Zhang, 2023), the 42-bus southern/eastern Australian Power System (Bahmanyar and Karami, 2014), the 32-bus Nordic system (Zhu et al., 2017; Zhu and Luo, 2021), the 36-bus 8 machine system (Zhang et al., 2023a), the 25-bus Java-Bali system (Sulistiawati et al., 2016), the 36-bus system China Electric Power Research Institute, CEPRI, (Zhang et al., 2023b), and the 41-bus Nordic system (Ren et al., 2020; Ren and Xu, 2023). Medium-sized systems used are the IEEE of 68 buses and 16 machines (Guo and Milanović, 2014; Guo

and Milanović, 2013; Gao et al., 2023; Zhou et al., 2016; Z. Zhang et al., 2023; Li et al., 2021; Gurung et al., 2021; Zhao et al., 2023a; Yousefian et al., 2017; Azman et al., 2020; Wang et al., 2021; Yousefian and Kamalasadán, 2016; Yousefian and Kamalasadán, 2018), the 74-bus Nordic System (Naderi et al., 2023), the 77-bus Nordic System (Zhu et al., 2021), the simplified Australian Electric System of 59 buses and 14 generators (Liu et al., 2018; Suprême et al., 2018), the Indian 75-bus system (Chang et al., 2005; Jain et al., 2003), the Iranian 66-bus power grid (Mohammadi et al., 2016; Mohammadi et al., 2018), the IEEE standard 118-bus system (Mukherjee and De, 2020; Nie et al., 2017; Maihemuti et al., 2021; Zhang et al., 2013; Xie and Sun, 2021; Anderson et al., 2023; Zhao et al., 2023b; Wang et al., 2019; Dharmapala et al., 2020), the 123-bus IEEE system (Wang and Pal, 2023), the 145-bus IEEE 50-generator test system (F. Luo et al., 2015; Zhang et al., 2012; Zhang et al., 2015; Xu et al., 2012; Velayati et al., 2015; Azman et al., 2020; Yu et al., 2018), the 162-bus IEEE 17 machine (Yu et al., 2018), the 300-bus IEEE system (Zhou and Zhang, 2023), the 179-bus WECC system (Senroy et al., 2006; Zheng et al., 2013; Malbasa et al., 2017; Mahdi and Genc, 2018), the 127-bus WSCC (Mahdi and Genc, 2017), the 181-bus Indian system (Suganyadevi et al., 2016), the 120-bus dynamic equivalent system of Chinas power grid load (Xu et al., 2012), the 176-bus Pacific AC Intertie (PACI) (Rovnyak et al., 2000), the 140-bus Northeast Power Coordinating Council (NPCC) (Zhou and Zhang, 2023; Wang et al., 2019), the 200-bus Illinois system (Ren, Yuan, et al., 2023; Ren, Wang, et al., 2023; Tan and Zhao, 2023; Zhao et al., 2023b), and the 360-bus subsystem within American Electric Power (AEP) (Nuqui et al., 2001), and the 153-bus North GuiZhou Power Grid in China (Zhu and Luo, 2021). The only large systems used, was the 1648-bus Power system simulator for engineering (PSS/E) (Liu et al., 2020). Of the 46 test systems, the most widely used is the 39-bus IEEE New England, with 81 publications.

4.2.2 Real systems

Several works have also used real-world system models to develop and validate their proposals. In these cases, the operational conditions are usually extracted from actual data during real events. Examples of real-world medium-size system models are the 600-bus WECC System (He et al., 2013), the 400-bus Western Danish power system (C. Liu et al., 2014), the 380-bus China Southern Power grid (He et al., 2016; Xu et al., 2010; Wang et al., 2021), the 500-bus South Carolina System (Xie and Sun, 2021), the 162-bus NICTA Energy System Test Case Archive (NESTA) (Arteaga et al., 2019), and the 246-bus Indian Northern Region Power Grid (NRPG) (Sajan et al., 2015a). Large system models are the 876-bus Greek mainland system projected to 2005 (Voumvoulakis et al., 2006), the 783-bus Hydro-Québec network (Kamwa et al., 2010; Kamwa et al., 2012), the 750-bus Power system of Liaoning province (Y. Li and Yang, 2017), the 17724-bus WECC bulk transmission (Rahmatian et al., 2017), the 16100-bus Eastern Interconnection in North America (Genc et al., 2010), the 2941-bus Turkish power system (Mahdi and Genc, 2018), the 2100-bus Entergy system 240-generator (Sun et al., 2008), the 2400-bus subsystem inside AEP (Diao et al., 2009), the 1140-bus Venezuela Power Grid (Gomez et al., 2011), the 1800-bus Chilean Northern Interconnected System (Ortiz-Villalba et al., 2020), the 2000-bus Northeast China Power Grid (Zhang et al., 2023a), the 2000-bus Guangdong Power Grid in South China (Zhu et al., 2021), and the 1700-bus Realistic provincial power grid in China (Hu et al., 2019).

Figure 6 summarizes the number of systems used to validate proposed models, depending on the size of the system and whether the system is real or synthetic. The figure shows that most proposals were validated in synthetic and small systems. Only a few works used large-scale or real-world power system models.

Figure 7 shows the number of works that have used the different test systems described above. From this figure, it can be seen that the most widely used system is the 39-bus IEEE New England, with 81 publications. The 68-bus IEEE 16-machine and the 14-bus IEEE Power Systems were used in more than 10 publications. As for real-world power systems, the 380-bus China Southern Power grid is the most widely used, with 3 publications. Interestingly, a large number of works (20 in total) have used real-world power system models only once.

4.3 Type of application

This subsection reviews the type of application for the IS, differentiating between off-line and on-line applications. In addition, there are preventive and corrective actions that the results of the IS may trigger. It is worth noting that many works focus on only assessing stability, without triggering any control actions.

4.3.1 Online and off-line applications

A typical off-line application is to perform a stability screening as part of operational planning and expansion studies (see, for example, Liu et al. 2018; Sun et al. 2008). The main idea is to support energy regulators and system operators in validating the results of these studies from a stability perspective, which confirms the validity of different operation schedules or expansion plans from a stability viewpoint. Another example of an off-line application is to design a specific control strategy (see, for example, Lin 2013; Krishnan and Thampatty 2020; Zhang et al. 2012; Chang et al. 2005; Ortiz-Villalba et al. 2020; Yuanhang

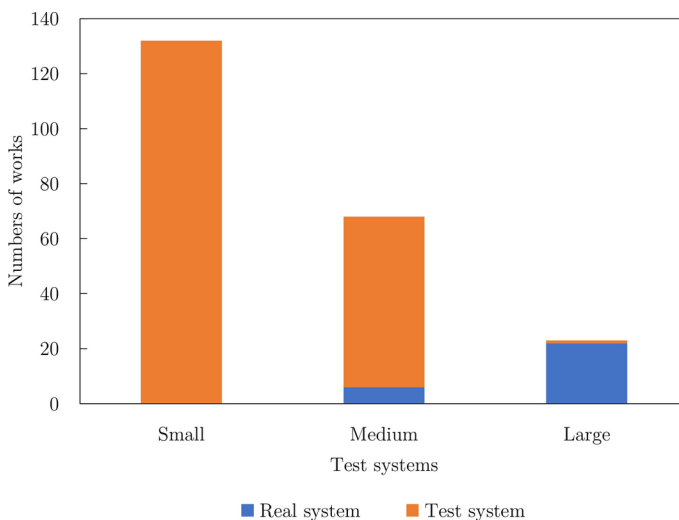


Fig. 6 Number of works by size and type of test system

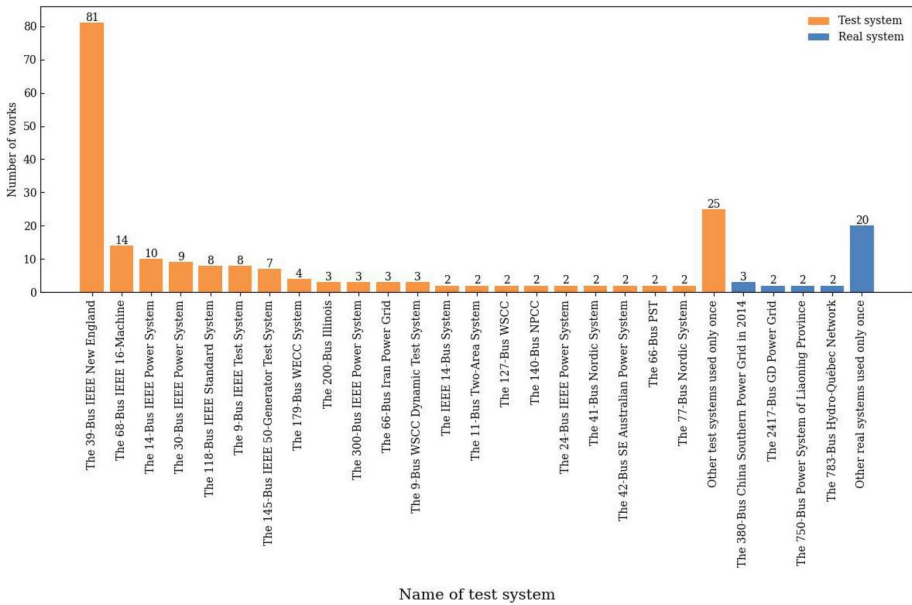


Fig. 7 Number of works by test systems

et al. 2015; He et al. 2016; Liu et al. 2020; Li et al. 2015; Baltas et al. 2018; Gurung et al. 2021; Arteaga et al. 2019; Wang et al. 2019; Zhang et al. 2016; Adewuyi et al. 2019). The main focus of off-line applications lies on the model’s accuracy since the response time of the IS is non-critical.

