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Artificial Intelligence/Machine Learning Technology in Power System Applications

March 2024

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U.S. DEPARTMENT OF ENERGY

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Executive Summary

The primary purpose of this report is to provide an overview of the advancement in artificial intelligence and machine learning (AI/ML) technologies and their applications in power systems. It offers a foundation for understanding the transformative role of AI/ML in power systems and aims to stimulate further research and development in this area.

This report begins with a historical perspective of AI/ML technologies, then explores their advancement to today's prominence. The document highlights key contributors to the success of AI/ML technologies, including increased computational power, greater data availability, innovative algorithms, and advanced tools. It further introduces various AI/ML techniques, including supervised, unsupervised and reinforcement learning, graph neural networks, and generative AI. It also emphasizes the critical importance of ensuring the safety, security, and trustworthiness of these AI/ML techniques within this sector.

The report reviews the recent representative advancements in various power system applications enhanced by AI/ML techniques, underscoring key developments and their transformative impact as evidenced by numerous studies. It also explores both the opportunities and challenges associated with the application of AI/ML technologies to improve power system applications.

While the report extensively covers AI/ML applications in power systems, focusing primarily on the technical and operational aspects, it may not thoroughly explore the sociopolitical, economic, and broader regulatory implications of AI/ML integration in power systems.

AI/ML techniques hold significant potential for enhancing power system applications; however, they are not omnipotent. It is crucial to acknowledge their limitations and understand that they may not be able to address all challenges in the power system domain. Various factors must be considered that influence the implementation, adoption, and effectiveness of AI/ML solutions, including but not limited to safety, security, transparency, and trustworthiness. Additionally, the incorporation of advanced human–machine interfaces is essential, as it enables humans to validate the effectiveness of AI/ML solutions while remaining actively engaged, fostering trust in AI/ML deployment.

Finally, the report summarizes AI/ML research activities supported by the Department of Energy (DOE) Office of Electricity (OE) through the Advanced Grid Modeling (AGM) program.

The work aligns with the interests and mission of DOE-OE AGM, with the report serving as a resource for identifying existing progress and for pinpointing future applications within AI/ML that need further exploration and support.

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Acronyms and Abbreviations

AGI	artificial general intelligence
AGM	Advanced Grid Modeling program
AI	artificial intelligence
ANL	Argonne National Laboratory
ANN	artificial neural network
AOCPO	AI-based online controller parameter optimization and adaption
BERT	bidirectional encoder representations from transformers.
BNL	Brookhaven National Laboratory
CGNN	convolutional graph convolution network
ChatGPT	chat generative pre-trained transformers
CLM	composite load model
CNN	convolution neural network
DFIG	doubly fed induction generator converters
DG	distributed generation
DNN	deep neural network
DOE	Department of Energy
DQN	deep-Q-network
DRL	deep reinforcement learning
DT	decision tree
EEAC	extended equal area criterion
EI	edge intelligence
EIA	U.S. Energy Information Administration
EV	electric vehicle
GAN	generative adversarial network
GCN	graph convolution network
CGNN	convolutional graph neural network
GNN	graph neural network
GPU	graphics processing unit
HIF	high-impedance fault
HMM	hidden Markov models
HPC	high-performance computing
IEEE	Institute of Electrical and Electronics Engineers
IL	imitation learning

IT	information technology
LAMP	local adaptive modular protection
LANL	Los Alamos National Laboratory
LLM	large language model
LLNL	Lawrence Livermore National Laboratory
LSTM	long short-term memory
LV	low voltage
MC	Monte Carlo
MDP	Markov decision problem
MIP	mixed-integer linear programming
ML	machine learning
MLP	multilayer perceptron
NILM	nonintrusive load monitoring
NN	neural network
NREL	National Renewable Energy Laboratory
OE	Office of Electricity
OPF	optimal power flow
ORNL	Oak Ridge National Laboratory
PEC	power electronic converters
PMU	phasor measurement unit
PNNL	Pacific Northwest National Laboratory
PV	photovoltaic(s)
QoS	quality-of-service
RAE	rainforest automation energy
RAS	remedial action scheme
RBM	restricted Boltzmann machines
RES	renewable energy source
RGNN	recurrent graph neural networks
RL	reinforcement learning
RNN	recurrent neural network
SCADA	supervisory control and data acquisition
SciML	scientific machine learning
SPS	special protection scheme
SNL	Sandia National Laboratories
SVM	support vector machine

TCSC	thyristor controlled series compensators
TSA	transient stability assessment
UFLS	under-frequency load shedding schemes
UP	uncertainty propagation
UQ	uncertainty quantification
VAE	variational autoencoder
WECC	Western Electricity Coordinating Council

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1.0 Introduction

Every industrial revolution in human history has been propelled by a major technology breakthrough—from manufacturing, energy production, and industrial sectors to information technology and the digital economy. As humans move beyond mobile communication and internet adoption, we will embrace new changes and transitions in our daily life to use heterogeneous and ubiquitous communication and computing technologies. To maximize the potential of proliferated compute and computing capabilities, artificial intelligence (AI) and machine learning (ML) have become widely recognized as the new catalyst in the fourth industrial revolution.

In the domain of power systems, the complexity of managing these systems is escalating with the increased dynamics and uncertainty resulting from the pursuit of deep decarbonization. Additionally, there is a surge in multi-dimensional data with shorter response time periods required. Current technologies are not sufficient to handle future complexities. AI/ML technologies have emerged as a transformative force to alleviate these challenges, heralding a new era of efficiency, reliability, and innovation. This report aims to provide an overview of state-of-the-art AI/ML technologies. More importantly, it aims to show their application and impacts on the planning and operation of power systems, the future opportunities that they present, and the challenges that accompany their integration into power systems. An examination of various ML techniques, including supervised, unsupervised, and reinforcement learning, forms the backbone of our exploration. We will discuss the representative applications of these techniques in power system management, spanning from fault detection, asset management and predictive maintenance, to oscillation detection.

The report is supported by the Department of Energy (DOE), Office of Electricity (OE), through its Advanced Grid Modeling (AGM) program. The AI/ML research activities supported by the AGM program are also summarized in this report. This report serves as a guide, helping navigate the exciting possibilities and potential challenges in the captivating blend of AI/ML and power system applications.

2.0 Why Does Machine Learning Work Today?

In the contemporary landscape, the effectiveness of ML stems from a confluence of factors that have propelled its success. One pivotal aspect is the unprecedented access to vast and diverse datasets—a critical ingredient for training sophisticated models. Notably, breakthroughs in data collection methodologies have empowered ML systems to learn intricate patterns and nuances which contribute to their robust performance.

As a branch of AI, ML uses algorithms and neural network (NN) models to build mathematical models using data sampling (training data) to make decisions based on logic and knowledge instead of scientific equations (Figure 1). ML has been studied since the 1950s to enable machines to "think" like human brains do and began to flourish in the 1980s to help efficiently solve science and engineering problems. Despite alternating periods of bust and boom, it was not until recently that AI started to deeply affect every domain of application and the average person's life (Copeland 2016). A remarkable event occurred in 2016, kicking off the blooming of the latest deep-learning wave when AlphaGo from Google DeepMind beat the human world champion in the game of Go. AlphaGO demonstrated the capability of ML to master complex games through reinforcement learning. This victory marked a paradigm shift, showcasing the potential of ML to tackle challenges that were once deemed insurmountable.

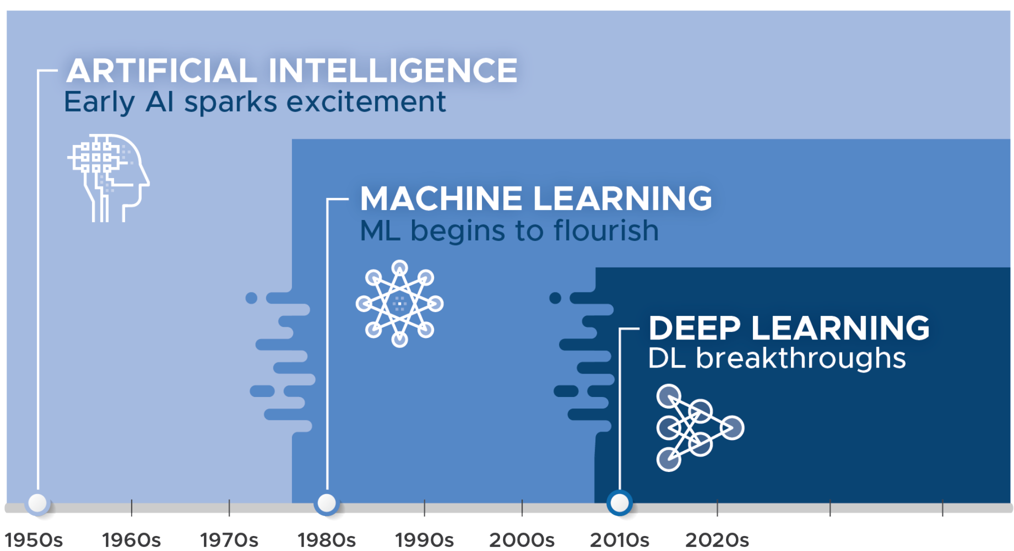

Figure 1. History and development of ML technology.

Since then, tremendous advancement of ML in various domains has been seen, including computer vision, image recognition, data compression, language processing, health care and robotics—with the most successes witnessed in the domain of deep learning. Deep learning employs a deep neural network (DNN) as the model. It typically has dozens of layers, with millions and even billions of free parameters. This complexity of the model is what makes deep learning powerful. Take AlphaGo as an example, it includes three components: the policy DNN, the value DNN, and the Monte Carlo (MC) tree search. The policy DNN is first trained by supervised learning from existing experience data, then reinforcement learning (RL) is applied to further improve the performance via millions of self-playing actions. The value DNN is a convolution neural network (CNN), which evaluates the proposal from the policy DNN. Finally, the MC tree eliminates branches and determines the final strategy.

Despite the tremendous success of DNNs, using NNs for ML is not something new (Figure 2). Researchers have experimented with DNNs for more than two decades but had only seen limited success (Lai 1998). For example, in 1990, the artificial neural network (ANN) had already been investigated for its application to power grid load forecasting (Feinberg and Genethliou 2005).

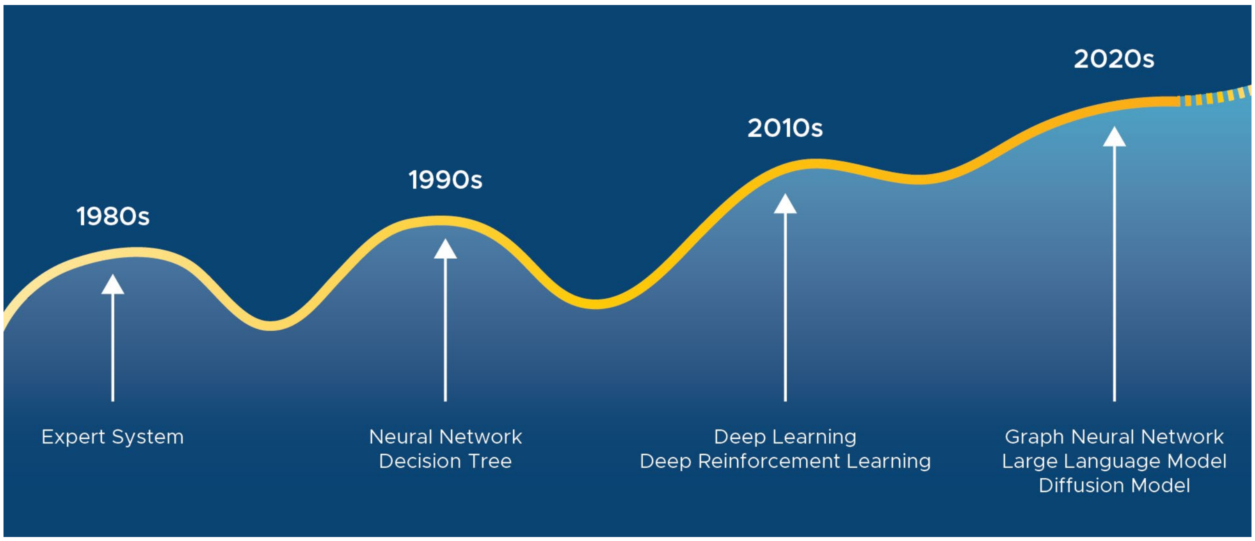

Figure 2. Four main waves of ML technology.

