A Review of Machine Learning Applications in Power System Resilience

Jian Xie, Inalvis Alvarez-Fernandez, and Wei Sun
Department of Electrical and Computer Engineering, University of Central Florida, Orlando, FL USA
jianxie@knights.ucf.edu, AlvarezFernandez@knights.ucf.edu, sun@ucf.edu

***Abstract*—The integration of power electronics enabled devices and the high penetration of renewable energy drastically increase the complexity of power system operation and control. Power systems are still vulnerable to large-scale blackouts caused by extreme natural events or man-made attacks. With the recent development in artificial intelligence technique, machine learning has shown a processing ability in computational, perceptual and cognitive intelligence. It is an urgent challenge to integrate the advanced machine learning technology and large amount of real-time data from wide area measurement systems and intelligent electronic devices, in order to effectively enhance power system resilience and ensure the reliable and secure operation of power systems. Therefore, this paper aims to systematically review the existing application of machine learning methods on power system resilience enhancement, to expand the interest of researchers and scholars in this topic, and to jointly promote the application of artificial intelligence in the field of power systems.**

***Index Terms*—Deep Learning, Machine Learning, Power System Control, Resilience, Restoration**

I. INTRODUCTION

THE power system provides the foundation for the normal operation of transportation, communication, water supply, and other basic production facilities. As the uncertainties in power systems have drastically increased [1] due to renewable energy and demand response, power system operation and planning have become more complex and vulnerable to extreme weather and natural disasters. Thus, enhancing power system resilience has become more prominent.

Significant efforts have been devoted to enable power grid modernization with the enhanced resilience. Most approaches in the literature are based on physical modeling and analysis, which has became challenging to handle the increased system complexity and uncertainty. Artificial Intelligence (AI) has the capability of self-learning from data with low dependence on mathematical models of physical systems, which provides an effective solution to break through the technical challenges.

There are two main driving forces for the application of AI in power system resilience: 1) the availability of large datasets from wide area monitoring systems in transmission system and from sensors and intelligent electronic devices in distribution system; and 2) the advancement in AI algorithms and the exponential growth in computational power.

First, the main application of harnessing the influx of data has been on model validation and state monitoring. These data provide detailed measurements with geographical information for system operators to be constantly informed about the health of power grid. These data also include readings of extreme weather events, power outages, transient responses, alarms, which could be useful for resilience enhancement. Moreover, the synchronous measurement and historical operation data of power systems contain rich information. In order to improve the resilience of power systems, it is imperative to analyze massive data and expose the hidden value in big data, which requires the implementation of AI technologies.

Secondly, among various AI technologies, such as machine learning (ML), there have been great breakthroughs in data resolution, learning and computing power [2]. Machine learning methods have been widely applied in power system operation and planning, such as load and wind speed forecasting, demand response, fault detection, stability assessment, stability control and restoration [3]. However, the up-to-date literature discussing the application of ML techniques in enhancing power system resilience is limited.

This paper presents a concise and thorough review on the application of ML in power system resilience enhancement, including outage prediction, stability assessment, stability control, and system restoration. The rest of paper is organized as follows. Section II summarizes different ML models and algorithms. Sections III to VI provide an overview of various resilience enhancement problems, different types of data, and literature review. Sections VII and VIII discuss the outstanding issues, identify new research trends, and conclude this paper.

II. MACHINE LEARNING MODELS

A ML model transforms its input data into meaningful outputs, as a process to learn from exposure to known examples of inputs and outputs. Considering the recent development in ML and its application in power systems, three groups of ML techniques are considered in this paper: traditional machine learning, deep learning (DL), and reinforcement learning (RL). Table I summarizes seven different types of learning with their corresponding models from the literature.