For online applications, the goal is to perform fast, real-time stability assessments to identify risky conditions so the system operator can take preventive/remedial actions. Works focused on online stability assessments are F. Luo et al. (2015); Liu et al. (2018); Sun et al. (2008); Yang et al. (2018); Zhang et al. (2019); Genc et al. (2010); N.G. Baltas et al. (2018); Guo and Milanović (2014); Karapidakis (2007); M. Mohammadi et al. (2010); M. He, Zhang, and Vittal (2013); Mohammadi et al. (2016); Mohammadi and Dehghani (2015); Mukherjee and De (2020); Senroy et al. (2006); Nuqui et al. (2001); Rahmatian et al. (2017); Rovnyak et al. (1994, 2000); Diao et al. (2009); Nandanwar et al. (2018); Guo and Milanović (2013); Teeuwesen et al. (2005); Zhang et al. (2019); Yang et al. (2017); Pannell et al. (2018); Zheng et al. (2013); Nie et al. (2017); Zhu et al. (2017); Zhang et al. (2023b); Naderi et al. (2023); Ren, Yuan, et al. (2023); Y. Luo et al. (2023); Zhang et al. (2023a); Ren, Wang, et al. (2023); Suprême et al. (2018); Kaci et al. (2014); Kamwa et al. (2010); Malbasa et al. (2017); Gao et al. (2023); Echeverría et al. (2017); Gomez et al. (2011); Geeganage et al. (2015); Mohammadi et al. (2018); Pérez-Londoño et al. (2017); Bo et al. (2014); M. Suganyadevi and Babulal (2014); Tian et al. (2019); Tang et al. (2017); Zhang et al. (2018); Zhou et al. (2016); Sajjan et al. (2015a); Zhou and Zhang (2023); Z. Zhang et al. (2023); Alizadeh and Amraee (2014); Cepeda et al. (2014); Suganyadevi et al. (2016); Maihemuti et al. (2021); Hu et al. (2019); Wang et al. (2016); Liu et al. (2019); Xu et al. (2010); Tan and Zhao (2023); Zhai et al. (2023); Zhu and Hill (2022); Gu and Li (2013); Xu et al. (2005); Suliman and Rahman (2010); Chen et al. (2019); Zhang et al. (2015); Bahbah and Girgis (2004); Frimpong et al. (2017); Mahdi and Genc (2017); Jayasankar et al.

(2010); Sajjan et al. (2014, 2015b); Sharifian and Sharifian (2015); Nakas et al. (2023); Li et al. (2021); Y. Li and Yang (2017); Li and Gu (2013); Ren and Xu (2020, 2019); Ren et al. (2020); Zhang et al. (2015); Sulistiawati et al. (2016); Wang et al. (2019); Xu et al. (2013); Y. Xu et al. (2011); Xu et al. (2012); Zhang et al. (2017, 2013); Xu et al. (2016); Velayati et al. (2015); Siddiqui et al. (2018); Innah and Hiyama (2011); Jain et al. (2003); Xie and Sun (2021); Ali et al. (2015); Bahmanyar and Karami (2014); Sawhney and Jeyasurya (2006); Shah and Verma (2016); Hashiesh et al. (2012); Zhang et al. (2018); Hossain and Kumar (2023); Abbass et al. (2023); Wang and Pal (2023); Anderson et al. (2023); Yousefian et al. (2017); Boudour and Hellal (2005); Goh et al. (2015); Liu et al. (1999); Zhao et al. (2023b); Azman et al. (2020); Tan et al. (2017); Wang et al. (2021); Bashiri Mosavi et al. (2018); Ren and Xu (2023); Song et al. (2020); Yu et al. (2018, 2017); Zhu et al. (2021); Zhu and Luo (2021); Mahdi and Genc (2018); T. Liu et al. (2020); Yousefian and Kamalasadani (2016, 2018); Dharmapala et al. (2020). In the case of online applications, the response time of the IS is critical, as it must be able to identify unstable conditions as quickly as possible.

4.3.2 Type of action

Stability assessments can be carried out preventively, before a contingency occurs (pre-disturbance), or done after the occurrence of a disturbance (post-disturbance). Pre-disturbance assessment focuses on evaluating the stability of the power system for a predefined set of disturbances that have not occurred, and the results may trigger preventive control actions (Zhang et al., 2015). Preventive controls involve changing the operating condition if a contingency could lead to instability. The most typical preventive action is a generation rescheduling (Bo et al., 2014). For example, a generation rescheduling is proposed in Genc et al. (2010) for a transient stability assessment, using DTs to evaluate the system stability, using SVM in Tian et al. (2019), and a Bayesian Neural Network in T. Liu et al. (2020). Work in Lin (2013) proposes two preemptive methods for offline transient stability margins based on DT and MLP. Both methods use variations of active power and terminal voltages at each generator and variations of active power and reactive power demand to increase the CCT rate and improve stability margins. Although both preventive controls perform well, DT-based preventive control requires triggering simultaneous control actions to work. In contrast, MLP-based control only determines one control action, thus being more flexible. Furthermore, Gurung et al. (2021) proposes an MLP architecture and a metaheuristic optimization to maximize the probabilistic small-signal stability (PSSS) margin. Control actions are changes in the parameters of the power oscillation damping controllers (PODC). Work in Jayasankar et al. (2010) presents another example of preventive control within power system planning, where an FFNN designed to monitor the voltage stability margin of lines. If it identifies a weak line, it will run a genetic optimization algorithm to locate a thyristor-controlled series capacitor (TCSC) optimally and improve the line's stability margin.

In contrast, post-disturbance assessment aims to predict a system's stability after the occurrence of a contingency. The objective is to identify such instability as soon as possible to trigger corrective control actions. Typical corrective control actions are the activation of under frequency load shedding (UFLS) (Bo et al., 2014; Alizadeh and Amraee, 2014; Jain et al., 2003; Xie and Sun, 2021) and UVLS (Ren et al., 2020; Zhu and Luo, 2021). Other corrective control actions are the modification of control system parameters (Yousefian et al., 2017; Hossain and Kumar, 2023; Zhao et al., 2023a; Yousefian and Kamalasadani, 2016;

Yousefian and Kamalasadani, 2018) and load shedding (Genc et al., 2010; Naderi et al., 2023; Tian et al., 2019).

As indicated earlier, many works only focus on evaluating system stability, without triggering any actions. We identified following works that falls into this case: F. Luo et al. (2015); Liu et al. (2018); Sun et al. (2008); Yang et al. (2018); Zhang et al. (2019); N.G. Baltas et al. (2018); Guo and Milanović (2014); Karapidakis (2007); M. Mohammadi et al. (2010); M. He, Zhang, and Vittal (2013); Mohammadi et al. (2016); Mohammadi and Dehghani (2015); Mukherjee and De (2020); Senroy et al. (2006); Nuqui et al. (2001); Rahmatian et al. (2017); Rovnyak et al. (1994, 2000); Diao et al. (2009); Nandanwar et al. (2018); Guo and Milanović (2013); Teeuwsen et al. (2005); Zhang et al. (2019); Yang et al. (2017); Pannell et al. (2018); Zheng et al. (2013); Nie et al. (2017); Zhu et al. (2017); Zhang et al. (2023b); Ren, Yuan, et al. (2023); Y. Luo et al. (2023); Zhang et al. (2023a); Ren, Wang, et al. (2023); Suprême et al. (2018); Kaci et al. (2014); Kamwa et al. (2010); Malbasa et al. (2017); Gao et al. (2023); Echeverría et al. (2017); Gomez et al. (2011); Geeganage et al. (2015); Mohammadi et al. (2018); Pérez-Londoño et al. (2017); Bo et al. (2014); M. Suganyadevi and Babulal (2014); Tang et al. (2017); Zhang et al. (2018); Zhou et al. (2016); Sajjan et al. (2015a); Zhou and Zhang (2023); Z. Zhang et al. (2023); Cepeda et al. (2014); Suganyadevi et al. (2016); Maihemuti et al. (2021); Hu et al. (2019); Wang et al. (2016); Liu et al. (2019); Xu et al. (2010); Zhai et al. (2023); Zhu and Hill (2022); Gu and Li (2013); Xu et al. (2005); Suliman and Rahman (2010); Chen et al. (2019); Zhang et al. (2015); Bahbah and Girgis (2004); Frimpong et al. (2017); Mahdi and Genc (2017); Jayasankar et al. (2010); Sajjan et al. (2014, 2015b); Sharifian and Sharifian (2015); Li et al. (2021); Y. Li and Yang (2017); Li and Gu (2013); Ren and Xu (2020, 2019); Zhang et al. (2015); Sulistiawati et al. (2016); Xu et al. (2013); Y. Xu et al. (2011); Xu et al. (2012); Zhang et al. (2017, 2013); Xu et al. (2016); Velayati et al. (2015); Siddiqui et al. (2018); Innah and Hiyama (2011); Jain et al. (2003); Ali et al. (2015); Bahmanyar and Karami (2014); Sawhney and Jeyasurya (2006); Shah and Verma (2016); Hashiesh et al. (2012); Zhang et al. (2018); Abbass et al. (2023); Wang and Pal (2023); Anderson et al. (2023); Nakas et al. (2023); Boudour and Hlلال (2005); Goh et al. (2015); Zhao et al. (2023b); Liu et al. (1999); Azman et al. (2020); Tan et al. (2017); Wang et al. (2021); Bashiri Mosavi et al. (2018); Ren and Xu (2023); Song et al. (2020); Yu et al. (2018, 2017); Zhu et al. (2021); Mahdi and Genc (2018); T. Liu et al. (2020); Dharmapala et al. (2020). Figure 8 shows the different actions that articles studied during this investigation have applied. This figure shows that most articles focus on evaluating system stability or estimating stability margin and less on performing corrective or preventive actions. Finally, we found only one paper that determines both preventive actions (generation rescheduling) and corrective ones (Load shedding schemes) (Genc et al., 2010).