The recent success in deep learning can be attributed to four main factors: increased computational power, greater data availability, innovative algorithms, and advanced tools, as described below.

- **Increased Computational Power:** Training such a large model requires a lot of computational power. Thanks to Moore's law, computational power has been increased 1 trillion-fold in the last 60 years. ML especially began to shine after the introduction of the modern graphics processing unit (GPU), whose parallelism perfectly matches the computational needs of ML. Today, training a typical DNN model for image classification requires days on a GPU cluster, which was not feasible a decade ago. With recent research on dedicated hardware for ML, such as a tensor processing unit, computer scientists have seen more powerful ML models with broader applications (Jouppi et al. 2017).
- **Greater Data Availability:** ML is data-driven and data-hungry. It is modern practice to digitize almost everything in our daily life and share everything on the internet. For example, photos are uploaded to Instagram, videos are published on YouTube, even books are digitized and 5G is deployed in modern cities. The internet, social networks, and mobile devices make it cheap and easy to generate a huge amount of data, which facilitates ML. Billions of internet users have provided an abundance of data which is required to fuel deep-learning algorithms. On today's power grid, a large amount of measurement data, including but not limited to supervisory control and data acquisition (SCADA), phasor measurement unit (PMU) data, smart meter data, and the data generated by grid-edge technologies, is available. In addition to these power system data, data come from other domains, such as climate, cybersecurity, and communications, are also important to support grid management. Besides these measurement data, there is also a large amount of simulation

data available that can help power system engineers conduct big data research. The increasing availability of data from diverse poses challenges but also opportunities to drive ML technology development.

- **Innovative Algorithms:** A common way to train a NN is called back-propagation which is an algorithm for training ANNs first introduced by Rumelhart in 1986. However, naively applying back-propagation is not effective for training a DNN. In the last few years, researchers started to understand the reasons for this and have developed novel techniques to overcome this training challenge.
  - Diminishing gradient is one of the major obstacles to training DNNs because the gradient tends to become smaller and smaller when propagating back through many layers. This can cause premature convergence. Researchers have developed better nonlinear activation, such as rectified linear unit (Nair and Hinton 2010) or leaky rectified linear unit (Maas et al. 2013) that replace the traditional sigmoid to combat diminishing gradient.
  - Optimizing a NN is a nonlinear optimization problem. Back-propagation will converge to local minima if the network weights are not initialized properly. Unsupervised pretraining is an effective way to initialize the network weights close to a good local minimum (Erhan et al. 2010).
  - Training a DNN is further complicated by the changing distribution of each layer's inputs because the weights in previous layers change. This slows down the training and requires careful weights initialization. Batch normalization normalizes the layer inputs and incorporates this normalization operation as part of the network architecture (Ioffe and Szegedy 2015).
  - Due to model complexity the DNN tends to overfit the data, which leads to poor generalization. Dropout is a novel invention for preventing overfitting, especially when the data are scarce (Srivastava et al. 2014).
  - Last but not least, researchers have also designed sophisticated NN architectures that are tailored for specific domains. For example, CNNs, ResNet, and DenseNet work great for image/vision tasks, while long short-term memory (LSTM) is good for sequence modeling and language processing (Goodfellow et al. 2016; He et al. 2016; Huang et al. 2017a; Schmidhuber and Hochreiter 1997). Most recently, meta-learning has emerged as an alternative that can automatically search for the optimal NN architecture for different problems (Hospedales et al. 2021).
- **Advanced Tools:** In most of the research and application of AI/ML before 2010, researchers and engineers had to develop their ML algorithms from scratch for different applications which significantly limited their application, verification, and acceptance by stakeholders. Since 2010, rapid development of ML tools (mostly open-sourced, for example, *Tensorflow*, *Pytorch*, and *Scikit-learn*) have democratized the application of AI/ML in many domains. This is particularly important for power system applications where there are a limited number of researchers and engineers who can develop ML algorithms without these tools.

Furthermore, the trajectory of ML success extends to language models, exemplified by ChatGPT. The advent of transformers and attention mechanisms has revolutionized natural language processing. ChatGPT, a product of OpenAI, epitomizes the prowess of large-scale language models. Its ability to generate coherent and contextually relevant responses reflects the synergy between advanced algorithms and expansive datasets, making it an indispensable tool for a myriad of applications.

The exponential growth in computational power has been another catalyst for the contemporary effectiveness of ML. The availability of high-performance hardware, including GPUs and tensor processing units, has expedited the training of complex models. This acceleration in computation not only enables quicker experimentation but also facilitates the training of larger and more sophisticated NNs, ultimately enhancing the capabilities of ML systems.

In essence, the success stories from AlphaGo to ChatGPT underscore the evolution of ML and its efficacy today. The convergence of extensive datasets, advanced algorithms, and enhanced computational power has ushered in a new era where ML not only works but excels, driving innovation across various domains, including power systems.

3.0 A Brief Introduction to Machine Learning Techniques

ML techniques can be broadly categorized into three main types: (1) supervised learning; (2) unsupervised learning; and (3) reinforcement learning, as depicted in Figure 3 and described below.

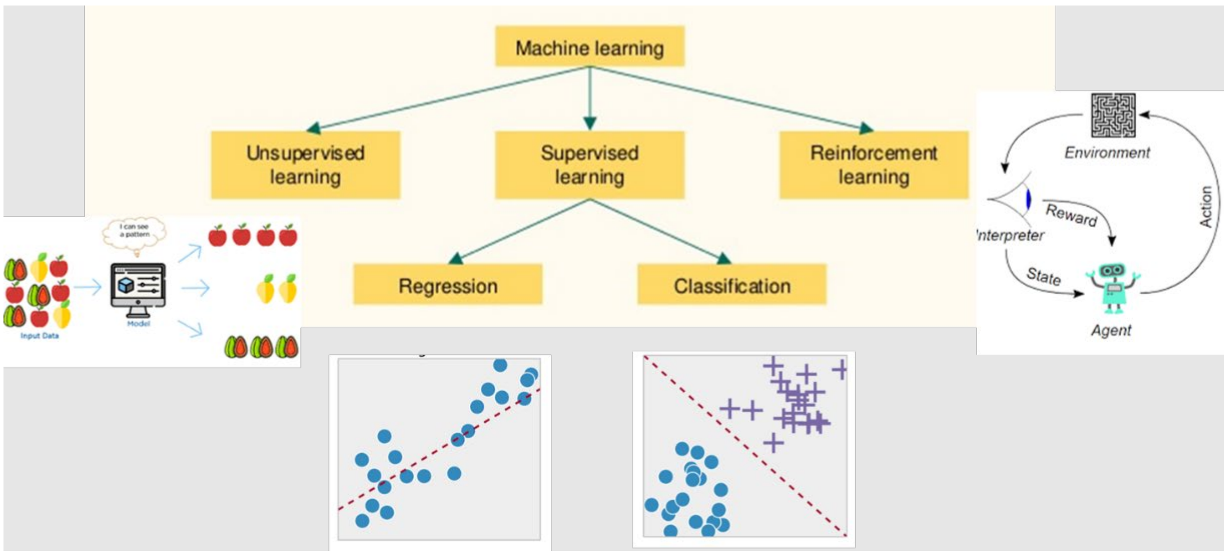

Figure 3. A simple illustration of ML techniques.

3.1 Supervised Learning

In supervised learning, predictive functions are found based on the data that is available. In the supervised setting, the goal is to find an $f: X \rightarrow Y$, where X is the input space and Y is the output (label) space. From a probabilistic point of view, many supervised ML models can be categorized as either discriminative models (i.e., learning the conditional probability distribution, $P(y|x)$) of the input x and the label y, or generative models (i.e., learning the joint probability distribution, $P(x, y)$). As labels are readily available for the data, the objective of learning is clear and the result of learning can be easily compared. Thus, supervised learning is by far the most common task in the field of ML. Generally speaking, a supervised learning task can be classified as either a classification or a regression task, which are both commonly seen in power systems. Commonly used supervised learning methods include, but are not limited, to SVMs, ANNs, digital twins, random forests, logistic regression, naive Bayes classifiers, k-nearest neighbors classifiers and regressors, Gaussian processes, and regularized linear regression models. (Ng and Jordan 2002).

In recent years, researchers have shown growing interest in DNNs because of their exceptional performance in certain tasks and their unprecedented flexibility. The learning task fulfilled by DNN is often referred to as deep learning (note that NNs are not limited to supervised learning). The implementation of DNNs allows different levels of representations to be learned from data, transforming the process of feature engineering in traditional ML pipelines (Goodfellow et al. 2016). Popular DNN networks include CNNs, recurrent neural networks (RNNs), and LSTM. Generally speaking, CNNs are often used to extract spatial features, and both RNNs and LSTM can be used to extract temporal features or model temporal dependence.

Applying deep learning to tasks in power systems has just started to gain attention because most DNN models are proposed by researchers who focus on tasks, such as computer vision (He et al. 2016), speech recognition (Hinton et al. 2012) and natural language processing (Wu et al. 2016), for which large amounts of high-quality data can be generated and shared (LeCun et al. 2015). For applications in power systems, however, accumulating high-quality data in large volumes is not an easy task. Supervised learning has been investigated for power grid applications, such as load/renewable energy forecasting, state estimation, fault detection and location, asset healthy monitoring, power system security assessment, and power system stability analysis. A detailed review of these applications is provided in later sections.

3.2 Unsupervised Learning

Unsupervised learning generally refers to learning tasks that learn from unlabeled data. Examples of unsupervised learning tasks include clustering; anomaly detection; dimensionality reduction, e.g., principal component analysis and independent component analysis; association rules analysis; graph structure discovery; etc. (Hastie et al. 2001; Murphy 2012). The most common unsupervised learning task is to cluster unlabeled data samples. Algorithms or models used for clustering include k-means, hierarchical clustering, spectral clustering, Gaussian mixture models, Dirichlet process mixture models, self-organizing maps, and density-based spatial clustering of applications with noise.

Recently, active research topics of unsupervised learning have included learning representations from data and generative models in the unsupervised setting:

1. **Learning representations from data:** A comprehensive review of representation learning was published in 2013 by Bengio and team. Generally speaking, learning representations reveal the inherent characteristics of the data samples within the dataset being studied, and complex tasks can be completed on the basis of these representations. From a single-layer learning module perspective, two representation learning paradigms can be identified, one focused on probabilistic graphical models (e.g., restricted Boltzmann machines [RBMs]), and the other one focused on learning direct encodings (e.g., autoencoders) (Bengio et al. 2013). RBMs and autoencoders can both be used to build DNNs in a layer-wise manner, although recent research has revealed that pretraining is not necessary. Nevertheless, the end-to-end nature of DNN models is also partially explained by the belief that expressive representations can be learned by the layers within the networks. Some recent work in the field of power systems—fault detection, asset healthy monitoring, load profiling, and nonintrusive load monitoring (NILM)—has highlighted the importance of representation learning, which is reviewed in detail in the following sections.
2. **Generative models in the unsupervised setting:** Two types of generative models have emerged recently and gained much attention: variational autoencoders (VAEs) (Rezende et al. 2014) and generative adversarial networks (GANs) (Goodfellow et al. 2014). VAEs and GANs both aim to generate new data points similar to those in a given dataset, but they do so using different approaches.

   VAEs work by learning a latent representation of the data, which is then used to generate new samples. They involve two neural networks, known as an encoder and a decoder, which are trained together to capture the underlying structure of the data. VAEs are useful when the true distribution of the data is complex and difficult to model directly.