First, in traditional ML, there are mainly five different models. 1) *Traditional Neural Network*: was widely used until the advent of back-propagation algorithms in the 1980s, including Multilayer Perceptron (MLP), Artificial Neural Network (ANN), and Extreme Learning Machines (ELM). 2) *Kernel Methods*: a class of algorithms for classification, e.g. Support Vector Machine (SVM), which use the kernel function to map any two points in the original space to the high-dimensional space and calculate the distance between them in the new space, thus simplifying the classification problem. 3) *Tree-Based Methods*: usually involve stratifying or segmenting

TABLE I
MACHINE LEARNING METHODS FOR RESILIENCE ENHANCEMENT

Learning Type	Outage Forecasting	Stability Asssessment	Control	Restoration
Traditional Neural Network	ANN	ELM	ANN	ANN
			ELM	
Kernel Methods	3D SVM	SVM	SVM	SVM
	TWSVM	CVM		
Tree-Based Methods		TSCC		
		QRF		
		Cost Sensitive DT		
Probabilistic Modeling	Logistic Regression		Naive bayes	
Ensemble learning	AdaBoost+		Ensemble DT	
Deep Learning	CNN	Deep Autoenconder Neural Network	CNN	SAE
	SAE	DCN		
		DBN		
	DNN	Cascaded CNN	DCN	
		SAE		
	RNN	CNN		
		RNN		
	LSTM	LSTM		
Reinforcement Learning			Multi-Agent RL	Q-Learning
			DQL	

the predictor space into multiple regions to classify input data, including Decision Tree (DT). 4) *Probabilistic Modeling*: based on the probability theory, uses mathematical statistics to build models for solving classification or regression problems, including Naive Bayes and Logistic Regression. 5) *Ensemble Learning*: integrates multiple learning models for better results, including Adaptive Boosting (AdaBoost) and Random Forest.

Secondly, DL has made breakthroughs with its excellent capability of feature extraction. It is a new take on learning representations from data that puts an emphasis on learning successive layers of increasingly meaningful representations, which allows a model to learn all layers of representation jointly. Major DL models include, Deep Belief Networks (DBN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long-short Term Memory (LSTM) Networks.

Thirdly, in RL, an agent receives information about its environment and learns to choose actions to maximize its reward. Therefore, the agent can learn self-improvement only by judging the feedback information generated by its own experience, with more powerful online self-learning ability than other ML methods.

Among different applications in power system resilience enhancement, first two of outage prediction and stability assessment are classification type of problem, and the last two of stability control and restoration are decision-making type of problem. Next, we will review the application of different ML methods in each of four resilience enhancement problems.

III. POWER OUTAGE PREDICTION AND VULNERABILITY IDENTIFICATION

A. Problem Identification

The accurate prediction of power outage after disturbances and vulnerable areas plays an important role in power system restoration. Due to the uncertainty of various factors such as weather and vegetation, model-based methods cannot provide practically accurate results. However, ML methods can better explore the relationship between various factors related to power outage. There are several different applications in outage forecast and vulnerability identification: 1) Feature extraction for detecting vulnerable areas; 2) Estimation of outages and their duration based on weather and animals events; 3) Rapid identification of alarm events based on historical data; 4) Development of grid hardening model based on extreme weather events; and 5) Damage prediction and prevention based on the path and intensity of hurricanes.

B. Data and ML Methods

There are two types of data: spatial and temporal weather data, and electrical data. 1) Weather data consist of characteristics of extreme events, such as wind speed, path of hurricanes, lightning strikes, distance of vulnerable areas from electrical systems to the center of hurricanes, vegetation and animal behavior. 2) Data associated with the electrical system consist of historical outage areas, vulnerable system components, synchrophasor readings, equipment failures, and consumer social media reports. As these two types of data are correlated, the major application of ML algorithms is feature extraction.

ML methods used in this application include deep and ensemble learning, neural network, kernel-based methods, and probabilistic modeling. Although most research in outage forecasting use the same type of data with similar problem formulation, there is a large variety of ML algorithms in the literature, as referred in Table I.