5 Conclusion

The use of AI-based techniques for DSA has gained increasing attention in the past years. The main reason is that predictive models based on AI have proved to provide high-accuracy results within very short computational time, thus providing a reliable and helpful tool that complements traditional DSA based on TDS. For offline DSA, AI-based techniques allow evaluation of a wide range of operating conditions with minimal human and computational effort (once the models are built), which can be helpful as a screening tool for power

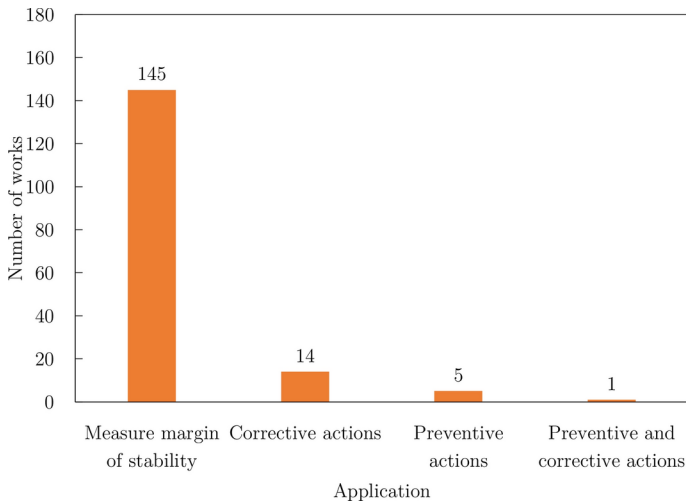


Fig. 8 Type of applications

system operations, expansion planning, and control design. On the other hand, for online DSA, rapid DSA can be extremely helpful in determining corrective control actions once a contingency occurs, which otherwise cannot be done using traditional TDS. The latter has also been possible due to the wide incorporation of PMUs in power systems.

Despite the significant advances in the use of AI for DSA, there are still research gaps. As seen throughout this review, most proposals use small test systems and synthetic (unrealistic) data to develop and validate their proposals, which challenges the validity of the models for their application in real-world power systems because they may exhibit different performance. Another important characteristic of AI-based techniques is that training AI-based models requires many operating conditions labeled using TDS, which poses a significant barrier to developing such models, especially for realistic-size power system models. In this regard, developing strategies and models that demand fewer operating conditions labeled with TDS will require much more research. One possibility to fill this gap is to develop models using steady-state or quasi-steady-state stability indices, which are cheap to compute, and then, to correct the models using a few operating conditions labeled with TDS, such as the transfer learning strategy.

A noteworthy feature identified in this review is the use of more advanced DL models. Here, we refer to DL models as multiple-layer ANNs that can capture more complex characteristics from the data than traditional ML algorithms. Even though most works still propose traditional ML-based models, the use of DL models has significantly increased in the past few years. Similarly, a growing trend exists to develop ensemble models instead of single ML models. Compared to their single-model counterparts, the good results in prediction accuracy obtained by ensemble models suggest that this trend toward ensemble models should continue in the future.

Regarding the types of stability, most works focus on transient stability and large disturbance voltage stability. Only a few works have focused on small disturbance angle stability, small disturbance voltage stability, and frequency stability. Furthermore, we only found one work focusing on resonance and converter-driven stability, respectively. Given the impor-

tance of these latter stability issues in future power systems dominated by CIG, there is an urgent need to integrate such stability issues within AI-based models for DSA.

From a practical perspective, i.e., for the development of AI-based models for real-world power system applications, there is a significant research gap in addressing challenges associated with such applications: most works assume full availability of PMU measurement, neglecting relevant issues such as measurement failures, noise, delays, and bad data. In addition, only a few works have dealt with adapting the prediction models to changes in power systems. The key is to develop advanced strategies to identify the need for adaptation and to adjust the models with minimum human and computational resources, especially in labeling new operating conditions using TDS. For applications in real-time, training time for adapting the models is also crucial.

In summary, using AI for DSA is a promising and growing research area that still requires further efforts to fill the research gap, especially toward using the proposed models in real-world power system applications.

Acknowledgements This work was supported in part by the Chilean Council of Scientific and Technological Research, ANID/FONDECYT/1201676, ANID/FONDECYT 1231739, ANID/FONDEF IT19I0129, AC3E (ANID/BASAL/FB0008) and ANID/FONDAP/1522A0006.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

References

- Abbass MJ, Lis R, Mushtaq Z (2023) Artificial neural network (ANN)-Based voltage stability prediction of test microgrid grid. *IEEE Access* 11:58994–59001 <https://doi.org/10.1109/ACCESS.2023.3284545https://ieeexplore.ieee.org/document/10147228>
- Adewole AC, Tzoneva R (2017) Surrogate-splits ensembles for real-time voltage stability assessment in the presence of missing synchrophasor measurements. *IET Sci Measure Technol* 11(5):545–552. <https://doi.org/10.1049/iet-smt.2016.0431>. ((**Publisher: IET Digital Library**))
- Adewuyi OB, Shigenobu R, Ooya K, Senjyu T, Howlader AM (2019) Static voltage stability improvement with battery energy storage considering optimal control of active and reactive power injection. *Electric Power Syst Res* 172:303–312. <https://doi.org/10.1016/j.epsr.2019.04.004>
- Ali AK, El-Amary NH, Ibrahim A, Mekhamer SF (2015) Voltage instability detector based on phasor measurement units using artificial neural network. *2015 Workshop on Engineering Applications - International Congress on Engineering (WEA)* (pp. 1–6). <https://ieeexplore.ieee.org/document/7370151>
- Alimi OA, Ouahada K, Abu-Mahfouz AM (2020) A review of machine learning approaches to power system security and stability. *IEEE Access* 8:113512–113531. <https://doi.org/10.1109/ACCESS.2020.3003568https://ieeexplore.ieee.org/document/9121208>
- Alizadeh M, Amraee T (2014) Adaptive scheme for local prediction of post-contingency power system frequency. *Electric Power Syst Res* 107:240–249. <https://doi.org/10.1016/j.epsr.2013.10.014https://www.sciencedirect.com/science/article/pii/S037877961300285X>

- Ameen AH, Mohammed MA, Rashid AN (2023) Enhancing security in IoMT: a blockchain-based cyber-security framework for Machine Learning-driven ECG signal classification. *Fusion: Practice and Applications, Volume 14*(Issue 1), 221–251. <https://doi.org/10.54216/FPA.140117> [2024-07-12]<https://americaspublishing.com/articleinfo/3/show/2343> American Scientific Publishing Group (ASPG)
- An J, Yu J, Li Z, Zhou Y, Mu G (2020) A data-driven method for transient stability margin prediction based on security region. *J Modern Power Syst Clean Energy* 8(6):1060–1069. <https://doi.org/10.35833/MPCE.2020.000457>
- Anderson AA, Jefferson BA, Kincic S, Wenskovitch JE, Fallon CK, Baweja JA, Chen Y (2023) Human-centric contingency analysis metrics for evaluating operator performance and trust. *IEEE Access* 11:109689–109707. <https://doi.org/10.1109/ACCESS.2023.3322133><https://ieeexplore.ieee.org/document/10273136>
- Arteaga J-MH, Hancharou F, Thams F, Chatzivasilieadis S (2019) Deep learning for power system security assessment. *2019 IEEE Milan PowerTech* pp. 1–6. <https://ieeexplore.ieee.org/document/8810906>
- Azman SK, Isbeih YJ, Moursi MSE, Elbassioni K (2020) A unified online deep learning prediction model for small signal and transient stability. *IEEE Trans Power Syst* 35(6):4585–4598 <https://doi.org/10.1109/TPWRS.2020.2999102><https://ieeexplore.ieee.org/document/9105102>
- Bahbah A, Girgis A (2004) New method for generators' angles and angular velocities prediction for transient stability assessment of multimachine power systems using recurrent artificial neural network. *IEEE Trans Power Syst* 19(2):1015–1022. <https://doi.org/10.1109/TPWRS.2004.826765><https://ieeexplore.ieee.org/document/1295012>
- Bahmanyar AR, Karami A (2014) Power system voltage stability monitoring using artificial neural networks with a reduced set of inputs. *Int J Electric Power Energy Syst* 58:246–256. <https://doi.org/10.1016/j.ijepes.2014.01.019><https://www.sciencedirect.com/science/article/pii/S0142061514000325>
- Baltas GN, Perales-González C, Mazidi P, Fernandez F, Rodríguez P (2018) A novel ensemble approach for solving the transient stability classification problem. *2018 7th international conference on renewable energy research and applications (ICRERA)* pp. 1282–1286. <https://ieeexplore.ieee.org/document/8566815> (ISSN: 2572-6013)
- Baltas NG, Mazidi P, Ma J, de Asis Fernandez F, Rodríguez P (2018) A comparative analysis of decision trees, support vector machines and artificial neural networks for on-line transient stability assessment. *2018 International conference on smart energy systems and technologies (SEST)* pp. 1–6. <https://ieeexplore.ieee.org/document/8495872>
- Bashiri Mosavi A, Amiri A, Hosseini H (2018) A learning framework for size and type independent transient stability prediction of power system using twin convolutional support vector machine. *IEEE Access* 6:69937–69947. <https://doi.org/10.1109/ACCESS.2018.2880273><https://ieeexplore.ieee.org/document/8540347>
- Bo Q, Wang X, Liu K (2014) Minimum frequency prediction of power system after disturbance based on the v-support vector regression. *2014 International conference on power system technology* (pp. 614–619). <https://ieeexplore.ieee.org/document/6993789>
- Boudour M, Hellal A (2005) Combined use of supervised and unsupervised learning for power system dynamic security mapping. *Engineering Applications of Artificial Intelligence* 18(6):673–683. <https://doi.org/10.1016/j.engappai.2005.01.005><https://www.sciencedirect.com/science/article/pii/S0952197605000096>
- Cepeda JC, Rueda JL, Colomé DG, Echeverría DE (2014) Real-time transient stability assessment based on centre-of-inertia estimation from phasor measurement unit records. *IET Gener Transm Distrib* 8(8):1363–1376. <https://doi.org/10.1049/iet-gtd.2013.0616>. ((**Publisher: IET Digital Library**))
- Chang R-F, Lu C-N, Hsiao T-Y (2005) Prediction of frequency response after generator outage using regression tree. *IEEE Trans Power Syst* 20(4):2146–2147. <https://doi.org/10.1109/TPWRS.2005.857259><https://ieeexplore.ieee.org/document/1525147?denied=>
- Chen M, Liu Q, Chen S, Liu Y, Zhang C-H, Liu R (2019) XGBoost-based algorithm interpretation and application on post-fault transient stability status prediction of power system. *IEEE Access* 7:13149–13158. <https://doi.org/10.1109/ACCESS.2019.2893448><https://ieeexplore.ieee.org/document/8620201>
- Cremer JL, Strbac G (2021) A machine-learning based probabilistic perspective on dynamic security assessment. *Int J Electric Power Energy Syst* 128:106571. <https://doi.org/10.1016/j.ijepes.2020.106571>
- Dharmapala KD, Rajapakse A, Narendra K, Zhang Y (2020) Machine learning based real-time monitoring of long-term voltage stability using voltage stability indices. *IEEE Access* 8:222544–222555. <https://doi.org/10.1109/ACCESS.2020.3043935>
- Diao R, Sun K, Vittal V, O'Keefe RJ, Richardson MR, Bhatt N, Sarawgi SK (2009) Decision tree-based online voltage security assessment using PMU measurements. *IEEE Trans Power Syst* 24(2):832–839. <https://doi.org/10.1109/TPWRS.2009.2016528><https://ieeexplore.ieee.org/document/4813188>