   On the other hand, GANs operate by training two neural networks simultaneously: a generative model (*G*) and a discriminative model (*D*). The generative model generates data samples that are likely to be sampled from the distribution of the training data using random noise in the latent space, while the discriminative model tries to distinguish between real and generated samples. When both *D* and *G* are NNs, they can be trained by back-propagation, after which *G* is able to generate realistic data samples. The generative models can be extended to the semi-supervised setting where limited labeled data are available—this is true for many power system applications. GANs are effective for generating high-quality, realistic data samples. They hold significant promise for power system applications, especially in the context of renewable energy generation and demand-side scenarios. These models not only capture information from existing data, but also facilitate the generation of data samples that are unobserved but likely to occur in the real world.

In summary, VAEs are suitable for learning complex data distributions and capturing latent features, while GANs excel at generating realistic data samples. The choice between VAEs and GANs depends on the specific requirements of the application and the nature of the data being used.

3.3 Reinforcement Learning

Unlike other ML techniques that require a large amount of labeled or unlabeled training data, in RL, the agent learns optimal decision-making by interacting with the environment through trial and error. In this setting, the agent can observe the state of the environment and receive reward signals from it. At the same time, the agent can apply actions to change the environment. The goal is to apply the optimal action given the current state so that the agent can accumulate the most rewards over time. Mathematically speaking, RL formulates and solves a Markov decision process (MDP), which involves the state space, the action space, the reward function, the distribution of the initial state, the transition probability, and the discount factor.

RL algorithms can be categorized into policy gradient methods and value-based methods, both aiming to optimize a policy that maps states to actions. A natural extension for building RL models is to incorporate the building blocks of deep learning, which is particularly helpful for large state spaces or action spaces. The technology of combing RL and deep learning are called deep reinforcement learning (DRL). Advanced DRL technology includes deep-q-network (DQN), deep deterministic policy gradients, normalized advantage functions, and Asynchronous Advantage Actor-Critic. (Sutton and Barto 2018). The state-of-the-art DRL technology has been proven to provide fast, adaptive, and reliable decisions or control policies in real time, even for complex systems with uncertainties. DRL has produced some of the most impressive intelligent agents in various applications, including AlphaGo (Silver 2016), video games (Mnih 2013), data center temperature control (Li et al. 2019a), and autonomous driving (El Sallab 2017). Many of these agents trained by DRL achieved superior performance to humans. Researchers have been using RL in a variety of applications related to power and energy systems for residential demand response, power system control, and electricity market, which are reviewed in detail in later sections.

3.4 Graph Neural Networks and Graph Machine Learning

Graphs serve as an omnipresent data structure and a universal means of articulating intricate systems. When viewed broadly, a graph essentially comprises entities (referred to as nodes) accompanied by a series of connections (denoted as edges) that link pairs of these entities. For instance, when translating a social network into a graph format, nodes might represent an individual and edges could symbolize friendships between two individuals. In the realm of biology, nodes could represent proteins within a graph and edges could depict diverse biological interactions, like the kinetic associations between proteins. The potency of the graph framework lies in its twin emphasis on interrelationships among points, rather than the attributes of individual points and its wide-ranging applicability. This same graph structure can seamlessly represent a spectrum of scenarios, encompassing social networks, interactions between drugs and proteins, intermolecular connections, or the interlinking of terminals within a telecommunications network, among a myriad of other possibilities.

There are two main classes of graph neural networks (GNNs): recurrent graph neural networks (RGNNs) and convolutional graph convolution networks (CGNNs).

3.4.1 Recurrent Graph Neural Networks

RGNNs are the first versions of GNNs. The primary difference between GNN methods and typically known CGNNs is that they use the same set of learnable weights across different layers, whereas CGNNs use different learnable weights in each layer of GNNs. One can say these are the first works that tried to use NNs to perform structure learning. However, these methods state that the recurrent function must be a contraction mapping to assure convergence, and a penalty factor-based technique is used to also help with the convergence during the learning process. Several highlights of RGNN evolution include:

- Due to computational hardware limitations, Sperduti and Starita (1997) and Micheli et al. (2004) proposed structure-based learning on acyclic directed graphs.
- Sperduti and Starita (1997) extended the work to that of Scarselli et al. (2008), where the RGNNs can be applied to different graph types, such as acyclic, cyclic, directed, and undirected graphs. This method alternates the stage of node state propagation and the stage of parameter gradient computation to minimize a training objective but is limited by the contraction mapping requirement on the recurrent function.
- Gallicchio and Micheli (2010) proposed the Graph Echo State Network to improve the accuracy issues reported by Scarselli et al. (2008). Such improved accuracy is achieved by using a contractive state transition function to update the states during recurrent functions updates.
- Dai et al. (2018) proposed an extension that helped the learning algorithms be scalable for large graph problems using stochastic, steady-state embedding.

3.4.2 Convolutional Graph Neural Networks

Convolutional GNN methods are slightly different than the RGNNs in the sense that each GNN layer uses different weights during the learning process. CGNNs can be primarily segregated into two types—spectral and spatial-based methods—depending on the how the convolution property is handled, as described below.

- Spectral methods use the filters from a signal processing perspective where the convolution step in the CGNNs is understood to be the process of removing noise from the graph signals during the learning process (Shuman et al. 2013). Prior to the advent of popular graph convolution networks (GCNs) in 2017, the signal processing domain had already conducted research about how to perform graph learning and analysis based on a solid mathematical foundation (Shuman et al. 2013) (Sandryhaila and Moura 2013) (Chen et al. 2015).
- Spatial methods aimed to create embeddings that preserved the global structure information. However, they could not take semantic information into account. To address this, spatial methods are introduced where they use not only the graph degree and

Laplacian matrixes, but also the adjacency, features, and label matrixes in their learning process. Kipf and Welling (2016) proposed an approach that combined the spectral and spatial methodologies using the GCN.

3.5 Generative Artificial Intelligence and Large Language Models

With the advancements in ML techniques and computing resources, approaches based on big data have gained favor across various domains, gradually replacing traditional methods in addressing complex problems (Chen et al. 2019). However, these methods exhibit critical disadvantages:

- AI-based approaches heavily depend on training models and sample size. For large systems featuring high renewables penetration, the requirement for extensive training data can result in significant costs (Kumar et al. 2023).
- Solutions derived from AI often stem from ANN models, making the evaluation of solution quality challenging for system planners or operators. Additionally, it is difficult to incorporate a planner's opinion, knowledge, and experience into the AI-generated solutions without undergoing the entire training procedure.

With the advancements in deep learning and natural language processing techniques, large language models (LLMs), including ChatGPT[1], have witnessed remarkable development and research interest. The past two years have seen remarkable development of large LLM, such as BERT and ChatGPT and their novel applications (Devlin et al. 2018). While LLMs were first developed for language prediction, they internally built a complicated knowledge representation of the world, including fundamentals of power system engineering, and showed emerging artificial general intelligence (AGI).

Recent developments have enabled LLMs to learn and intelligently decide when and how to use external tools for business use cases. More recently, LLMs have been successfully augmented and applied to assist engineers and researchers in performing complex mechanical engineering design and chemistry experiments, which has inspired this work. A key capability of the ChatGPT model—which sets it apart from existing AI models—is its proficiency in understanding and processing user-provided instructions, resulting in contextually appropriate responses. In other words, users can offer comments and instructions for solutions generated by ChatGPT, leading to responses that closely resemble human-like interactions. This opens the potential possibility of using ChatGPT as an intelligent co-planner in power systems planning study. The power utility companies also see the potential of using ChatGPT and are exploring energy and utility enterprise use cases.

One such example is from Ontario Power Generation and Microsoft; they implemented Microsoft 365 infused with AI capabilities and designed an AI-powered chatbot named ChatOPG. It functions as a digital personal assistant, supports employees on topics ranging from information technology to human resources, and benefits the staff with quick connection to essential information and a simplified process for planning[2]. More importantly, LLMs and ChatGPT open the pathway for flexible integration of various AI/ML platforms and tools, which may benefit the deep dive of domain use cases by experienced engineers.

[1] Introducing ChatGPT (openai.com)

[2] Ontario Power Generation transforms operations with ChatGPT mentioned by Microsoft.

Table 1. A summary of different ML techniques used in power system applications.

Category	Power System Applications
Supervised Learning	• renewable energy forecasting • power system stability analysis • load forecasting • fault diagnosis for transmission lines and distribution systems • nonintrusive load monitoring • power equipment fault diagnosis • electricity market forecasting • electricity theft detection • false data injection detection • power system security assessment • power quality analysis • power system state estimation
Unsupervised Learning	• renewable energy data generation and analysis • power system stability analysis • demand response • load profiling • nonintrusive load monitoring • false data injection detection • PMU data generation
Reinforcement Learning	• power system control • demand response • electricity market operation • power system economic dispatch
Graph ML	• power system fault studies, including transformer fault diagnosis, fault location, fault detection and isolation, power outage prediction • time-series prediction, including solar power prediction, wind power/speed prediction, and residential load prediction • power flow estimation studies, including power flow approximation, OPF, and optimal load shedding • power system data generation, including scenario generation, synthetic feeder generation • many other grid-related topics, including coupled power and transportation networks analysis, line flow control, distributed energy resource control, safe methodologies for power grid operations, synchrophasor applications, transient stability assessment, network reconfiguration, and thermodynamic modeling of generators
Large Language Model	An LLM (including ChatGPT) could be applied to utility enterprise-level supports and planning, as well as engineering studies and customer services. It may serve as the entrance to the knowledge base of asset management, information technology, human resources, and more.

3.6 Safe, Secure, and Trustworthy Artificial Intelligence/Machine Learning for Grid Applications

Emerging technologies present new opportunities and challenges with the wide adoption by practical applications—especially for those ground-breaking yet long-lasting technologies, such as AI/ML and others found in the utility sector. Assuring the safe, secure, and trustworthy AI/ML in power grid systems is paramount for the stability and reliability of our energy infrastructure. As these technologies play an increasingly pivotal role in optimizing grid operations, predictive maintenance, and fault detection, it becomes imperative to address the unique challenges associated with their implementation in critical infrastructure.

To harness the potential of AI/ML technologies, it is crucial to develop, test, and improve the consensus among scientists, researchers, practitioners, policymakers, compliance, and law enforcement. This must occur throughout the full life cycle of technology adoption to establish a safe, secure, and trustworthy boundary. Drawing from the successful management of our electricity system, we can see how this experience can facilitate and accommodate the safe, secure, and trustworthy implementation of AI.

In addition, following the landmark Executive Order[3] signed by President Biden to advance agencies' efforts across the federal government, the Executive Order directs the following actions[4]:

- New Standards for AI Safety and Security
- Protecting American's Privacy
- Advancing Equity and Civil Rights
- Standing up for Consumers, Patients, and Students
- Supporting Workers
- Promoting Innovation and Competition
- Advancing American Leadership Abroad
- Ensuring Responsible and Effective Government Use of AI.

Each area above may impact and transform power systems management and operation, especially when aligned with the accelerated transition to 100 percent decarbonized energy production, transmission, distribution, and prosumer (producer-consumer) participation in the form of distributed energy resources and energy storage.

By harnessing the AI/ML benefit and testing new technologies in a controlled environment, the DOE-OE AGM program[5] supports building capacity and capability within the electric sector to analyze the electricity delivery system using big data, advanced mathematical theory, and high-performance computing to assess the current state of the grid, mitigate reliability risks, and understand future needs. The following sections will layout the current landscape of AI/ML

[3] https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/
[4] https://www.whitehouse.gov/briefing-room/statements-releases/2023/10/30/fact-sheet-president-biden-issues-executive-order-on-safe-secure-and-trustworthy-artificial-intelligence/
[5] https://www.energy.gov/oe/advanced-grid-modeling

applications in power systems, OE AGM program wide efforts in AI/ML domain, as well as provide a detailed analysis and examination from the risk perspective.