C. Literature Review

There are several recent efforts on ML-based power outage prediction. In [4], an ensemble learning approach, AdaBoost, is proposed for estimating weather-caused power outages to help utilities in outage management and system design. It shows that the proposed ensemble model can present more accurate results than regression and neural network models. Aiming to provide an accurate power outage detection, a supervised learning model based on temporal and spatial information is proposed in [5], and verified using actual tweets and outage cases. This work can assist utilities to accurately locate actual outage areas with existing measurement and communication infrastructures. In [6], a 3-dimensional SVM model is proposed to predict the outage of power system components caused by extreme events. The inputs for this model are component state, distance from the center of the extreme event, and the category of the extreme event. The comparison shows that the proposed 3-D SVM has better performance than logistic regression.

Components' vulnerability is another critical concern for resilience enhancement. In [7], a decision boundary to separate components' operation status into damaged or normal states after extreme weather events is obtained via logistic regression. The key parameters for decision boundary prediction are hurricane wind speed and the component distance from the center of hurricane. In [8], an SVM model is trained to predict components into damaged or normal condition in response to a hurricane. The predictions are adopted to determine the optimal locations of distributed generation units installment for hardening power system resilience.

Compared to predicting power outage amount after failure, the prediction of power outage duration is more valuable for customers. In [9], an RNN model that considers environmental factors, physical factors and engineering knowledge is proposed to predict the duration of outages during extreme weather events, with the validation through experiments on a large collection of outages.

A general framework of ML-based prediction of power grid vulnerable components is described in [10]. It has been applied to New York City power gird and demonstrated that the prediction can be used to assist utilities in preventing grid failures. An ANN using weather data (hurricane and drought), load, reserve margin and misoperation rate is proposed in [11] to estimate the vulnerability of concerned areas based on the conditions of system components, which is tested on Texas grid. A deep spatial-temporal data-driven model is proposed in [12] for detecting power system static security margins based on meteorological and electrical parameters, and tested using the Guangdong Power grid in China.

IV. Stability Assessment

A. Problem Identification

The stability assessment of power system is to evaluate transient stability, short term voltage stability, and contingency screening. The evaluation methods mainly include fault enumeration, energy function, and time domain simulation. Different from traditional methods, the AI-based method directly establishes the mapping between fault data and system stability categories to assess system stability. In literature, the following applications have been investigated for stability assessment: 1) Feature extraction to anticipate system states and security status for multiple contingencies; 2) Uncertainty prediction of interconnected generators; 3) Acceleration of N-1 contingency analysis; 4) Identification of stable or unstable operating points based on systems topology, loading condition and transient data; 5) Determination of system stability to enhance grid planning and day-ahead dispatch; 6) Time series classification for online short-term voltage stability assessment; and 7) Prediction of post-fault transient stability status.

B. Data and ML Methods

As the stability assessment mostly covers transient responses, most data are time dependent and extremely dimensional. For example, the transient data before, during and post fault have been used to predict system stability, enhance system planning, and address uncertainties. Time series data are useful to validate models and compare simulations results. Due to the scale and complexity of power system, it requires the dimensionality reduction and feature extraction to train models from time series data for prediction and categorization with the improved model accuracy. In literature, ML methods for this application include neural networks, DL, kernel and tree-based methods, as referred in Table I.

C. Literature Review

In order to avoid the curse of dimensionality caused by the increasing scale of modern power grid, a framework of data-driven Transient Stability Assessment (TSA) is proposed in [13]. Sixteen variables were chosen as the inputs for SVM to predict whether the transient stability is stable or unstable.

Recently, several advanced DL models have been applied on TSA problem. A DL-based system security assessment method with a novel feature extractor is proposed in [14], which is validated through multi-case studies on the French transmission system. The proposed method can be extended for other applications such as scenario reduction and data compression. In [15], authors propose a novel framework for probabilistic coherency prediction of unstable generators, and operators can adopt different control strategies for different parts of the network based on the prediction.