- Diao R, Vittal V, Logic N (2010) Design of a real-time security assessment tool for situational awareness enhancement in modern power systems. *IEEE Trans Power Syst* 25(2):957–965. <https://doi.org/10.1109/TPWRS.2009.2035507><https://ieeexplore.ieee.org/document/5342461>
- Dong ZY, Xu Y, Zhang P, Wong KP (2013) Using IS to assess an electric power system's real-time stability. *IEEE Intell Syst* 28(4):60–66. <https://doi.org/10.1109/MIS.2011.41><https://ieeexplore.ieee.org/document/6682954>
- Echeverria JDE, Cepeda CJC, Colomé DG (2017) Real-time transient stability assessment of electric power systems using predictive-SIME based on machine learning. *2017 IEEE PES innovative smart grid technologies conference - Latin America (ISGT Latin America)* (pp. 1–6). <https://ieeexplore.ieee.org/document/8126760>
- Fang J, Li H, Tang Y, Blaabjerg F (2019) On the inertia of future more-electronics power systems. *IEEE J Emerg Sel Topics Power Electron* 7(4):2130–2146. <https://doi.org/10.1109/JESTPE.2018.2877766><https://ieeexplore.ieee.org/document/8506338>
- Frimpong EA, Okyere PY, Asumadu J (2017) On-line determination of transient stability status using MLPNN. *2017 IEEE PES PowerAfrica* (pp. 23–27). <https://ieeexplore.ieee.org/document/7991194>
- Gao H, Yang D, Cai G, Chen Z, Ma J, Wang L, Duan F (2023) Machine learning-based reliability improvement of ambient mode extraction for smart grid utilizing isolation forest. *IEEE Trans Power Syst* 38(5):4752–4760. <https://doi.org/10.1109/TPWRS.2022.3226263><https://ieeexplore.ieee.org/document/9970387>
- Geeganage J, Annakkage UD, Weekes T, Archer BA (2015) Application of energy-based power system features for dynamic security assessment. *IEEE Trans Power Syst* 30(4):1957–1965. <https://doi.org/10.1109/TPWRS.2014.2353048><https://ieeexplore.ieee.org/document/6902826?denied=>
- Genc I, Diao R, Vittal V, Kolluri S, Mandal S (2010) Decision tree-based preventive and corrective control applications for dynamic security enhancement in power systems. *IEEE Trans Power Syst* 25(3):1611–1619. <https://doi.org/10.1109/TPWRS.2009.2037006><https://ieeexplore.ieee.org/abstract/document/5374083>
- Glavic M (2019) (Deep) Reinforcement learning for electric power system control and related problems: a short review and perspectives. *Annu Rev Control* 48:22–35. <https://doi.org/10.1016/j.arcontrol.2019.09.008>
- Goh HH, Chua QS, Lee SW, Kok BC, Goh KC, Teo KTK (2015) Evaluation for voltage stability indices in power system using artificial neural network. *Proced Eng* 118:1127–1136. <https://doi.org/10.1016/j.proeng.2015.08.454><https://www.sciencedirect.com/science/article/pii/S1877705815021098>
- Gomez FR, Rajapakse AD, Annakkage UD, Fernando IT (2011) Support vector machine-based algorithm for post-fault transient stability status prediction using synchronized measurements. *IEEE Trans Power Syst* 26(3):1474–1483. <https://doi.org/10.1109/TPWRS.2010.2082575><https://ieeexplore.ieee.org/document/5617329>
- Goodfellow IJ, Bengio Y, Courville A (2016) *Deep Learning*. MIT Press, Cambridge
- Gu X, Li Y (2013) Bayesian multiple kernels learning-based transient stability assessment of power systems using synchronized measurements. *2013 IEEE Power & Energy Society General Meeting* (pp. 1–5). <https://ieeexplore.ieee.org/document/6672810> (ISSN: 1932-5517)
- Guo T, Milanović JV (2013) The effect of quality and availability of measurement signals on accuracy of on-line prediction of transient stability using decision tree method. *IEEE PES ISGT Europe 2013* (pp. 1–5). <https://ieeexplore.ieee.org/document/6695256> (ISSN: 2165-4824)
- Guo T, Milanović JV (2014) Probabilistic framework for assessing the accuracy of data mining tool for online prediction of transient stability. *IEEE Trans Power Syst* 29(1):377–385. <https://doi.org/10.1109/TPWRS.2013.2281118><https://ieeexplore.ieee.org/document/6606932>
- Gurung S, Naetiladdanon S, Sangswang A (2021) A surrogate based computationally efficient method to coordinate damping controllers for enhancement of probabilistic small-signal stability. *IEEE Access* 9:32882–32896. <https://doi.org/10.1109/ACCESS.2021.3060502><https://ieeexplore.ieee.org/document/9358149>
- Hadidi R, Jeyasurya B (2013) Reinforcement learning based real-time wide-area stabilizing control agents to enhance power system stability. *IEEE Trans Smart Grid* 4(1):489–497. <https://doi.org/10.1109/TSG.2012.2235864><https://ieeexplore.ieee.org/abstract/document/6410470>
- Hashiesh F, Mostafa HE, Khatib A-R, Helal I, Mansour MM (2012) An intelligent wide area synchrophasor based system for predicting and mitigating transient instabilities. *IEEE Trans Smart Grid* 3(2):645–652. <https://doi.org/10.1109/TSG.2012.2187220><https://ieeexplore.ieee.org/document/6184356>
- Hatziazgryriou N, Milanovic J, Rahmann C, Ajarapu V, Canizares C, Erlich I, Vournas C (2021) Definition and classification of power system stability - revisited & extended. *IEEE Trans Power Syst* 36(4):3271–3281. <https://doi.org/10.1109/TPWRS.2020.3041774><https://ieeexplore.ieee.org/document/9286772>
- He C, Guan L, Mo W (2016) A method for transient stability assessment based on pattern recognition. *2016 International conference on smart grid and clean energy technologies (ICSGCE)* (pp. 343–347). <https://ieeexplore.ieee.org/document/7876081>