In addition, worldwide efforts regarding AI related policy, regulation, and laws are underway. For example, the European Commission proposed its first EU regulatory framework for AI in 2021[6], and the first AI act reached a deal between the Parliament and Council in December 2023. A key proposal includes the following regulatory framework for four levels of risk of AI[7]:

- Unacceptable risk
- High risk
- Limited risk
- Minimal or no risk.

All the four levels may cover specific categories and groups of definitions centered around AI and perspectives covering human, data, model, user, market, governance entities are reflected.

The evolution and iteration of AI/ML continues as one of the hottest topics in AGI. One of the definitions for AGI is from *OpenAI*[8]*:* "AI systems that are generally smarter than humans—benefits all of humanity". To further clarify this concept, the Google DeepMind team published a research paper to introduce levels of AGI performance, generality, and autonomy (Morris et al. 2023). A list of five performance levels of AGI is given as follows:

- Level 1: Emerging
- Level 2: Competent
- Level 3: Expert
- Level 4: Virtuoso
- Level 5: Superhuman.

Utilizing the classification process and following the risk assessment regarding AI autonomy, especially the interaction between human and AGI, Google DeepMind team also proposed the following five levels of autonomy:

- Autonomy Level 1: AI as a Tool
- Autonomy Level 2: AI as a Consultant
- Autonomy Level 3: AI as a Collaborator
- Autonomy Level 4: AI as an Expert
- Autonomy Level 5: AI as an Agent.

For the power grid, the reliability of AI/ML algorithms is crucial for power grid operations. The ML models must be resilient to various uncertainties and dynamic conditions inherent in the power grid environment. Rigorous testing and validation procedures are essential to assure that AI/ML models operate reliably under diverse scenarios, safeguarding the power grid stability.

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[6] https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence
[7] https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai
[8] https://openai.com/blog/planning-for-agi-and-beyond

As AI/ML systems become integral to power grid management, cybersecurity measures must be rigorously implemented to protect against potential threats. Securing data integrity, maintaining confidentiality, and preventing unauthorized access to critical AI models are critical. Assuring the transparency of these models is crucial for building trust among stakeholders. Clear communication of how AI/ML algorithms reach specific conclusions or make predictions, fosters confidence in their use and aids in decision-making processes for power grid management.

In summary, a new paradigm is needed to be reached through collaborative efforts, and a consensus among scientists, researchers, practitioners, policymakers, compliance, and law enforcement, must be developed, tested, improved, and evolved along the full life cycle of technologies being adopted to establish the safe, secure, and trustworthy boundary. By providing a high-level purview of AI classification mechanism, as well as a deep dive into power system applications of AI/ML, the authors aim to build a foundational understanding for stakeholders and readers to reveal an exciting future where the clean energy transition harnesses all available technologies and there is a possible pathway forward to embrace challenges.

4.0 Power System AI/ML Applications in the Literature

In recent years, numerous power system applications have undergone enhancements through AI/ML integration. Many publications delve into the exploration of these applications and their implications within the AI/ML domain. This section reveals a curated selection of power system applications that have been enhanced by the transformative capabilities of AI and ML. These applications are mainly focused on the transmission systems, covering grid monitoring, management, and planning. A selective list of publications is used as examples to illustrate the enhancements AI/ML techniques bring to these applications.

4.1 Fault Detection/Protection

Protection is a must-have function in power systems to assure personnel safety and avoid equipment damage. Traditional protection schemes mainly rely on commercial relays to issue tripping commands when certain preset thresholds are exceeded. However, it is sometimes very difficult to determine accurate thresholds because they usually depend on many factors, such as operating conditions, knowledge of equipment parameters, system transients, and fault types. The threshold settings represent the trade-off between protection sensitivity and security. Therefore, in practice, there are protection gaps in power systems and traditional relays cannot provide reliable or secure protections against faults or transients under certain circumstances. For example, the monitored measurements may resemble normal conditions when some fault happens. In this case, relays cannot detect this type of fault due to insufficient sensitivity. However, these faults, including transmission line high-impedance faults, transformer interturn faults, and minor circuit faults in distributed energy resources (mainly photovoltaic [PV]), are detrimental to the system. With recent development of more powerful computers, better measurement-acquiring devices, and better training algorithms, researchers are starting to explore the feasibility of using data-driven approaches to bridge the above-mentioned protection gaps in power systems. In their research, Cui et al. provide a method for extracting electrical features from high-impedance fault (HIF) currents, voltage signals, and building an effective feature set via a ranking algorithm (Cui et al. 2017). Therefore, only a small number of signal channels are required to build a statistical classifier for fault detection. Jiang and team also provide an effective method for reducing the huge volume of PMU data while retaining the critical information for fault detection in a power system (Jiang et al. 2016). Manohar's work proposes a CNN-based protection scheme to discriminate between inverter faults in the PV system and symmetrical/unsymmetrical faults in the distribution line, in addition to detecting/classifying the faults and identifying the faulty section (Manohar et al. 2019).

Gao and team implemented the RL-based algorithm, to improve the performance of doubly fed induction generator converters (DFIG) on wind turbines during grid fault conditions; a surrogate-gradient-based evolution strategy is used to control the DFIG power and capacitor DC-link voltage by adjusting the optimal reference signals (Gao et al. 2022). Research by Jones and team shows that no communication is needed and there are additional benefits, such as high accuracy and the use of relays without settings, when the adopted SVM is embedded inside each relay to classify grid faults, determine tie line switch positions, and estimate fault locations (Jones et al. 2021). Research by Ojetola and team compared five ML techniques regarding DC microgrid fault classification, and identified that only the multilayer perceptron (MLP) algorithm achieves 99 percent classification accuracy when based on fault type and fault resistance (Ojetola et al. 2022). Research by Poudel explored the coordination of local adaptive modular protection (LAMP) units and other conventional relays; within LAMP, the paper utilizes SVM to estimate the circuit topology, identify fault type, and detect fault zone with high accuracy (Poudel et al. 2022).

Table 2. ML in fault detection.

Reference	ML Method	Data	Strength	Shortcoming
Cui et al. 2017	Bayes Networks and Support Vector Machine (SVM)	Six different distribution systems with 1944 HIF events	High accuracy of HIF detection.	The method is not adaptive; it is conducted for each and system separately with different training and testing sets.
Jiang et al. 2016	Hidden Markov models (HMMs) and ANN	IEEE-39 bus and IEEE-118 bus simulation data	• Provides substantial data volume reduction. • Keeps comprehensive information from PMU measurements in spatial and temporal domains.	Only tested on synthetic PMU datasets, and the test systems are small.
Manohar et al. 2019	Convolutional neural network (CNN)	Measurements from microgrids in OPAL-RT digital simulator	• Outperforms decision tree (DT) and SVM-based methods. • Validated in hardware in the loop platform.	• A limited number of different power flow scenarios are tested. • Not adaptive to different microgrid configurations.
Liao et al. 2020	CGNN with self oops in convolution	Fault dataset from real-world state corporation of China	• Considers structure and semantic information. • Considers self-loops in convolution layers.	Accuracy depends on data volume and difficulty to obtain real-world transformer fault data.
de Freitas and Coelho 2021	Gated GNNs	Ten real distribution systems from CEMIG, the state of Minas Geraisa in Brazil	• Model performs well for an unseen feeder data during training. • In-depth understanding of fault localization domain knowledge for validating ML techniques.	Architecture’s limitation to achieve best learning as it requires more hyper parameter tuning, better pooling techniques, and attention mechanism.

Reference	ML Method	Data	Strength	Shortcoming
Khorasgani et al. 2019	Spectral-based CGNN	Water tank component dataset	• Method explains its relationship to power grids as industrial network component analysis.	• The results are only shown on water tank component network. • Computationally expensive due to Eigenvalue decomposition.
Fan et al. 2020	Spectral-based CGNN	PVWatts National Renewable Energy Laboratory (NREL) dataset with nine features per node and five graph labels	Benchmarking with other methods, such as K-nearest neighbor classifier, random forest classifier, SVM, and ANNs.	The adaptability performance is not demonstrated.
Owerko et al. 2018	Spectral-based CGNN	Weather data of New York City; power outage data obtained from EIA Electric Power Monthly	Showcases different parameters can improve the prediction accuracy over a baseline implementation.	• The proposed method may only work for selective weather-induced power outage prediction problems. • Feature selection is not complete for power outage prediction.
Gao et al. 2022	Reinforcement Learning	Grid-connected DFIG system in PSCAD	Better repeatability and adaptivity for DFIG control interface; improve DFIG rotor over-current and DC-link over-voltage.	• Needs larger network model testing.
Jones et al. 2021	SVM	IEEE 123-bus feeder	High accuracy (selectivity and sensitivity) as distributed manner.	• Requires further testing under distributed energy resources (DER) scenarios and active reconfiguration.
Ojetola et al. 2022	Supervised Learning, comparing SVM,	ETL-KAFB DC Microgrid model	Significant data and comprehensive Comparison among five ML methods.	• Limited fault type, small network model and testing system.

Reference	ML Method	Data	Strength	Shortcoming
	Bernoulli NB, DT, NC, MLP			
Poudel et al. 2022	SVM	IEEE 123-bus feeder	LAMP can be setting-free, estimate circuit topology, identify fault type, and detect fault zone.	• Small network model and testing system.

4.2 State Estimation

Power grids are being challenged by rapid and sizable voltage fluctuations caused by the large-scale deployment of renewable generators, electric vehicles (EVs), and demand response programs. In this context, monitoring the grid's operating conditions in real time becomes increasingly critical. With the emergent large-scale and nonconvexity, existing power system state estimation schemes may become computationally expensive or often yield suboptimal performance. By exploiting valuable information from abundant real-time and historical data, data-driven approaches hold promise to significantly enhance monitoring accuracy and improve the performance of state estimation. To that end, Manitsas and team have used NN approaches to estimate the bus injections from the real-time measurements (Manitsas et al. 2012). The estimated bus injections can be used as pseudo-measurements to compensate for the scarcity of real-time measurements. In addition, plain feed-forward NNs were proposed to estimate the power grid state from the measurements (Barbeiro et al. 2014). This approach reduces the complexity of the state estimation task to matrix-vector multiplications by shifting the computational burden to an offline training stage using historical or simulated data. However, it is often challenging to avoid exploding or vanishing gradients while training these feed-forward NNs, and thus the provided estimates are less accurate than any optimization-based approach. A joint optimization/learning approach was proposed where the key is to learn to initialize a Gauss-Newton solver (Zamzam et al. 2019). This entails a special design of the learning cost function, but in turn a shallow NN suffices to learn to initialize, keeping sample complexity and run-time complexity low, while benefiting from the high accuracy of the properly initialized Gauss-Newton solver. Zhang and team devised a learning approach where a DNN is constructed by unfolding an iterative solver for the least-absolute-value formulation of the state estimation problem (Zhang et al. 2019). All past learning models for state estimation overlook the physics of the underlying distribution network, hence leading to over-parameterization of the mapping from the measurements to the network states (Zamzam and Sidiropoulos, 2019).

In Zhang's work, a DNN was applied to predict full AC power flow models and active learning with informative instances and sampling strategies were tested and evaluated to resolve data imbalance issues, especially for high-dimensional data and available samples (Zhang et al. 2019). Khazeiynasab and team proposed a conditional VAE for PMU data-based model parameter calibration, which is targeted for a synchronous generator, including machine model, governor, exciter, and power system stabilizer model for turning two parameters or eighteen parameters (Khazeiynasab et al. 2022a). Kurup and team applied DNN and SVM for power distribute systems topology estimation and fault detection, it is observed that DNN outperforms SVM in topology estimation, and additional fault detection prior to the fault classification might be helpful to lower the overall test error (Kurup et al. 2021). Garcia and team identified that SVM with a linear kernel function performs better in power distribution network circuit topology estimation, compared with logistic regression as well as SVM with other kernel functions (Garcia et al. 2022).