In [16], power flow profiles, including line active and reactive power flows, bus voltage magnitudes and angles, are collected as inputs for DBN to assess transient stability. Simulation results show that the out-performance of SVM-based method since SVM is sensitive to hyper-parameters. In order to decrease the computational burden of traditional model-based N-1 contingency screening, a CNN method is adopted to calculate AC power flow and operation security assessment in [17]. The inputs include active/reactive power injection vector and bus susceptance matrix, and the outputs are bus voltage magnitude and angle. In [18], authors developed the cascaded CNNs to assess the probability of transient stability. The inputs are rotor angles obtained from various time-domain simulations. Once the prediction is obtained, the time-domain simulation (TDS) for N-1 contingencies can be terminated, which the average simulation time can be shortened.

In order to improve the accuracy of ML-based transient stability prediction, authors in [19] propose a stacked sparse autoencoder method. Different from previous approaches, the inputs are voltage magnitude measurements collected from the entire fault-on time period. Simulation results based on the Western States Coordinating Council and Turkish power systems show a remarkable prediction accuracy and speed. An offline training and online application framework for TSA has been proposed in [20]. In the offline process, a core vector machine is trained based on TDS and applied for TSA based on PMU data.

In general, balanced classes can benefit a ML method for regression or classification. However, in power system operation after faults, there are much more stable cases than unstable cases, which results in a serious class imbalance problem that could weaken the prediction accuracy. In order to mitigate the class skewness, authors in [21] employ a cost-sensitive learning idea to impose more bias on unstable cases, which is verified on the Nordic test system.

V. Stability Control

A. Problem Identification

The stability control includes load shedding, generation control, and emergency management. Compared with previous two applications, stability control falls into the decision making type of problems, which is more applicable for probabilistic modeling and RL. Different applications in stability control include: 1) Emergency management and optimal control strategy; 2) Adaptive control actions to prevent cascading failures; 3) Automatic generation control schemes; 4) Time series data transformation for correlation-based feature selection; and 5) Undervoltage load shedding (UVLS) estimation.

B. Data and ML Methods

The data for stability control consist of system status, emergency and dynamic data, including operating conditions, power output, frequency, generator dynamic data such as angle and speed, voltage and load shedding. These data provide critical information for decision making, such as the optimization of system's energy management, control actions, and economic dispatch. Different ML algorithms, such as DL, RL, ensemble learning, kernel methods and neural networks, have been implemented on stability control, as referred in Table I. Especially, RL algorithms such as Deep Q-Learning and Multi-agent RL are used to optimize the control decisions and reduce the negative impact of those decisions on power grid.

C. Literature Review

RL-based stability control can improve the efficiency and accuracy of traditional model-based methods, which is limited to different topologies, operating modes and fault types. In general, RL-based control strategies can be categorized by three key elements: devices, agents, and observations. The observations are first implemented on power system and then transmitted to the agents, who analyze and control the devices that they are responsible for. In [22], a framework of RL-based power system control is proposed.

Several RL methods have been used to solve generator control problem. A multi-agent RL is integrated with a multi-objective optimization model to solve the distributed multi-area generator control problem in [23]. In order to better balance the power mismatches due to the integration of large-scale renewable energy sources, a RL-based method for complementary generation control is designed in [24] for interconnected power grids with the high-penetration of renewable energy sources and electric vehicles. An imitation learning and a transfer learning process are introduced to accelerate the learning rate in RL.

Moreover, ML-based methods have been applied for load shedding to improve system stability. Short-term voltage instability (STVS) has been a challenging problem due to the increasing penetration of motor loads. The UVLS is an effective control strategy to protect the system against STVS. In [25], the STVS margin and the UVLS amount and location are estimated by a random subspace-based SVM ensemble.

As power systems become more complex, model-based methods are limited in scalability and data-driven methods heavily depend on the data sample. The decrease in the number and quality of the sample may cause the prediction accuracy to decrease. Aiming to overcome the shortcomings of both methods, an integration of model-based and data-driven method is proposed in [26] for low frequency load shedding and frequency stability assessment.