- He M, Vittal V, Zhang J (2013) Online dynamic security assessment with missing pmu measurements: a data mining approach. *IEEE Trans Power Syst* 28(2):1969–1977. <https://doi.org/10.1109/TPWRS.2013.2246822><https://ieeexplore.ieee.org/document/6475215>
- He M, Zhang J, Vittal V (2013) Robust online dynamic security assessment using adaptive ensemble decision-tree learning. *IEEE Trans Power Syst* 28(4):4089–4098. <https://doi.org/10.1109/TPWRS.2013.2266617><https://ieeexplore.ieee.org/document/6547746>
- Hornik K, Stinchcombe M, White H (1989) Multilayer feedforward networks are universal approximators. *Neural Netw* 2(5):359–366. [https://doi.org/10.1016/0893-6080\(89\)90020-8](https://doi.org/10.1016/0893-6080(89)90020-8) [2024-07-12]<https://www.sciencedirect.com/science/article/pii/0893608089900208>
- Hossain RR, Kumar R (2023) Machine learning accelerated real-time model predictive control for power systems. *IEEE/CAA J Autom Sin* 10(4):916–930. <https://doi.org/10.1109/JAS.2023.1231355><https://ieeexplore.ieee.org/document/10085977>
- Hosseini SMH, Olamaei J, Gholami V, Jahangir M (2012) Decision tree based online identification of critical voltage control area. *2012 Asia-Pacific power and energy engineering Conference* (pp. 1–4). <https://ieeexplore.ieee.org/document/6307562> (ISSN: 2157-4847)
- Hu W, Lu Z, Wu S, Zhang W, Dong Y, Yu R, Liu B (2019) Real-time transient stability assessment in power system based on improved SVM. *J Mod Power Syst Clean Energy* 7(1):26–37. <https://doi.org/10.1007/s40565-018-0453-x><https://ieeexplore.ieee.org/document/9028808>
- Huang J, Guan L, Su Y, Yao H, Guo M, Zhong Z (2020) Recurrent graph convolutional network-based multi-task transient stability assessment framework in power system. *IEEE Access* 8:93283–93296. <https://doi.org/10.1109/ACCESS.2020.2991263>
- Innah H, Hiyama T (2011) A real time PMU data and neural network approach to analyze voltage stability. *2011 International conference on advanced power system automation and protection* (Vol. 2, pp. 1263–1267). <https://ieeexplore.ieee.org/document/6180572>
- IRENA (2022). *Renewable Capacity Statistics 2022* (Tech. Rep.). The International Renewable Energy Agency, Abu Dhabi
- Jain T, Srivastava L, Singh S (2003) Fast voltage contingency screening using radial basis function neural network. *IEEE Trans Power Syst* 18(4):1359–1366. <https://doi.org/10.1109/TPWRS.2003.818607><https://ieeexplore.ieee.org/abstract/document/1245558>
- Jayasankar V, Kamaraj N, Vanaja N (2010) Estimation of voltage stability index for power system employing artificial neural network technique and TCSC placement. *Neurocomputing* 73(16):3005–3011. <https://doi.org/10.1016/j.neucom.2010.07.006><https://www.sciencedirect.com/science/article/pii/S0925231210003309>
- Jensen C, El-Sharkawi M, Marks R (2001) Power system security assessment using neural networks: feature selection using Fisher discrimination. *IEEE Trans Power Syst* 16(4):757–763. <https://doi.org/10.1109/59.962423><https://ieeexplore.ieee.org/document/962423>
- Jia J, Yang G, Nielsen AH (2018) A review on grid-connected converter control for short-circuit power provision under grid unbalanced faults. *IEEE Trans Power Deliv* 33(2):649–661. <https://doi.org/10.1109/TPWRD.2017.2682164><https://ieeexplore.ieee.org/abstract/document/7878663>
- Kaci A, Kamwa I, Dessaint LA, Guillon S (2014) Phase angles as predictors of network dynamic security limits and further implications. *2014 IEEE PES General Meeting | Conference & Exposition* (pp. 1–6). <https://ieeexplore.ieee.org/document/6939281> (ISSN: 1932-5517)
- Kamwa I, Samantaray SR, Joos G (2010) Catastrophe predictors from ensemble decision-tree learning of wide-area severity indices. *IEEE Trans Smart Grid* 1(2):144–158. <https://doi.org/10.1109/TSG.2010.2052935><https://ieeexplore.ieee.org/document/5545486>
- Kamwa I, Samantaray SR, Joos G (2012) On the accuracy versus transparency trade-off of data-mining models for fast-response pmu-based catastrophe predictors. *IEEE Trans Smart Grid* 3(1):152–161. <https://doi.org/10.1109/TSG.2011.2164948>
- Karapidakis ES (2007) Machine learning for frequency estimation of power systems. *Appl Soft Comput* 7(1):105–114. <https://doi.org/10.1016/j.asoc.2005.04.002><https://www.sciencedirect.com/science/article/pii/S1568494605000281>
- Krishnan KC, Thampatty KS (2020) Prediction of sub-synchronous resonance oscillations - a machine learning approach. *2020 IEEE students conference on engineering & systems (SCES)* (pp. 1–6). <https://ieeexplore.ieee.org/document/9236775>
- Kundur P, Paserba J, Ajarapu V, Andersson G, Bose A, Canizares C, Vittal V (2004) Definition and classification of power system stability IEEE/CIGRE joint task force on stability terms and definitions. *IEEE Trans Power Syst* 19(3):1387–1401. <https://doi.org/10.1109/TPWRS.2004.825981>
- Li F, Wang Q, Tang Y, Xu Y, Dang J (2021) Hybrid analytical and data-driven modeling based instance-transfer method for power system online transient stability assessment. *CSEE J Power Energy Syst*, <https://doi.org/10.17775/CSEEJPES.2020.03880><https://ieeexplore.ieee.org/document/9420351>

- Li Y, Gu X (2013) Power system transient stability assessment based on online sequential extreme learning machine. *2013 IEEE PES Asia-Pacific power and energy engineering conference (APPEEC)* (pp. 1–4). <https://ieeexplore.ieee.org/document/6837163> (ISSN: 2157-4847)
- Li Y, Li G, Wang Z (2015) Rule extraction based on extreme learning machine and an improved ant-miner algorithm for transient stability assessment. *PLoS ONE*, *10*(6), e0130814, <https://doi.org/10.1371/journal.pone.0130814> <http://arxiv.org/abs/1810.00658> (arXiv:1810.00658 [eess])
- Li Y, Yang Z (2017) Application of EOS-ELM With binary jaya-based feature selection to real-time transient stability assessment using PMU data. *IEEE Access* *5*:23092–23101. <https://doi.org/10.1109/ACCESS.2017.2765626><https://ieeexplore.ieee.org/document/8081764>
- Lin Y-J (2013) Comparison of CART- and MLP-based power system transient stability preventive control. *Int J Electric Power Energy Syst* *45*(1):129–136. <https://doi.org/10.1016/j.ijepes.2012.08.066><https://www.sciencedirect.com/science/article/pii/S0142061512005169>
- Liu C, Sun K, Rather ZH, Chen Z, Bak CL, ThÅ,gersen, P., Lund, P. (2014) A systematic approach for dynamic security assessment and the corresponding preventive control scheme based on decision trees. *IEEE Trans Power Syst* *29*(2):717–730. <https://doi.org/10.1109/TPWRS.2013.2283064>
- Liu C-W, Su M-C, Tsay S-S, Wang Y-J (1999) Application of a novel fuzzy neural network to real-time transient stability swings prediction based on synchronized phasor measurements. *IEEE Trans Power Syst* *14*(2):685–692. <https://doi.org/10.1109/59.761898><https://ieeexplore.ieee.org/document/761898>
- Liu J, Peng X, Wu L, Li Y, Liu J, Niu S, Ren C (2021) Incremental learning method for online transient stability assessment of power system based on KKT condition. *2021 IEEE sustainable power and energy conference (ISPEC)* (pp. 3968–3974)
- Liu R, Verbič G, Ma J (2019) A new dynamic security assessment framework based on semi-supervised learning and data editing. *Electric Power Syst Res* *172*:221–229. <https://doi.org/10.1016/j.epr.2019.03.009><https://www.sciencedirect.com/science/article/pii/S0378779619301014>
- Liu R, Verbič G, Ma J, Hill DJ (2018) Fast stability scanning for future grid scenario analysis. *IEEE Trans Power Syst* *33*(1):514–524. <https://doi.org/10.1109/TPWRS.2017.2694048><https://ieeexplore.ieee.org/document/7898836>
- Liu S, Liu L, Fan Y, Zhang L, Huang Y, Zhang T, Mao D (2020) An integrated scheme for online dynamic security assessment based on partial mutual information and iterated random forest. *IEEE Trans Smart Grid* *11*(4):3606–3619. <https://doi.org/10.1109/TSG.2020.2991335><https://ieeexplore.ieee.org/document/9082004>
- Liu T, Liu Y, Liu J, Wang L, Xu L, Qiu G, Gao H (2020) A Bayesian learning based scheme for online dynamic security assessment and preventive control. *IEEE Trans Power Syst* *35*(5):4088–4099. <https://doi.org/10.1109/TPWRS.2020.2983477>
- Liu X, Zhang X, Chen L, Xu F, Feng C (2020) Data-driven transient stability assessment model considering network topology changes via mahalalanobis kernel regression and ensemble learning. *J Mod Power Syst Clean Energy*, *8*(6), 1080–1091, <https://doi.org/10.35833/MPCE.2020.000341><https://ieeexplore.ieee.org/document/9275596>
- Luo F, Dong Z, Chen G, Xu Y, Meng K, Chen Y, Wong K (2015) Advanced pattern discovery-based fuzzy classification method for power system dynamic security assessment. *IEEE Trans Ind Inf* *11*(2):416–426. <https://doi.org/10.1109/TII.2015.2399698><https://ieeexplore.ieee.org/document/7029678>
- Luo Y, Lu C, Zhu L, Song J (2023) Graph convolutional network-based interpretable machine learning scheme in smart grids. *IEEE Trans Autom Sci Eng* *20*(1):47–58. <https://doi.org/10.1109/TASE.2021.3090671><https://ieeexplore.ieee.org/document/9502909>
- Mahdi M, Genc VMI (2017) Artificial neural network based algorithm for early prediction of transient stability using wide area measurements. *2017 5th international istanbul smart grid and cities congress and fair (ICSG)* (pp. 17–21). <https://ieeexplore.ieee.org/document/7947611>
- Mahdi M, Genc VMI (2018) Post-fault prediction of transient instabilities using stacked sparse autoencoder. *Electric Power Syst Res* *164*:243–252. <https://doi.org/10.1016/j.epr.2018.08.009>
- Maihemuti S, Wang W, Wang H, Wu J, Zhang X (2021) Dynamic security and stability region under different renewable energy permeability in IENGs system. *IEEE Access* *9*:19800–19817. <https://doi.org/10.1109/ACCESS.2021.3049236><https://ieeexplore.ieee.org/document/9314149>
- Malbasa V, Zheng C, Chen P-C, Popovic T, Kezunovic M (2017) Voltage stability prediction using active machine learning. *IEEE Trans Smart Grid* *8*(6):3117–3124. <https://doi.org/10.1109/TSG.2017.2693394><https://ieeexplore.ieee.org/document/7898513>
- Milano F, Dörfler F, Hug G, Hill DJ, Verbič G (2018) Foundations and challenges of low-inertia systems (invited paper). *2018 power systems computation conference (pssc)* (p.1-25)
- Mohammadi H, Dehghani M (2015) PMU based voltage security assessment of power systems exploiting principal component analysis and decision trees. *Int J Electric Power Energy Syst* *64*:655–663. <https://doi.org/10.1016/j.ijepes.2014.07.077><https://www.sciencedirect.com/science/article/pii/S0142061514005213>