Table 3. ML in state estimation.

Reference	ML Method	Data	Strength	Shortcoming
Manitsas et al. 2012	ANNs	• 95-bus distribution model • Half-hourly active power load profiles over 1 year	Better quality for generating pseudo-measurement compared with average load profiles.	Only works well for small-size medium voltage networks and experiences issues when scaled.
Barbeiro et al. 2014	Autoencoder s	Low voltage (LV) network with 57 buses	Accurate when a large historical dataset exists.	Only works well for small-size LV networks and experiences issues when scaled.
Zamzam et al. 2019	Shallow NN	IEEE 37-node distribution feeder	Obtains a better initialization point through shallow NN.	Only works well for small-size LV networks and experiences issues when scaled.
Zhang et al. 2019	Deep neural network	IEEE 57-bus system IEEE 118-bus system	Easy-to-train and computationally inexpensive.	Not tested on large transmission networks and experiences issues when scaled.
Zhang et al. 2022	Deep neural networks	IEEE 39-bus system, NPCC 140-bus system	Under sampling strategy to resolve data imbalance between unsolvable and solvable samples; actively select most informative instances.	Testing accuracy is around 90%; further improvement is needed.
Khazeiynasab et al. 2022a	Conditional variational autoencoder	PSS/E and Pacific Northwest National Laboratory (PNNL) PMU data	Robustness showing for two-parameter tuning and 18-parameter turning scenarios; tolerate parameters out of the prior distribution.	Testing is limited to selected generator dynamic model.

Reference	ML Method	Data	Strength	Shortcoming
Kurup et al. 2021	Convolutional neural network, SVM	IEEE 123-bus feeder	Compared CNN with SVM and demonstrates significant topology estimation performance margin.	False alarm rate is higher in four-class SVM fault detector compared to than three-class SVM fault detector.
Garcia et al. 2022	Logistic regression, SVM	IEEE 123-bus feeder	High accuracy for classifying the prevailing circuit topology; low impact by data noise.	Small test systems.

4.3 Asset Management, Predictive Maintenance, and Health Monitoring

Adequate monitoring of the health condition of electrical equipment and predictive maintenance are vital to minimize downtime and assure reliable power system operations through data collection and analysis algorithms. In a typical power system, many sensors and monitoring systems are installed to collect data, and gradual changes are analyzed. However, because of the complexity of recorded data, defects or faults at an early stage cannot be easily recognized.

He and team conducted a comparative analysis of three neural network modeling techniques—static neural networks, temporal processing neural networks, and recurrent neural networks—for predicting the top-oil temperature of transformers (He et al. 2000). Their study indicates that the recurrent neural network model outperformed the others in terms of both mean squared errors and peak error.

Zhao and team propose taking advantage of high-level discriminative CNNs to extract the features of the insulators and identify their defects (Zhao et al. 2016). The experimental results show that the proposed method can achieve an accuracy of 93 percent. When considering unlabeled oil chromatography online-monitoring data before power transformer failure happens, traditional diagnosis methods often fail to fully utilize unlabeled samples when assessing transformer health conditions.

Shi and Zhu propose a power transformer health condition monitoring method based on a DNN (Shi and Zhu 2015). A large amount of unlabeled data from oil chromatogram online monitoring devices and a small number of labeled data from dissolved gas-in-oil analysis are fully used in the training process. Testing results indicate that the diagnosis performance is better than three other methods based on radio, back-propagation NN, and SVM. In their research, Zhao and team review and summarize the emerging research work of deep learning on machine health monitoring into four categories based on deep-learning architecture, including autoencoder models, restricted Boltzmann machines models, convolutional NNs, and RNNs (Zhao et al. 2019). In summary, deep learning is one effective means for monitoring the health condition of power grid devices and the above-mentioned references prove this.

However, some problems need to be resolved, such as how to solve the small sample learning problems, how to identify the small differences between normal conditions and pre-faulted conditions, and how to satisfy the need for real-time defects identification. Zhao and team also give research trends and potential future research directions for applying deep learning for power grid device health condition monitoring: (1) open-source large dataset; (2) use of domain knowledge; (3) transferred deep learning; and (4) imbalanced data and class issue (Zhao et al. 2019).

Table 4. ML in predictive maintenance.

Reference	ML Method	Data	Strength	Shortcoming
He et al. 2000	Static neural networks, temporal processing neural networks, recurrent neural networks (RNN)	Top-oil temperature, load and ambient temperature of distribution transformers	Achieves good performance with a comparison.	May have overfitting issue is the model is too complex.
Zhao et al. 2016	CNN	Field insulator measurements	Achieves good accuracy.	Need large amount of labeled historical data.
Shi and Zhu 2015	DNN	Oil chromatography online-monitoring data	Better performance than back-propagation NN and SVM.	May have overfitting issue.
Zhao et al. 2019	Autoencoder, convolutional neural network (CNN), recurrent neural network (RNN)	Field measurement from machine sensors	Achieves good performance and accuracy.	Need large amounts of labeled historical data.
Sun et al. 2022	Graph attention networks	Generated by simulation of three S-CO_2 power systems in MATLAB	Surrogate representation of thermodynamic generator model.	Limited system types in paper.

4.4 Transient Stability Analysis

There are three broad classes of methods for transient stability analysis or assessment (TSA): time-domain simulation, the direct methods, and data-driven or AI-based methods.

The conventional and most accurate method is time-domain simulation; however, this approach is especially time consuming for large-scale power systems which basically prevents it from being used for real-time operation applications. To overcome the time burden, direct methods, (e.g., energy function, extended equal area criterion [EEAC], etc.) were proposed. However, these methods work only for simplified modeling of the system dynamics.

In light of the challenges with the analytical-based approaches discussed above, ML-based approaches were first proposed in the early 1980s to make TSA fast enough for real-time operation and applicable for large-scale power systems (Sa Da Costa 1982).

Sa Da Costa was amongst the earliest attempts in this field in the 1980s when applying a pattern-recognition approach TSA (Sa Da Costa, 1982). And then in 1989, Sobajic and Pao applied an ANN-based approach for TSA (Sobajic and Pao 1989). These methods only tackled the part of problem of assessing the stability of power systems. Another part of the problem is providing or suggesting remedial control actions whenever needed. Wehenkel et al. introduced using DTs as an inductive inference method for TSA (Wehenkel et al. 1989). The DT-based method automatically built decision rules in the form of binary trees, which are basically hierarchical representations of relationships between static, pre-fault operating conditions of a power system and its robustness to withstand assumed contingencies. The rules can be applied to online TSA. In the early 1990s, a practical feasibility study of this DT-based TSA method was carried out on the French electric high-voltage power system comprising 561 buses, 1,000 lines, and 61 generators (Wehenkel et al. 1994).

These studies represent the early exploration of AI, and only a limited number of AI approaches were considered which focused on ANN and DT. The scale of the systems to which these approaches could be applied were limited, mainly due to computing power and memory limitations. However, these early efforts demonstrated the potential of AI for addressing TSA problems and thus ignited interest from many researchers.

In the early 2000s, different AI techniques were developed to leverage available measurements in the control room used to enhance TSA. Del Angel and team used ANN to estimate rotor angles and speeds from phasor measurements for transient stability assessment and control in real time (Del Angel et al. 2003). While Sun and team used ensembles of ANNs for transient stability prediction (Sun et al. 2007). Yu and team leveraged the recent ML developments in LSTM to learn the temporal data dependencies of the input data and balance the trade-off between assessment accuracy and response times to achieve a temporal self-adaptive TSA scheme (Yu et al. 2018). Another recent breakthrough for CNNs was used by Yan and team to achieve fast TSA (Yan et al. 2019). Research by Zhou and team used an ensemble of CNNs to predict TSA results while considering errors in measurements and operational variability (Zhou et al. 2019).

Pan and team observed and showed that 1D-CNN is better in post-fault transient response prediction of bus voltage compared to LSTM; nodal voltage and nearby line currents are inputs, and the proposed 1D-CNN approach doesn’t require turning integer hyper-parameters (Pan et al. 2018). To further improve the computational efficiency and improve the power grid post-fault voltage prediction, Zheng and team leveraged group Lasso regularization for encoder/decoder transformer architecture, namely GLassoformer, and showed a reduced error rate compared to 1D-CNN and other methods (Zheng et al. 2022). Zhao introduced a deep Koopman inference network (DKIN) which is a conditional VAE-like structure with an embedded Koopman layer (Zhao et al. 2023). Both a synchronous machine and inverter-based-resource were tested and show consistency in fault conditions. It is expected that as a linear and low-dimensional operator, the Koopman operator is more suitable for online implementation. Moya and team also developed automated uncertainty quantification (UQ) for a deep operator network (DeepONet) and used it to support a power system post-fault trajectory. Two methods were proposed to quantify the uncertainty—one is a Bayesian framework and the other is a probabilistic one—and both use DeepONet and provide confidence interval as part of the results. The DeepONet-based method was explored to approximate the local solution operator of a synchronous generator (SG); such a trained model shows potential to serve as individual component that interacts with the overall grid through by a data aggregation algorithm (Moya et al. 2023a).

Roberts and team proposed continuous-time echo state networks to predict power system dynamics and overcome the stiffness-related challenges shown in physics-informed NN and LSTM. Continuous-time echo state networks is one type of RNN which was further improved by the nonlinear projection method, called radial basis function (Roberts et al. 2022).

In addition, GNN and spatial-temporal learning provide new perspectives for power systems transient stability analysis. For example, Nandanoori proposed the combination use of a GNN and Koopman models to formulate a Spatial-Temporal graph convolutional neural network, which showed a satisfactory temporal and spatial accuracy in the PMU data training and testing (Nandanoori et al. 2022). Zhao and team used deep-learning neural representation based on a GNN to learn both the network topologies dependency and generator dynamics and to test the accuracy of grid events, including load variation, topological change, and transient contingency which are more than 98% (Zhao et al. 2022). Sun and team adopted deep graph operator network, called DeepGraphONet, which is used to predict power system transient contingency trajectories. DeepGraphONet allows for unique exploration of zero-shot learning and extended testing of new sub-graphs; additional flexibility is also demonstrated due to the resolution-independent design (Sun et al. 2023).

Lastly, it is important to understand control features and derive proper actions, especially when power system transient behavior triggers protection relay and schemes and such actions could be considered as part of grid emergency control to improve system frequency and voltage profile. Li and team utilized multinominal logistic regression to evaluate the interrelationship among continuous and discrete control features using a full year of SCADA data from a Western Electricity Coordinating Council (WECC) system (Li et al. 2019b). Tan and team utilized a Bayesian NN to identify feature relationship in the form of gradient SHAP (Shapley Additive exPlanations) and shapley value, the variation of wind farm output and related voltage are visible and therefore explainable by this method (Tan et al. 2022). Research by Zhang and team proposed DRL with an off-policy soft actor-critic architecture to improve the actions and possible impacts of a power system under a voltage load shedding scheme. Using this method, they observed higher adaptivity and efficiency compared with a traditional fixed-parameter setting and DQN-based methods (Zhang 2023). In their research, Su and team adopted DNN and implemented proactive control in the form of transient stability constrained optimal power flow (OPF). Therefore, the new dispatch may resolve potential transient stability issue, such as rotor angle stability (Su et al. 2024). Ye and team utilized Gaussian process (GP)-based learning approaches improved with sparse and variational techniques to resolve the scalability issue. Testing with a 2,000-bus system and a combination of different generator dynamic models show good scalability and feasibility of UQ (Ye et al. 2023). Huang and team proposed using DRL with a parallel augment random search (PARS) for large-scale grid emergency load shedding to overcome the scalability issue and make implementation more adaptive and flexible. Under these conditions, the learning speed almost scales linearly with the number of used CPU cores. Compared to when only using conventional thyristor controlled series compensators (TCSC) power oscillation damping controllers, performance is better when using RL applications with a natural evolution strategy to control TCSCs in the power systems transmission network to damp inter-area oscillation with TCSC’s fast responding nature (Huang et al. 2022a). Verzi and team utilized DQN and a group of grid stability index to navigate in multi-dimensional generator control space and explore feasible and stable trajectory of power system dynamics. Under these circumstances, the trained RL agent can achieve close performance to the greedy agent, which combines information about its potential rewards completely to form its decision policy in DQN (Verzi et al. 2022).