Traditional RL methods are limited in performance for large-scale power system control due to the curse of dimensionality and calculation efficiency. Thus, DRL methods that integrate the perception of DL and the decision making of RL have been developed for power system control. In [27], a DRL method is employed to design the load shedding scheme. Based on transient voltage measurements, a feature extracted by CNN is adopted by DRL to achieve UVLS. In [28], authors employed DRL for generator dynamic brake and UVLS.

VI. System Restoration

A. Problem Identification

Similar to stability control, system restoration problems require the application of decision making algorithms to provide optimal restoration strategies. Furthermore, prediction type of algorithms are used to provide consumers with information about restoration times. In literature, the following topics in system restoration have been investigated: 1) Estimation of restoration time; 2) Evaluation of restoration strategies: prediction of system final configuration and load pickup; and 3) Rapid restoration following catastrophic events.

B. Data and ML Methods

Various data, including smart meter data, generation and line status, provide information for decision making type of ML algorithms to obtain an optimal restoration strategy. Furthermore, in terms of outage prediction, the usage of DL, neural network and Kernel methods are applied to historical power outage data due to extreme events.

The application of ML methods in system restoration is summarized in Table I. Due to the similar problem formulation of system restoration and stability control, an integration of decision-making type of ML methods with optimization techniques could be beneficial for further advancement of computational intensive optimization problems.

C. Literature Review

Compared with other three areas of resilience enhancement, there are only few research work on ML-based power system restoration. The application is generally limited in a module during restoration period to overcome the time-consuming time-domain simulation or complex optimization algorithms. In [29], a data-driven framework is developed for utilizing smart meter data to predict the customer-level demand increase due to cold load pick up. A SVM model is trained for prediction based on historical outage data.

In order to address the online generator start-up problem after blackout, authors in [14] integrate the Monte Carlo tree search (MCTS) algorithm with the sparse automatic encoder (SAE) to achieve online decision-making. A large number of samples can be generated by offline optimization, and SAE can quickly estimate the maximum power generation capacity of the unit in a certain state. The estimation can be guided in the simulation process to improve the MCTS search efficiency. In [30], a multi-agent based RL method is proposed to optimize the reliability of a system while considering the trade-off of load balancing.

VII. Challenges and Opportunities

Although a large number of advanced measurement and ML technologies have been applied to enhance the resilience of power grid, the risk of large-scale blackouts still exists. With more and more stochastic renewable energies connected in power systems, there are abundant research opportunities in the area of resiliency enhancement. Suggestions of several future applications are listed below, which could be either explored individually or combined in order to achieve a more resilient power system.

- *ML input data quality*: 1) data-driven scenario generation can generate useful stochastic data-sets, such as wind and solar power generation based on history measurements. This can provide sufficient data to perform a comprehensive evaluation of system resilience considering all possible scenarios; 2) for ML-based classification problem, such as stability assessment and vulnerability prediction, input feature selection and sample generation are critical to achieve an efficient and accurate model.
- *Advanced ML algorithms*: modern DL methods have shown powerful performance on image and video processing, but with limited application in power system. It is promising to transfer power system measurements to images or videos inputs, which could maximize the capability of advanced DL methods.
- *Power outage prediction*: the prediction of power outage duration is very beneficial to 1) keep customers informed with critical updates, and 2) better assist in restoration planning and resource allocation. The fusion of model-based and data-driven methods could enable a more accurate prediction of power outage duration.
- *System recovery and restoration*: there are many optimization problems in the restoration process, including network reconfiguration and load restoration. It is promising to combine optimization techniques and RL/DL methods for online or real-time decision making.
- *Cyber-physical resilience*: considering the interdependence between power and other critical infrastructure, the data and inputs from different cyber and physical systems could be integrated for a resilient cyber-physical system.

VIII. Conclusion

The powerful learning ability of ML provides technical support for online resilience enhancement of power systems based on real-time data. This paper reviews the research progress and prominent issues of ML in power system resilience applications. The potential of ML-based power system resilience enhancement is analyzed based on the performance curve of a system after an event. Furthermore, there is a numerous amount of topics that require research attention in order to realize a resilient power system.

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