- Mohammadi H, Khademi G, Dehghani M, Simon D (2018) Voltage stability assessment using multi-objective biogeography-based subset selection. *Int J Electric Power Energy Syst* 103:525–536. <https://doi.org/10.1016/j.ijepes.2018.06.017><https://www.sciencedirect.com/science/article/pii/S0142061517319075>
- Mohammadi H, Khademi G, Simon D, Dehghani M (2016) Multi-objective optimization of decision trees for power system voltage security assessment. *2016 annual IEEE systems conference (SysCon)* (pp. 1–6). <https://ieeexplore.ieee.org/document/7490524?denied=>
- Mohammadi M, Gharehpetian GB, Niknam T (2010) On-line small-signal stability assessment of power systems using ball vector machines. *Electric Power Compon Syst*. <https://doi.org/10.1080/15325001003735150>
- Mukherjee R, De A (2020) Development of an ensemble decision tree-based power system dynamic security state predictor. *IEEE Syst J* 14(3):3836–3843. <https://doi.org/10.1109/JSYST.2020.2978504><https://ieeexplore.ieee.org/document/9044298>
- Naderi S, Javadi M, Mazhari M, Chung CY (2023) A machine learning-based framework for fast prediction of wide-area remedial control actions in interconnected power systems. *IEEE Trans Power Syst* 38(1):242–255. <https://doi.org/10.1109/TPWRS.2022.3165210><https://ieeexplore.ieee.org/document/9750882>
- Nakas GA, Dirik A, Papadopoulos PN, Matavalam ARR, Paul O, Tzelepis D (2023) online identification of cascading events in power systems with renewable generation using measurement data and machine learning. *IEEE Access* 11:72343–72356. <https://doi.org/10.1109/ACCESS.2023.3294472><https://ieeexplore.ieee.org/document/10179902>
- Nandanwar SR, Kolhe ML, Warkad SB, Patidar NP, Singh VK (2018) Voltage security assessment by using PFDT and CBR methods in emerging power system. *Energy Procedia* 144:170–181. <https://doi.org/10.1016/j.egypro.2018.06.023><https://www.sciencedirect.com/science/article/pii/S1876610218301292>
- Nandanwar SR, Warkad SB (2016) Voltage Security Assessment with Application of PMUs Using Decision Tree. *2016 8th International Conference on Computational Intelligence and Communication Networks (CICN)* (pp. 365–369). <https://ieeexplore.ieee.org/document/8082668> (ISSN: 2472-7555)
- Nie Z, Yang D, Centeno V, Jones KD (2017) A PMU-based voltage security assessment framework using hoefding-tree-based learning. *2017 19th international conference on intelligent system application to power systems (ISAP)* (pp. 1–6). <https://ieeexplore.ieee.org/document/8071402>
- Niu S, Huo C, Ke X, Wei P, Ren C, Zhang G, Sun H (2021) Research on power system transient security prediction based on AdaBoost-SVM. *2021 IEEE sustainable power and energy conference (iSPEC)* (pp. 3975–3981)
- Nuqui R, Phadke A, Schulz R, Bhatt N (2001) Fast on-line voltage security monitoring using synchronized phasor measurements and decision trees. *2001 IEEE power engineering society winter meeting. conference proceedings (Cat. No.01CH37194)* (Vol. 3, pp. 1347–1352 vol.3). <https://ieeexplore.ieee.org/document/917282>
- Nuthalapati SN (2021) Use of voltage stability assessment and transient stability assessment tools in grid operations. Springer International Publishing, Cham
- Ortiz-Villalba D, Rahmann C, Alvarez R, Canizares CA, Strunck C (2020) Practical framework for frequency stability studies in power systems with renewable energy sources. *IEEE Access* 8:202286–202297. <https://doi.org/10.1109/ACCESS.2020.3036162><https://ieeexplore.ieee.org/document/9249237>
- Pannell Z, Ramachandran B, Snider D (2018) Machine learning approach to solving the transient stability assessment problem. *2018 IEEE Texas power and energy conference (TPEC)* (pp. 1–6). <https://ieeexplore.ieee.org/document/8312089>
- Pérez-Londoño SM, Olivar-Tost G, Mora-Florez JJ (2017) Online determination of voltage stability weak areas for situational awareness improvement. *Electric Power Syst Res* 145:112–121. <https://doi.org/10.1016/j.epsr.2016.12.026><https://www.sciencedirect.com/science/article/pii/S0378779616305399>
- Qiao J, Wang X, Ni J, Shi M, Ren H, Chen E (2021) Graph neural network based transient stability assessment considering topology changes. *2021 international conference on power system technology (POWERCON)* (pp. 1999–2003). (ISSN: 2642-6226)
- Rahmann C, Ortiz-Villalba D, Álvarez R, Salles M (2017) Methodology for selecting operating points and contingencies for frequency stability studies. *2017 IEEE power & energy society general meeting* (pp. 1–5). <https://ieeexplore.ieee.org/abstract/document/8274423> (ISSN: 1944-9933)
- Rahmatian M, Chen YC, Palizban A, Moshref A, Dunford WG (2017) Transient stability assessment via decision trees and multivariate adaptive regression splines. *Electric Power Syst Res* 142:320–328. <https://doi.org/10.1016/j.epsr.2016.09.030><https://www.sciencedirect.com/science/article/pii/S0378779616303935>
- Ren C, Wang T, Yu H, Xu Y, Dong ZY (2023) EFedDSA: an efficient differential privacy-based horizontal federated learning approach for smart grid dynamic security assessment. *IEEE J Emerg Select Topics Circuits Syst* 13(3):817–828. <https://doi.org/10.1109/JETCAS.2023.3293253><https://ieeexplore.ieee.org/document/10183839>

- Ren C, Xu Y (2019) A fully data-driven method based on generative adversarial networks for power system dynamic security assessment with missing data. *IEEE Trans Power Syst* 34(6):5044–5052. <https://doi.org/10.1109/TPWRS.2019.2922671> <https://ieeexplore.ieee.org/document/8736295>
- Ren C, Xu Y (2020) Transfer learning-based power system online dynamic security assessment: using one model to assess many unlearned faults. *IEEE Trans Power Syst* 35(1):821–824. <https://doi.org/10.1109/TPWRS.2019.2947781> <https://ieeexplore.ieee.org/document/8871201>
- Ren C, Xu Y (2023) A universal defense strategy for data-driven power system stability assessment models under adversarial examples. *IEEE Internet Things J* 10(9):7568–7576. <https://doi.org/10.1109/JIOT.2022.3202267> <https://ieeexplore.ieee.org/document/9868826>
- Ren C, Xu Y, Zhang Y, Zhang R (2020) A hybrid randomized learning system for temporal-adaptive voltage stability assessment of power systems. *IEEE Trans Ind Inf* 16(6):3672–3684. <https://doi.org/10.1109/TII.2019.2940098> <https://ieeexplore.ieee.org/document/8827296>
- Ren C, Yuan H, Li Q, Zhang R, Xu Y (2023) Pre-fault dynamic security assessment of power systems for multiple different faults via multi-label learning. *IEEE Trans Power Syst* 38(6):5501–5511. <https://doi.org/10.1109/TPWRS.2022.3223166> <https://ieeexplore.ieee.org/document/9954911>
- Rovnyak S, Kretsinger S, Thorp J, Brown D (1994) Decision trees for real-time transient stability prediction. *IEEE Trans Power Syst* 9(3):1417–1426. <https://doi.org/10.1109/59.336122> <https://ieeexplore.ieee.org/document/336122>
- Rovnyak S, Taylor C, Sheng Y (2000) Decision trees using apparent resistance to detect impending loss of synchronism. *IEEE Trans Power Deliv* 15(4):1157–1162. <https://doi.org/10.1109/61.891496> <https://ieeexplore.ieee.org/document/891496>
- Sajan KS, Kumar V, Tyagi B (2015) Genetic algorithm based support vector machine for on-line voltage stability monitoring. *Int J Electric Power Energy Syst* 73:200–208. <https://doi.org/10.1016/j.ijepes.2015.05.002> <https://www.sciencedirect.com/science/article/pii/S0142061515002070>
- Sajan KS, Kumar V, Tyagi B (2015b) ICA based artificial neural network model for voltage stability monitoring. *TENCON 2015 - 2015 IEEE region 10 conference* (pp. 1–3). <https://ieeexplore.ieee.org/document/7372938> (ISSN: 2159-3450)
- Sajan KS, Tyagi B, Kumar V (2014) Genetic algorithm based artificial neural network model for voltage stability monitoring. *2014 Eighteenth national power systems conference (NPSC)* (pp. 1–5). <https://ieeexplore.ieee.org/document/7103798>
- Sawhney J, Jeyasurya B (2006) A feed-forward artificial neural network with enhanced feature selection for power system transient stability assessment. *Electric Power Syst Res* 76(12):1047–1054. <https://doi.org/10.1016/j.epsr.2005.12.026> <https://www.sciencedirect.com/science/article/pii/S0378779606000034>
- Senroy N, Heydt G, Vittal V (2006) Decision tree assisted controlled islanding. *IEEE Trans Power Syst* 21(4):1790–1797. <https://doi.org/10.1109/TPWRS.2006.882470> <https://ieeexplore.ieee.org/document/1717583>
- Sepehr A, Gomis-Bellmunt O, Pouresmaeil E (2022) Employing machine learning for enhancing transient stability of power synchronization control during fault conditions in weak grids. *IEEE Trans Smart Grid* 13(3):2121–2131. <https://doi.org/10.1109/TSG.2022.3148590> <https://ieeexplore.ieee.org/document/9701593>
- Shah H, Verma K (2016) PMU-ANN based approach for real time voltage stability monitoring. *2016 IEEE 6th international conference on power systems (ICPS)* (pp. 1–5). <https://ieeexplore.ieee.org/document/7584137>
- Shahzad U (2021) Probabilistic transient stability assessment of power systems using artificial neural network. *J Electric Eng Electron Control Comput Sci* 8(1):35–42
- Shahzad U (2022) Application of supervised machine learning for prediction of probabilistic transient stability. *Aust J Electric Electron Eng* 19(1):65–78. <https://doi.org/10.1080/1448837X.2021.2013418>
- Shahzad U (2022b) *Artificial neural network for transient stability assessment: a review*. arXiv. (arXiv:2206.06800 [cs, eess])
- Shahzad U (2022) A comparative analysis of artificial neural network and support vector machine for online transient stability prediction considering uncertainties. *Aust J Electric Electron Eng* 19(2):101–116. <https://doi.org/10.1080/1448837X.2021.2022999>
- Sharifian A, Sharifian S (2015) A new power system transient stability assessment method based on Type-2 fuzzy neural network estimation. *Int J Electric Power Energy Syst* 64:71–87. <https://doi.org/10.1016/j.ijepes.2014.07.007> <https://www.sciencedirect.com/science/article/pii/S0142061514004396>
- Shi Z, Yao W, Zeng L, Wen J, Fang J, Ai X, Wen J (2020) Convolutional neural network-based power system transient stability assessment and instability mode prediction. *Appl Energy* 263:114586. <https://doi.org/10.1016/j.apenergy.2020.114586>
- Siddiqui SA, Verma K, Niazi KR, Fozdar M (2018) Real-time monitoring of post-fault scenario for determining generator coherency and transient stability through ANN. *IEEE Trans Ind Appl* 54(1):685–692. <https://doi.org/10.1109/TIA.2017.2753176> <https://ieeexplore.ieee.org/abstract/document/8038834>