One special topic of power system emergency response and protection schemes is a remedial action scheme (RAS)—also known as special protection scheme (SPS). Research by Fan and team has been granted a U.S. patent in 2021, for an end-to-end RAS design and evaluation method, which utilized logistic regression and ANN. A featured importance evaluation process was also proposed to assess and further reduce controller inputs (Fan et al. 2021). Research by Zhao used DNN to estimate system frequency and load behavior during grid emergencies and RAS action process, and a customized loss function was developed to reflect conservative design regarding under-frequency load shedding impacts (Zhao et al. 2021). Moreover, all were using full-size WECC models and data (Dong et al. 2023).

Table 5. Selected recent ML applications in transient stability analysis.

Cited Work	ML Method	Data	Strength	Shortcoming
Sun et al. 2007	Ensemble of NNs	PSB4 and New England 39-bus test systems; 248 samples and 300 samples respectively	Overcomes the errors of using only one model, such as DT or NN for prediction.	Faces scalability or curse of dimensionality issues because it requires training of $m(m-1)/2$ NNs for systems with m generators.
Yu et al. 2018	DTs with a new classification method involving each whole path of a DT instead of only classification results at terminal nodes	Cases: 2,100-bus, 2,600-line, 240-generator operational model of the Entergy system	• Online TSA. • Able to identify key security indicators and give reliable and accurate online dynamic security predictions using PMU data.	• Only considers the snapshot of the system, not the time-series trend. • Not flexible to handle system topology changes.
Yan et al. 2019	LSTM network	• Cases: New England 39-bus system, 162-bus system, 145-bus system • Input: PMU measurements (i.e., voltage magnitude and angles, maximum angle deviation data)	• Extracts both spatial and temporal data dependency from the input power system state for security assessment. • Time-adaptive.	• Assumes PMU measurements have a sufficiently wide coverage of the system. • Assumes all the PMUs are always available.

Cited Work	ML Method	Data	Strength	Shortcoming
Zhou et al. 2019	CNN ensembled	• Cases: New England 39-bus system; Northeast Power Coordinating Council (NPCC) 48-machine 140-bus system • Input: generator relative rotor angle, speed, acceleration, etc.	• Can process multi-dimensional data directly and provides accurate prediction even under certain measurement errors. • Can update the classifier using only a few labeled instances.	When the operating conditions change substantially, the trained model must be updated, but no network topology information was considered in the input data.
Yu et al. 2019	GAN and graph representation learning (combination of GCN and LSTM)	The New England 10-machine system, Nordic system, Iceland network system	Learn from both the graphical (network) and temporal characteristics of the power system dynamics.	Large graph size computation.
Huang et al. 2020	Graph representation learning (combination of GCN and LSTM)	IEEE 39, 300-bus systems	Spatiotemporal multi-task prediction for stability classification and critical generator identification.	Large graph size computation.
Qin and Yu 2023	CGNN	119-bus distribution feeder and hourly kWh data for 5,567 households in London	Formulation of topology reconfiguration problem as a link prediction problem.	• Combinatorial problem in dataset. • Generation and the method relies on large dataset.
Guddanti et al. 2022	CGNN	IEEE 14, 118-bus systems, and synthetic data generated from real-world European grid.	No need to re-train to predict unseen data scenarios.	• Large graph size computation. • Requires custom message passing equation.
Hossain et al. 2021	CGNN	Data is generated from Alliander's grids for up to 40 years in advance.	The model performs well for specific scenarios that it is trained on.	Difficult to extend to unseen scenarios.
Luo et al. 2021	Spatial-temporal graph convolutional	Samples of Guangdong Power Grid generated by	Results demonstrate higher assessment accuracy and better robustness and	Does not capture the spatial information, like

Cited Work	ML Method	Data	Strength	Shortcoming
	network (a combination of Chebyshev filter, Gate linear unit (GLU), 1-D Convolution)	PSD-BPA software.	adaptability than conventional methods.	message passing networks.
Zhong et al. 2022	GAN	• New England 39-bus system, IEEE 300-bus system. • PSD-BPA is used for generation of data.	Multivariate stability indices prediction for each bus and adapts to minor topological changes.	Large grid validation and topology change impact study.
Hu et al. 2022	CNN	16-generator 68-bus model	Compared performance with current-only or voltage-only input shows better performance than Prony method for post-fault scenario.	Small testing case; scalability needs to be verified.
Zheng et al. 2022	Encoder-decoder	16-generator 68-bus model	The proposed GLassorformer has better prediction accuracy, is smaller by parameter size, and has faster inference speed.	Small testing case, scalability needs to be verified.
Zhao et al. 2022	Graph NN	IEEE 39-bus system and 300-bus system	Predicting dynamic trajectory based on real-time measurements.	• Training data preparation for high-quality dynamic simulation. • Extendibility/transferability needs to be assessed.
Zhang et al. 2023	RL	Two-area four-machine model, 16-generator 68-bus model	Improve performance efficiency and voltage constraint satisfaction under transient voltage recovery criteria; faster convergency of reward.	Small testing case.
Sun et al. 2023	Graph NN	16-generator 68-bus model	Good accuracy, flexible for discrete input function representation with arbitrary resolution,	Small testing case; computational efficiency unknown.

Cited Work	ML Method	Data	Strength	Shortcoming
			transferable and achieves zero-shot learning.	
Zhao et al. 2023	Encoder-decoder	IEEE 68-bus system	A combined structure with multiple NN modules, provide high accuracy in linear approximation for high-dimensional nonlinear dynamic behavior; online.	Small testing case.
Moya et al. 2023a	DNN	16-generator 68-bus model	Defines metric for prediction uncertainty; reliable prediction reduces false-negative alarms.	Small testing case; computational efficiency unknown.
Moya et al. 2023b	DNN	Single generator infinite bus model	High accuracy with use of data aggregation algorithm; incorporating mathematical model through residual model design.	• Minimal example. • Further testing with network model and a multitude of units are needed.
Roberts et al. 2022	Echo state network, RNN	IEEE 14-bus model, and WSCC 9-bus variations (up to 144 Bus)	High accuracy; good speedup in execution time.	• Small test case; relative. • Simple network condition.
Tan et al. 2022	DNN	IEEE 39-bus system	• Improved accuracy in stability assessment. • Gradient SHAP is used to explain the trained NN model and the features.	Small test case.
Su et al. 2024	DNN	IEEE 39-bus system, South Carolina 500-bus system	• Better performance than heuristic algorithms. • Provide preventive strategy with improvement in convergency and iteration time.	
Ye et al. 2023	DNN	IEEE 118-bus model and synthetic Texas 2000-bus systems	Physics-informed sparse Gaussian process is proposed to improve computation efficiency	The robustness of online application may be impacted by data quality.

Cited Work	ML Method	Data	Strength	Shortcoming
			and be scalable for large network.	
Zhao et al. 2021	DNN	WECC 240-bus system model by NREL	Improved performance for adaptive RAS with customized loss function to avoid complication due to under-frequency load shedding.	Limited testing; requires other RAS examples.
Dong et al. 2023	Random forest and ANN	WECC full-size model	Significant speedup for stability prediction using frequency nadir and critical clearing time (CCT) values.	Sample case from utility energy management system (EMS) may have issues and requires further tuning before used to generate training data.
Li et al. 2019b	ANN	Utility SCADA data, WECC full-size model for specific RAS	• Feature analysis for continuous and discrete variables. • Feature assessment and reduction used for RAS control.	Limited testing requires other RAS examples.
Fan et al. 2021	ANN, MLP	WECC full-size model for specific RAS	• Practical sampling process for large network model. • Control feature analysis and assessment. • Comprehensive scenario and fault simulation.	Limited testing requires further hardware and/or hardware-in-the-loop testing.
Nandanoori et al. 2022	Spatio-temporal graph NN	IEEE 68-bus system	The proposed STGNN is compared with Koopman operator theory enabled dynamic model decomposition, showing good performance for load change induced system responses.	• Longer observation window for STGNN leads to better prediction results, • No scalability testing with larger network model.
Huang et al. 2022a	Reinforcement learning	Two-area, four-machine model and miniWECC model	Improving the damping control performance.	• Testing single RL-based controller.

Cited Work	ML Method	Data	Strength	Shortcoming
				• Additional testing regarding scalability and multi-controller coordination is needed.
Huang et al. 2022b	Reinforcement learning, DQN	IEEE 39-bus system and 300-bus system	Derivative-free DRL is more robust against the exploding gradient issue; highly scalable and parallelizable.	Needs to be investigated to solve safety- and robustness-related issues.
Verzi et al. 2022	Reinforcement learning, deep Q network	Three-machine, Nine-bus model in power system toolbox	• Combination of different grid stability metrics when formulating reward policy. • Acceptable performance when comparing to greedy method.	Need to verify small test system scalability.

All these reviewed methods focused on conventional transient stability (angle stability), while frequency and voltage stability have barely been considered.

4.5 Contingency Analysis

Contingency analysis is one integral part of power system security assessment. It is used to assess a power system’s capability to sustain essential element failures, such as loss of a single critical component (i.e., N-1 contingency), or more components (i.e., N - k contingency). Typical components include a generator, transmission line, or transformer. It is a safety measure to help prevent widespread outages and maintain the stability of the electrical network and has a role in both planning and operational planning domains.

Currently, contingency screening in a control room usually evaluates deterministic N-1 contingency via linearized direct current power flow, which has been implemented with fast enough computational speed for operational needs. However, a broad sense of contingency analysis could be easily extended to N - k multiple contingency analysis or cascading failure analysis. This discretized analysis scenarios grows significantly for a large interconnection, which poses an enormous challenge for intelligent real-time contingency identification to grid operators—not to mention the operation uncertainties under the trending renewable paradigm, such as wind/solar generation variations and potential impacts from demand response.

With the evolutionary application of ML and worldwide burst of computational power, many researchers have dived into contingency analysis by introducing high-performance computing (HPC) techniques and ML and AI concepts. More specifically, the combination of HPC and AI techniques can effectively provide solutions in the broad sense of contingency analysis for which more traditional methods are ineffective or intractable, especially for large real systems.

Research by Chen and team proposes an ANN model-based methodology for power system contingency analysis (Chen et al. 2019). The methodology can more effectively assess the system's vulnerability level under contingencies and propose potential remediation and restoration strategies. An advantage of the proposed method is that it is physical-model-free. It does not require a complicated mixed-integer optimization solution process, but it can quickly provide solutions that are unavailable using commercial tools. This feature gives operators and engineers greater flexibility in enhancing grid reliability and resiliency.

Alternatively, Du et al. consider a scenario tree representing power system uncertainties during real-time operation, followed by a NN model that could be trained through either supervised learning with historical measured data or RL with offline simulations. This methodology could potentially skip the traditional power flow analysis for every system state for contingency ranking; therefore, the trained DNN will output severity evaluation results to support the decision-making process of grid operators (Du et al. 2019).

On the other hand, multi-contingency clustering is another direction in which researchers are applying AI techniques. Fuzzy classification techniques have been applied to select the most proper numbers of security clusters, but this classification method is limited to specific system topologies because the training is done offline (Matos et al. 2000). Other classification methods including particle swarm optimization and multiclass support vector machines can also be used for feature extraction and contingency classification (Kalyani and Swarup 2011).

Note that for both contingency evaluation and contingency clustering, the security index is the target output. As a result, each contingency is classified with a qualitative label, such as "secure" and "insecure," otherwise a composite quantitative index considering system violations will be derived. For example, Srivastava and her research group have contributed several works on voltage contingency ranking, using ANN along with numerous improved methods (Jain et al. 2003).