- Song S, Jung Y, Han C, Jung S, Yoon M, Jang G (2020) Recurrent neural-network-based maximum frequency deviation prediction using probability power flow dynamic tool. *IEEE Access* 8:182054–182064. <https://doi.org/10.1109/ACCESS.2020.3028707><https://ieeexplore.ieee.org/document/9212358>
- Suganyadevi M, Babulal C (2014) Fast assessment of voltage stability margin of a power system. *J Electric Syst* 10:305–316
- Suganyadevi MV, Babulal CK, Kalyani S (2016) Assessment of voltage stability margin by comparing various support vector regression models. *Soft Comput* 20(2):807–818. <https://doi.org/10.1007/s00500-014-1544-x>
- Suliman SI, Rahman TKA (2010) Artificial immune system based machine learning for voltage stability prediction in power system. *2010 4th international power engineering and optimization conference (PEOCO)* (pp. 53–58). <https://ieeexplore.ieee.org/document/5559230>
- Sulistiawati IB, Priyadi A, Qudsi OA, Soeprijanto A, Yorino N (2016) Critical Clearing Time prediction within various loads for transient stability assessment by means of the Extreme Learning Machine method. *Int J Electric Power Energy Syst* 77:345–352. <https://doi.org/10.1016/j.ijepes.2015.11.034><https://www.sciencedirect.com/science/article/pii/S0142061515004548>
- Sun K, Likhate S, Vittal V, Kolluri S, Mandal S (2008) An online dynamic security assessment scheme using phasor measurements and decision trees. *2008 IEEE power and energy society general meeting - conversion and delivery of electrical energy in the 21st century* (pp. 1–1). <https://ieeexplore.ieee.org/document/4596398> (ISSN: 1932-5517)
- Suprême H, Dessaint L-A, Kamwa I, Heniche-Oussédik A (2018) Development of new predictors based on the concept of center of power for transient and dynamic instability detection. *IEEE Trans Smart Grid* 9(4):3605–3615. <https://doi.org/10.1109/TSG.2016.2636816>
- Taeho J (2021) *Machine learning foundations: supervised, unsupervised, and advanced learning*. Springer, Cham
- Tan B, Yang J, Pan X, Li J, Xie P (2017) Representational learning approach for power system transient stability assessment based on convolutional neural network. *J Eng* 13:1847–1850
- Tan B, Zhao J (2023) Debiased Uncertainty Quantification Approach for Probabilistic Transient Stability Assessment. *IEEE Trans Power Syst* 38(5):4954–4957. <https://doi.org/10.1109/TPWRS.2023.3276207><https://ieeexplore.ieee.org/document/10124366>
- Tang Y, Cui H, Wang Q (2017) Prediction model of the power system frequency using a cross-entropy ensemble algorithm. *Entropy* 19(10):552. <https://doi.org/10.3390/e19100552><https://www.mdpi.com/1099-4300/19/10/552> (Number: 10 Publisher: Multidisciplinary Digital Publishing Institute)
- Teeuwssen S, Erlich I, El-Sharkawi M (2005) Small-signal stability assessment for large power systems using computational intelligence. *IEEE power engineering society general meeting, 2005* (pp. 2661–2668 Vol. 3). <https://ieeexplore.ieee.org/document/1489375> (ISSN: 1932-5517)
- Tian F, Zhou X, Yu Z, Shi D, Chen Y, Huang Y (2019) A preventive transient stability control method based on support vector machine. *Electric Power Syst Res* 170:286–293. <https://doi.org/10.1016/j.epsr.2019.01.030><https://www.sciencedirect.com/science/article/pii/S0378779619300422>
- Velayati MH, Amjady N, Khajevandi I (2015) Prediction of dynamic voltage stability status based on Hopf and limit induced bifurcations using extreme learning machine. *Int J Electric Power Energy Syst* 69:150–159. <https://doi.org/10.1016/j.ijepes.2015.01.005><https://www.sciencedirect.com/science/article/pii/S0142061515000241>
- Voumvoulakis, E., Gavoyiannis, A., Hatziazgryriou, N. (2006). Decision trees for dynamic security assessment and load shedding scheme. *2006 IEEE power engineering society general meeting* (pp. 7). (ISSN: 1932-5517)
- Wang B, Fang B, Wang Y, Liu H, Liu Y (2016) Power system transient stability assessment based on big data and the core vector machine. *IEEE Trans Smart Grid* 7(5):2561–2570. <https://doi.org/10.1109/TSG.2016.2549063><https://ieeexplore.ieee.org/abstract/document/7445227>
- Wang C, Li B, Liu C, Li P (2021) Convolutional neural network-based power system frequency security assessment. *IET Energy Syst Integr* 3(3):250–262. <https://doi.org/10.1049/esi2.12021>
- Wang Q, Li F, Tang Y, Xu Y (2019) Integrating model-driven and data-driven methods for power system frequency stability assessment and control. *IEEE Trans Power Syst* 34(6):4557–4568. <https://doi.org/10.1109/TPWRS.2019.2919522><https://ieeexplore.ieee.org/document/8723612>
- Wang Tw, Guan L, Zhang Y (2008) A modified pattern recognition algorithm and its application in power system transient stability assessment. *2008 IEEE power and energy society general meeting - conversion and delivery of electrical energy in the 21st century* (pp. 1–7). (ISSN: 1932-5517)
- Wang Y, Pal BC (2023) Destabilizing attack and robust defense for inverter-based microgrids by adversarial deep reinforcement learning. *IEEE Trans Smart Grid* 14(6):4839–4850. <https://doi.org/10.1109/TSG.2023.3263243><https://ieeexplore.ieee.org/document/10089185>

- Wang Y, Silva-Saravia H, Pulgar-Painemal H (2019) Actuator placement for enhanced grid dynamic performance: a machine learning approach. *IEEE Trans Power Syst* 34(4):3119–3128. <https://doi.org/10.1109/TPWRS.2019.2895019><https://ieeexplore.ieee.org/document/8625444>
- Xie J, Sun W (2021) A transfer and deep learning-based method for online frequency stability assessment and control. *IEEE Access* 9:75712–75721. <https://doi.org/10.1109/ACCESS.2021.3082001><https://ieeexplore.ieee.org/document/9435326>
- Xu C, Liang J, Yun Z, Zhang L (2005) The small-disturbance voltage stability analysis through adaptive ar model based on PMU. *2005 IEEE/PES transmission & distribution conference & exposition: Asia and Pacific* (pp. 1–5). <https://ieeexplore.ieee.org/abstract/document/1547097> (ISSN: 2160-8644)
- Xu Y, Dai Y, Dong ZY, Zhang R, Meng K (2013) Extreme learning machine-based predictor for real-time frequency stability assessment of electric power systems. *Neural Comput Appl* 22(3):501–508. <https://doi.org/10.1007/s00521-011-0803-3>
- Xu Y, Dong ZY, Meng K, Zhang R, Wong KP (2011) Real-time transient stability assessment model using extreme learning machine. *IET Gen Transm Distrib* 5(3):314–322. <https://doi.org/10.1049/iet-gtd.2010.0355>. ((Publisher: IET Digital Library))
- Xu Y, Dong ZY, Zhao JH, Zhang P, Wong KP (2012) A reliable intelligent system for real-time dynamic security assessment of power systems. *IEEE Trans Power Syst* 27(3):1253–1263. <https://doi.org/10.1109/TPWRS.2012.2183899><https://ieeexplore.ieee.org/document/6158623?denied=>
- Xu Y, Guan L, Dong ZY, Wong KP (2010) Transient stability assessment on China Southern power grid system with an improved pattern discovery-based method. *2010 International conference on power system technology* (pp. 1–6). <https://ieeexplore.ieee.org/document/5666045>
- Xu Y, Zhang R, Zhao J, Dong ZY, Wang D, Yang H, Wong KP (2016) Assessing short-term voltage stability of electric power systems by a hierarchical intelligent system. *IEEE Trans Neural Netw Learn Syst* 27(8):1686–1696. <https://doi.org/10.1109/TNNLS.2015.2441706><https://ieeexplore.ieee.org/document/7284703>
- Yang H, Zhang W, Chen J, Wang L (2018) PMU-based voltage stability prediction using least square support vector machine with online learning. *Electric Power Syst Res* 160:234–242. <https://doi.org/10.1016/j.epsr.2018.02.018><https://www.sciencedirect.com/science/article/pii/S0378779618300610>
- Yang Y, Huang Y, Liu J, Liu Y, Liu T, Xiang Y (2017) Measurement-based cell-DT method for power system transient stability classification. *CSEE J Power Energy Syst*, 3(3), 278–285. <https://doi.org/10.17775/CSEEJPES.2015.01230><https://ieeexplore.ieee.org/document/8057662>
- Yousefian R, Bhattarai R, Kamalasadani S (2017) Transient stability enhancement of power grid with integrated wide area control of wind farms and synchronous generators. *IEEE Trans Power Syst* 32(6):4818–4831. <https://doi.org/10.1109/TPWRS.2017.2676138><https://ieeexplore.ieee.org/abstract/document/7867871>
- Yousefian R, Kamalasadani S (2016) A Lyapunov function based optimal hybrid power system controller for improved transient stability. *Electric Power Syst Res* 137:6–15. <https://doi.org/10.1016/j.epsr.2016.03.042>
- Yousefian R, Kamalasadani S (2018) Energy function inspired value priority based global wide-area control of power grid. *IEEE Trans Smart Grid* 9(2):552–563. <https://doi.org/10.1109/TSG.2016.2555909>
- Yu JJQ, Hill DJ, Lam AYS, Gu J, Li VOK (2018) Intelligent Time-Adaptive Transient Stability Assessment System. *IEEE Trans Power Syst* 33(1):1049–1058. <https://doi.org/10.1109/TPWRS.2017.2707501><https://ieeexplore.ieee.org/document/7932885>
- Yu JJQ, Lam AYS, Hill DJ, Li VOK (2017) Delay aware intelligent transient stability assessment system. *IEEE Access* 5:17230–17239. <https://doi.org/10.1109/ACCESS.2017.2746093><https://ieeexplore.ieee.org/document/8017541>
- Yuanhang D, Lei C, Weiling Z, Yong M (2015) Multi-support vector machine power system transient stability assessment based on relief algorithm. *2015 IEEE PES Asia-Pacific power and energy engineering conference (APPEEC)* (pp. 1–5). <https://ieeexplore.ieee.org/document/7381006?denied=>
- Zhai C, Nguyen HD, Zong X (2023) Dynamic security assessment of small-signal stability for power grids using windowed online gaussian process. *IEEE Trans Autom Sci Eng* 20(2):1170–1179. <https://doi.org/10.1109/TASE.2022.3173368><https://ieeexplore.ieee.org/document/9773283>
- Zhang C, Li Y, Yu Z, Tian F (2016) Feature selection of power system transient stability assessment based on random forest and recursive feature elimination. *2016 IEEE PES Asia-Pacific power and energy engineering conference (APPEEC)* (pp. 1264–1268)
- Zhang R, Wu J, Shao M, Li B, Lu Y (2018) Transient stability prediction of power systems based on deep belief networks. *2018 2nd IEEE conference on energy internet and energy system integration (EI2)* (pp. 1–6). <https://ieeexplore.ieee.org/document/8582609>
- Zhang R, Xu Y, Dong ZY, Hill DJ (2012) Feature selection for intelligent stability assessment of power systems. *2012 IEEE power and energy society general meeting* (pp. 1–7). <https://ieeexplore.ieee.org/document/6344780> (ISSN: 1944-9925)

- Zhang R, Xu Y, Dong ZY, Wong KP (2015) Post-disturbance transient stability assessment of power systems by a self-adaptive intelligent system. *IET Gen Transm Distrib* 9(3):296–305. <https://doi.org/10.1049/iet-gtd.2014.0264>
- Zhang R, Xu Y, Dong ZY, Zhang P, Wong KP (2013) Voltage stability margin prediction by ensemble based extreme learning machine. *2013 IEEE power & energy society general meeting* (pp. 1–5). <https://ieeexplore.ieee.org/document/6672489> (ISSN: 1932-5517)
- Zhang R, Yao W, Shi Z, Ai X, Tang Y, Wen J (2023) Encoding time series as images: a robust and transferable framework for power system DIM identification combining rules and VGGNet. *IEEE Trans Power Syst* 38(6):5781–5793. <https://doi.org/10.1109/TPWRS.2023.3234287><https://ieeexplore.ieee.org/document/10006407>
- Zhang R, Yao W, Shi Z, Ai X, Tang Y, Wen J (2023) Towards multi-scenario power system stability analysis: an unsupervised transfer learning method combining DGAT and data augmentation. *IEEE Trans Power Syst* 38(6):5367–5380. <https://doi.org/10.1109/TPWRS.2022.3220569><https://ieeexplore.ieee.org/document/9942331>
- Zhang T, Sun M, Cremer JL, Zhang N, Strbac G, Kang C (2021) A confidence-aware machine learning framework for dynamic security assessment. *IEEE Trans Power Syst* 36(5):3907–3920. <https://doi.org/10.1109/TPWRS.2021.3059197>
- Zhang Y, Dong ZY, Zhang R, Xu Y (2018) A noise-tolerant temporal-adaptive approach for short-term voltage stability assessment of power systems. *2018 IEEE innovative smart grid technologies - Asia (ISGT Asia)* (pp. 62–67). <https://ieeexplore.ieee.org/document/8467941?denied=>
- Zhang Y, Li T, Na G, Li G, Li Y (2015) Optimized extreme learning machine for power system transient stability prediction using synchrophasors. *Math Probl Eng*, 2015, 1–8. <https://doi.org/10.1155/2015/529724> <http://arxiv.org/abs/1810.08652> (arXiv:1810.08652 [cs, math])
- Zhang Y, Xu Y, Dong ZY (2018) Robust ensemble data analytics for incomplete pmu measurements-based power system stability assessment. *IEEE Trans Power Syst* 33(1):1124–1126. <https://doi.org/10.1109/TPWRS.2017.2698239><https://ieeexplore.ieee.org/document/7913716>
- Zhang Y, Xu Y, Dong ZY, Xu Z, Wong KP (2017) Intelligent early warning of power system dynamic insecurity risk: toward optimal accuracy-earliness tradeoff. *IEEE Trans Ind Inf* 13(5):2544–2554. <https://doi.org/10.1109/TII.2017.2676879><https://ieeexplore.ieee.org/document/7869388>
- Zhang Y, Xu Y, Dong ZY, Zhang R (2019) A hierarchical self-adaptive data-analytics method for real-time power system short-term voltage stability assessment. *IEEE Trans Ind Inf* 15(1):74–84. <https://doi.org/10.1109/TII.2018.2829818><https://ieeexplore.ieee.org/document/8345652>
- Zhang Y, Xu Y, Zhang R, Dong ZY (2019) A missing-data tolerant method for data-driven short-term voltage stability assessment of power systems. *IEEE Trans Smart Grid* 10(5):5663–5674. <https://doi.org/10.1109/TSG.2018.2889788><https://ieeexplore.ieee.org/document/8588381>
- Zhang Z, Sun M, Deng R, Kang C, Chow M-Y (2023) Physics-constrained robustness evaluation of intelligent security assessment for power systems. *IEEE Trans Power Syst* 38(1):872–884. <https://doi.org/10.1109/TPWRS.2022.3169139><https://ieeexplore.ieee.org/document/9761730>
- Zhao T, Yue M, Wang J (2023) Deep-learning-based koopman modeling for online control synthesis of nonlinear power system transient dynamics. *IEEE Trans Ind Inf* 19(10):10444–10453. <https://doi.org/10.1109/TII.2023.3240939><https://ieeexplore.ieee.org/document/10032610>
- Zhao T, Yue M, Wang J (2023) Robust power system stability assessment against adversarial machine learning-based cyberattacks via online purification. *IEEE Trans Power Syst* 38(6):5613–5622. <https://doi.org/10.1109/TPWRS.2022.3233735><https://ieeexplore.ieee.org/document/10005029>
- Zheng C, Malbasa V, Kezunovic M (2013) Regression tree for stability margin prediction using synchrophasor measurements. *IEEE Trans Power Syst* 28(2):1978–1987. <https://doi.org/10.1109/TPWRS.2012.2220988><https://ieeexplore.ieee.org/document/6331026?denied=>
- Zhou Y, Wu J, Yu Z, Ji L, Hao L (2016) A hierarchical method for transient stability prediction of power systems using the confidence of a SVM-based ensemble classifier. *Energies* 9(10):778 <https://doi.org/10.3390/en9100778><https://www.mdpi.com/1996-1073/9/10/778> (Number: 10 Publisher: Multidisciplinary Digital Publishing Institute)
- Zhou Y, Zhang P (2023) Noise-resilient quantum machine learning for stability assessment of power systems. *IEEE Trans Power Syst* 38(1):475–487
- Zhu L, Hill DJ (2022) Networked time series shapelet learning for power system transient stability assessment. *IEEE Trans Power Syst* 37(1):416–428
- Zhu L, Hill DJ, Lu C (2021) Intelligent short-term voltage stability assessment via spatial attention rectified RNN learning. *IEEE Trans Ind Inf* 17(10):7005–7016. <https://doi.org/10.1109/TII.2020.3041300><https://ieeexplore.ieee.org/document/9273219>
- Zhu L, Hill DJ, Lu C (2022) Semi-supervised ensemble learning framework for accelerating power system transient stability knowledge base generation. *IEEE Trans Power Syst* 37(3):2441–2454. <https://doi.org/10.1109/TPWRS.2021.3117402>

- Zhu L, Lu C, Dong ZY, Hong C (2017) Imbalance learning machine-based power system short-term voltage stability assessment. *IEEE Trans Ind Inf* 13(5):2533–2543. <https://doi.org/10.1109/TII.2017.2696534><https://ieeexplore.ieee.org/document/7906492>
- Zhu L, Luo Y (2021) Deep feedback learning based predictive control for power system undervoltage load shedding. *IEEE Trans Power Syst* 36(4):3349–3361. <https://doi.org/10.1109/TPWRS.2020.3048681><https://ieeexplore.ieee.org/document/9312447>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Authors and Affiliations

Miguel Cuevas¹ · Ricardo Álvarez-Malebrán² · Claudia Rahmann¹ · Diego Ortiz³ · José Peña² · Rodigo Rozas-Valderrama²

✉ Ricardo Álvarez-Malebrán
ricardo.alvarezma@usm.cl

Miguel Cuevas
miguel.cuevas@ing.uchile.cl

Claudia Rahmann
crahmann@ing.uchile.cl

Diego Ortiz
ddortiz5@espe.edu.ec

José Peña
pepepena_zamudio@hotmail.com

Rodigo Rozas-Valderrama
rodrigo.rozas@usm.cl

¹ Department of Electrical Engineering, University of Chile, Santiago 8320000, Chile

² Department of Electrical Engineering, Universidad Técnica Federico Santa María, Santiago 8940000, Chile

³ Department of Electrical Engineering, Universidad de las Fuerzas Armadas ESPE, Sangolqui 171103, Ecuador