Table 6. ML in contingency analysis.

Reference	ML Method for Contingency Analysis	Data	Strength	Shortcoming
Chen et al. 2019	ANN for contingency ranking and optimal corrective action is recommended.	IEEE 118-bus system and PNNL 563-bus system	• Physical-model-free overcomes the limitation on mixed-integer programming due to generator switching on/off. • Leverages the high-performance computing -enabled Massive Contingency Analysis tool.	No topology information is used.
Du et al. 2019	DNN for bus voltage estimation and contingency	IEEE 9-, 30-, 57-, 118-bus systems and 181-, 300-,	• Data-driven. • More than 100x speedup with good classification accuracy.	Only uses limited information in the reactance

Reference	ML Method for Contingency Analysis	Data	Strength	Shortcoming
	screening; no ranking.	1,354-bus systems		matrix; no topology information is used.
Matos et al. 2000	Fuzzy classification for multi-contingency clustering.	Hellenic grid and 240-bus system	Contingency clustering for each contingency and then global aggregation.	Limited to specific topology.
Kalyani and Swarup 2011	Support vector machine for feature extraction and contingency classification.	IEEE 39-bus system	• Multiclass classification through error-correcting output codes. • Multiple meta-heuristic methods tested.	Small system; limited to specific topology.
Jain et al. 2003	Radial basis NN for contingency ranking on voltage violation.	IEEE 14-, 30-bus system and Indian system with 75 buses	Input feature selection.	• Limited to specific topology. • Only relies on voltage metric.

4.6 Renewable Energy and Load Forecasting

Abundant and environment-friendly renewable energy sources (RES), such as wind and PV energies, are expected to be the dominant energy source for the next generation of the power grid. However, their intermittent characteristics are obstacles for stable, large-scale utilization. To address these challenges and achieve improved dispatch planning, maintenance scheduling, and regulation, an accurate and reliable RES forecasting approach has become the focus of researchers around the world (Zhang et al. 2018). For example, Wu and Peng proposed a data mining-based method consisting of *k*-means and NNs (Wu and Peng 2017). Meteorological information found in historical records is used to execute a clustering approach to classify the days into different categories. Then the bagging algorithm-based NN is trained to get forecasting results for wind energy. In addition, Khodayar and team studied ultra-short-term wind forecasting using the deep-learning method through unsupervised feature learning from the unlabeled historical wind speed data (Khodayar et al. 2017). The forecasting of distributed solar energy systems from both macro- and micro-aspects are broadly discussed in Zhao and team's research. Their approaches involve clustering PV system capacity and locations (Zhao et al. 2017). The data-driven forecasting approach of PV diffusion is proposed based on cellular automation in microscopic analysis. By decomposing the time-series data with discrete wavelet transforms, the proposed RNN model described by Nazaripouya's research is developed for ultra-short-term solar power prediction (Nazaripouya et al. 2016).

Like the renewable energy prediction, an accurate short-term load forecasting is the essential basis for energy management, system operation, and market analysis. As is mentioned by Zhang's research, an increase in forecasting accuracy may bring many benefits, including cost savings (Zhang et al. 2018). With the emerging active role of smart grid customers, the efficiency of the dynamic electricity market hinges on a reliable prediction of electricity consumption. To address impacts of weather conditions on electricity consumption, Liu's research proposed a map/reduce programming framework for distributed load forecasting by partitioning the geographical area according to local weather information (Liu et al. 2018). Ahmad and team use an extreme learning machine ensembled with a novel wavelet transformation for electricity consumption after conditional mutual information-based feature selection (Ahmad et al. 2017). To overcome the volatility and uncertainty of load profiles, the RNN is adopted with a novel pooling layer to avoid the overfitting problems described by Shi and team's research (Shi et al. 2018). In comparison to forecasting the aggregated load, the energy consumption in a single house is usually volatile and difficult to predict. In response to the recent success of deep learning, research by Cai and team applies a LSTM RNN-based framework to the residential load forecasting as the latest deep-learning technique. This allows them to consider the impact of social activities on the prosumers' arrangements for their generation and consumption patterns and further discuss the overall impact on the final load and the network usage (Cai et al. 2017).

Table 7. ML in forecasting.

Reference	ML Method	Data	Strength	Shortcoming
Wu and Peng 2017	K-means and NN	Historical wind data	Achieves high accuracy for hourly wind forecast.	Does not work well for very short-term wind forecasts.
Khodayar et al. 2017	Unsupervised deep learning	Historical wind data	Works well for very short-term wind forecasts.	Needs a large amount of historical data.
Zhao et al. 2017	Unsupervised deep learning	Historical solar data	Achieves high accuracy for hourly solar forecasts.	Does not work well for very short-term solar forecasts.
Nazaripouya et al. 2016	RNN model	Historical solar data	Works well for very short solar forecasts.	High computational complexity.
Liu et al. 2018	Neural network, gray model, autoencoder	Historical load data	Different forecasting models are used for different local loads.	Does not work well for very short-term load forecasts and has high uncertainty.
Ahmad et al. 2017	Extreme learning machine	Historical load data	Achieves high accuracy for hourly load forecast.	Does not work well for very short-term load forecasts and has high uncertainty.
Shi et al. 2018	RNN model	Historical load data	Works well for very short-load forecasts.	May suffer overfitting issue.
Kong et al. 2019	LSTM RNN	Historical load data at house level	Works well for single house load forecasting.	Needs a large amount of historical data.
Karimi et al. 2021	Spatiotemporal GNNs	316 PV systems from California, Hawaii, and New York with	Better performance than models that only use temporal formulation.	Learning covariance is heavily dependent on dataset quality.

Reference	ML Method	Data	Strength	Shortcoming
		National Oceanic and Atmospheric Administration		
Yu et al. 2020	Spatiotemporal GNNs	Open wind power data from NREL.	• Better accuracy than k-nearest neighbors. • Support vector regression, and LSTM NN.	The structure of GNN changes as the size of the graph changes, resulting in retraining from scratch.

4.7 Load Profiling and Nonintrusive Load Monitoring

Load profiling is a way to characterize the typical behavior of electric consumption, which is usually represented in the time domain for load forecasting, demand-side management, and capital planning. To better understand the information behind the stochasticity and irregularity of residential energy consumption, an in-depth analysis is presented by Granell and team that includes a finite mixture model-based clustering technique (Granell et al. 2016). As one of the main tasks of load profiling, a better understanding of the flexibility of customers' electricity consumption is the basis for demand response, which can be used to release the pressure of power system in terms of thermal and voltage constraints. A multiresolution analysis method based on a wavelet analysis is proposed by Li and team to extract the spectral and time-domain features of load data (Li et al. 2016). Different permutations of typical load profiles provide a more flexible load profiling with a reduction of computation. With the popularization of EVs, learning their charging load patterns is becoming a key step for the stability of power grids. Munshi and Mohamed use an unsupervised clustering algorithm to extract the pattern of EV charging loads with real power measurements. Furthermore, the flexibility of the collective EV charging demand is analyzed with Bayesian maximum likelihood (Munshi and Mohamed 2018). Research done by Wang and team focuses on the problem introduced by the huge load profile data with the popularity of smart meters installed at the household level, which poses challenges to the communication and storage of measurement data as well as the extraction of vital information from massive records (Wang et al. 2017). The *K*-SVD sparse representation technique is used to decompose the load profiles into several partial usage patterns for a linear SVM-based method to recognize the type of customers.

Load disaggregation is also known as nonintrusive load monitoring (NILM) and it aims to disaggregate the overall load profiles at the household level into the energy consumption of individual appliances. Unlike the direct appliance monitoring framework, the NILM from only one smart meter installed in a house is more easily be accepted by customers (Zhang et al. 2018). Because different types of household electric appliances have different potentials to be involved in the demand response program, the appliance-level load profiles allow utilities to better understand customer behavior and help develop a more energy-efficient strategy. Kong and team adopt the hidden Markov models (HMMs) with the segmented integer quadratic constraint programming to disaggregate the household power profile at an average frequency of 0.3 Hz into the appliance-level (Kong et al. 2019). Research by Henao and team proposed an NILM approach based on the subtractive clustering the maximum likelihood classifier for a date set with 1 Hz sampling rate (Henao et al. 2017). The appliances are modeled as being in ON/OFF states in this event-based load disaggregation algorithm. As a single channel blind source separation problem, the dictionary learning-based approaches can be used in NILM. A deep-learning approach with multiple layers of dictionaries trained for each device as “deep sparse coding” is used by Singh and Majumdar (2018). Compared with HMM, the latter method is not suitable for real-time application. By combining the DT and nearest-neighbor algorithms, the semi-supervised ML is applied to the NILM problem by Gillis and Morsi and the signal features are extracted by matching a set of net wavelets to the load classes (Gillis and Morsi 2017).

Aggregated representation of load models connects the power distribution network and power transmission network—one of such load representations is known as the WECC composite load model (CLM), including a large number of parameters. Khazeiynasab and team applied a conditional variational autoencoder for 64 CLM parameter identification using time-series data representing different events for power and voltage measurements, which shows matching output with the identified parameters (Khazeiynasab et al. 2022b).

Table 8. ML in load monitoring/profiling.

Reference	ML Method	Data	Strength	Shortcoming
Granell et al. 2016	Finite mixture model-based clustering	House level load data	Improves the clustering of electricity load profiles by considering time resolution.	Needs large amount of labeled data.
Munshi and Mohammed 2018	Unsupervised clustering	Smart meter data	Accurately extracts the EV charging load patterns.	High offline computation complexity.
Wang et al. 2017	*K*-SVD sparse representation technique	Smart meter data	Accurately extracts vital information from massive smart meter data.	High offline computation complexity.
Kong et al. 2019	Hidden Markov models	Smart meter data	Accurately disaggregates the household power profile to the appliance level.	High sampling rate at 0.3 Hz is required for smart meters.
Henao et al. 2017	Subtractive clustering of the maximum likelihood classifier	Smart meter data	The appliances are accurately modeled as being in ON/OFF states.	High sampling rate at 1 Hz is required for smart meter.
Singh and Majumdar 2018	DNN	Smart meter data	Accurately disaggregates the household power profile to the appliance level.	Not suitable for real-time application.

Reference	ML Method	Data	Strength	Shortcoming
Gillis and Morsi 2017	DT, nearest-neighbor algorithms	Smart meter data	Accurately disaggregates the household power profile to the appliance level.	High offline, computation complexity.
Dinesh et al. 2019	Graph spectral clustering	Reference Energy Disaggregation Data Set, and Rainforest Automation Energy Dataset	Modeling joint appliance behavior via an appliance graph.	The time-of-day context is not considered in the model.
Chen et al. 2022	CGNN	Two variations of 54-bus distribution model	• Hyperstructures CGNN is developed. • New metric (U-Score) explores the efficiency of information flow among different types of electrical nodes.	Testing accuracy varies between 75% and 92%.
Khazeiynasab et al. 2022b	Conditional variational autoencoder	IEEE 39-bus system with composite load model	Shows good performance for 60-parameter load model.	• Limited testing with different bus fault locations. • Small testing system.

4.8 Oscillation Detection

With the widespread deployment of PMUs over the past decade, synchrophasor-based data analytics have significantly advanced in both research and industry applications. Nowadays, many U.S. control centers are equipped with oscillation detection functions based on incoming PMU measurement streams. But the ever-growing data volume and the high sampling rate present challenges for oscillation-related situational awareness applications in transmission systems and the potential extension of such applications to distribution systems. Therefore, the development of practical ML and data analytics algorithms, capable of spatiotemporal monitoring of frequency dynamics and distinguishing between normal and emergency operation conditions, holds great promise.

ML techniques could be used for event and anomaly detection to aid operators in their decision-making processes. Research conducted by Hou and the team explored multiple feature selection approaches to identify factors of great influence on the damping and frequency of the Montana-Northwest mode in the Western Interconnection. Such insights could improve the grid operator’s situational awareness because the existing mode estimates are usually delayed (Hou et al. 2018).

Table 9. ML in oscillation detection.

Reference	ML Method	Data	Strength	Shortcoming
Hou et al. 2018	Principal component analysis, support vector machine	System conditions, equipment status, damping, frequency.	Quantify the nonlinear individual influences and their interactions among major factors	Needs large amount of labeled data across regions with different operating conditions.

5.0 AI/ML Opportunities and Challenges in Power Systems

In the field of power system applications, the combination of AI and ML offers numerous opportunities and challenges. AI-driven smart edge devices are capable of real-time data analysis and enhancing grid monitoring and decentralized decision-making to improve grid resilience. Additionally, high-performance computing (HPC) accelerates complex simulations and data processing. Nevertheless, a significant challenge persists in dealing with uncertainty, particularly regarding renewable energy fluctuations. This highlights the importance of AI/ML algorithms that are proficient in managing risk under uncertain conditions and quickly adapting to unforeseen situations. Emerging techniques, like meta-learning-enabled systems, are used to generalize knowledge from various sources. Safety is paramount, as AI/ML plays a central role in decision-making, necessitating advancements in safety-constrained learning. This section will briefly discuss these opportunities and challenges.

5.1 Grid Edge

The grid edge represents an unprecedented opportunity to drastically enhance the reliability, availability, and efficiency of the electric grid with the rise of decentralized energy systems. These enhancements will mostly be achieved through smart sensing, communication, and control at the edges of the electric grid network rather than in the utility back-office and follow the migration of computing trend, including data analytics and decision-making, from a central cloud server to edge devices, such as smart meters and sensors, for consumer Internet of Things and many other domains.

Among all the responsive characteristics of an electric grid, adaptively and effectively managing the balance of power supply and the demand of the grid system consistently remains the primary task. Traditionally, this has been achieved by collecting raw information from terminal meters and sensors through utility-maintained communication channels and protocols, performing analysis and making decisions at a central server, and then feeding back to the appropriate controllers for a response. However, this process has several drawbacks, such as

- **Long response latency:** Major electric system outages are often caused by the lack of timely awareness of grid status and immediate response to power disturbance events before they cascade into interruptions of critical facilities and services.
- **Low communication efficiency:** The deployment of an electric grid network usually and necessarily covers a large space, including both dense urban areas and lower-density rural areas. Therefore, reliable bandwidth for communication among the enormous number of meters and grid devices can be extremely valuable, particularly when connecting to “hard-to-reach” devices.

One of the essentials of current AI is its ability to intelligently “preprocess” raw data from terminal sensors. To prevent the overflow of information and repeated processing, the raw data can be locally processed instead of automatically transmitted to the centralized server. What is really needed is the ability to intelligently preprocess the raw data in the terminal sensors so that only the key data are produced and transmitted. The concept of edge intelligence describes the migration of knowledge discovery and application from the cloud to the edge devices where data are generated, acquired, or sampled. Edge intelligence allows local and *in situ* data processing and decision-making, reducing delay and energy consumption in communication, storage, and data movement.

AI/ML in the context of grid-edge will be characterized by distributed computing, decentralized AI/ML models, robust communication infrastructure, and interoperability. These elements will enhance efficiency and responsiveness to grid operating conditions and consumer needs.

Edge intelligence brings the following potential benefits: (1) by moving ML to the edges, instant local decision-making becomes feasible; (2) security and privacy are assured by keeping data local and following local management policy; (3) communication efficiency is enhanced by only transmitting decisions or alarms rather than raw data; (4) adaption and resiliency are increased in response to temporary or regional failure; (5) decision-making becomes more robust, resulting from local information exchange and integration.

5.2 High-Performance Computing and Workflow Management

HPC and efficient workflow management have become indispensable components in AI/ML. These two technologies create a powerful synergy that offers crucial opportunities. The integration of HPC and AI/ML marks an exciting opportunity in power system applications as AI/ML tasks necessitate the use of HPC resources. This synergy offers a gateway to optimizing grid operations, improving energy efficiency, and enhancing grid resilience. HPC's computational power enables real-time analysis of vast datasets, thereby facilitating scalable power system simulations. In tandem, AI/ML algorithms leverage this computational strength to enhance the speed and efficiency of power system applications. Faster interaction between HPC and AI/ML can enable more complex and powerful functions. Their synergistic interaction holds the potential to elevate the performance of both, empowering power systems to tackle the complexities of renewable energy integration and ushering in an era of intelligent, efficient, and sustainable energy networks.

The integration between HPC and AI/ML is critical for shaping the future grid, particularly when considering the evolving architecture of the power system, especially when grid edge is considered. Meanwhile, the effectiveness of HPC in AI/ML relies heavily on streamlined workflow management. Workflow management orchestrates the various components in HPC and AI/ML functions. From data preprocessing to model training and evaluation as well as combining diverse applications across various HPC platforms, operating systems, and software tools—whether open-source, commercial tools, or customized codes, workflow management assures that tasks are executed in the right sequence, dependencies are managed, and resources are allocated efficiently. Workflow management not only facilitates the development of more complex and powerful applications but also minimizes the potential for errors. Moreover, by automating repetitive and time-consuming tasks, workflow management allows researchers to focus on higher-level challenges, creativity, and innovation.

5.3 Risk Control Under Uncertainty

With more complex power systems and increased penetration of variable energy resources, it is important to understand the impacts of generation and load uncertainties on grid reliability, resiliency, and security. Advanced algorithms are necessary to manage the variables that affect the variations in generations, loads, and contingencies, etc. However, many inputs impacting grid security are unknown. Determining how these unknowns affect the accuracy of the assessments under uncertainty is essential. This effort lines at the core of the field of uncertainty quantification (UQ). Specifically, rigorously quantifying how input uncertainties affect model outputs is the goal of forward UQ or uncertainty propagation (UP) problem.

The simplest method for tackling the UP problem is the MC method. The basic idea of the MC method is computing empirical estimates of the statistics of a quantity of interest through sample averages. The MC method is guaranteed to converge given an infinite number of samples. However, the convergence requires a large number of samples, typically on the order of hundreds of thousands or millions. As a result, the MC methods can be impractical for UQ in tasks with high computational complexity, such as power grid dynamic security assessments.

Researchers propose addressing tasks of high computational complexity by building a cost-effective surrogate for the response surface. This involves selectively choosing a set of locations within the uncertain parameter space and evaluating the forward model at these locations. The number of simulations to perform is determined by the computational budget and desired accuracy. Because the surrogate model is inexpensive to query, it can replace the original simulator and perform UQ tasks using MC techniques. Popular choices for surrogate models in the literature include: Gaussian processes (Rasmussen and Williams 2006), polynomial chaos expansions (Najm 2009), and relevance vector machines (Bilionis and Zabaras 2012). Despite their success, these methods become intractable for problems with a large number of stochastic input dimensions. Constructing a surrogate response surface for a multivariate function with many uncertain parameters requires overcoming the phenomenon known as “the curse of dimensionality” (Keogh and Mueen 2011). In the context of statistical sampling and ML, the curse of dimensionality implies that to sufficiently explore a high-dimensional space, it requires visiting an exponentially large number of points. Therefore, effective dimensionality reduction techniques are needed to address this challenge.

A recent advancement in dimensionality reduction is constructing surrogate models using DNNs (Tripathy and Bilionis 2018). The powerful nonlinear function approximation capabilities coupled with the scalability of DNNs to high dimensions offers a very promising direction for research by the UQ community, with the potential to significantly improve upon state-of-the-art capabilities. Researchers also extend the DNNs methodology to a Bayesian treatment of DNNs (Blundell et al. 2015). This approach imposes a prior probability on the weights of the DNN and uses approximate inference techniques, such as variational inference, to estimate the posterior distribution over the weights (Graves 2011). Additionally, this kind of Bayesian approach would allow one to better quantify the epistemic uncertainty induced by limited data. DNNs are also naturally suited for tasks of multilevel/multifidelity UQ (Peherstorfer et al. 2018). For instance, fully convolutional networks do not impose constraints on input dimensionality and can be trained on data obtained from several simulators at varying levels of fidelity. The hierarchical representation of information with a DNN can be used to learn correlations between heterogeneous information sources.

Power systems are highly nonlinear systems with high dimensionality and uncertainty. The dynamics of power systems are complicated and stochastic in both space and time, and the amount of measurement data (e.g., PMU data, SCADA data, etc.) is massive. The state-of-the-art technologies of deploying deep-learning methods for UQ could be leveraged in power grid dynamic security assessment to (1) develop high-fidelity prediction models for very short-term (seconds ahead) and short-term (minutes ahead) prediction of the uncertain variables in the power grid; and (2) to identify an effective input sample set for the AI-based learning and control, which is condensed from the massive data and presents the key features of the power grid operation conditions.

5.4 Meta-Learning

Meta-learning, also known as “learning to learn,” intends to design ML methods and models that could improve the process of learning new tasks or adapting to new environments rapidly with a few training examples. This is achieved by leveraging the learning experience gained from solving predecessor problems that are somewhat similar. For instance, Finn et al. (2017) introduced Model-Agnostic Meta-Learning (MAML), which learns an initialization to enable fast learning via gradient-based optimization, showing enhanced performance across diverse meta-learning tasks.

Currently, a good ML model often requires training with many samples and the trained model can only work for a single task or single environment. Humans, in contrast, make use of past experiences for not only repeating the same task in the future but also learning completely new tasks, too. That is, if the new problem that humans try to solve is similar to a few past experiences, it becomes easier for humans to solve the new problem. For example, people who know how to ride a bike are likely to discover the way to ride a motorcycle fast with little or even no demonstration. Is it possible to design an ML model with similar properties—learning new concepts and skills quickly with few training examples by transferring past experience of one or more source tasks to boost learning in a related target task? That is essentially what meta-learning and transfer learning aim to solve. Meta-learning and transfer learning are gaining more and more attention from the research and industry application communities and becoming the trend for the next generation of new ML methods because the concept is more intelligent and similar to the procedure humans use to learn new tasks in new environments.

The concept of meta-learning and transfer learning is critical for power grid control and operations with high penetrations of renewables. It provides new directions and approaches to enable fast online power grid control and adaption for new grid operation scenarios with uncertainties introduced by the high penetration of renewables at both the power grid assets level (for controller parameters fast adaption) and the power grid control center level (for emergency control and remedy actions fast adaption). Currently, power system reliability and security are mainly achieved through (1) protection relays, as well as controllers of conventional generators, (e.g., automatic voltage regulators, automatic generation control, power system stabilizers); and (2) grid operators’ emergency control and remedy actions at the control center. The protection relay and controller parameters are manually tuned and evaluated in simulations, which are only designed optimally at a few selected operating points through a tedious offline design and online tuning process. The control logics are fixed once they are deployed in the field. On the other side, most of the emergency control and remedy action schemes used by grid operators today are predefined through offline studies based on a few forecasted system conditions and contingency scenarios, which are either over-conservative or not very effective when applied in real time because of the differences between the forecast grid state and actual gird state. With increasing penetration of renewables, the power grid suffers increasing uncertainties and unconventional dynamics that may have never been seen before. As a result, there is an increasing risk of a lack of sufficient reliability, stability, and resilience in the current power grid because both the controllers of power grid assets and the emergency control and remedy actions at the control center level have very limited adaptability or robustness relative to the increasing changes and uncertainties of the power grid.

Innovative meta-learning and transfer learning methodologies could be used for power grid real-time control and operations at two levels:

- **At the protection relay and controller of power grid assets level**, the new technologies could provide robust AI-based online controller parameter optimization and adaption methodologies to enable multi-time-scale decentralized control for different power grid assets and controllers for enhancing the resilience of power systems with increasing renewables penetration levels, uncertainties, and dynamics. Gao et al. 2022 provides an example of how a meta-learning algorithm can help improve the performance of doubly fed induction generator (DFIG) during grid faults by reducing the DFIG rotor over-current and DC-link over-voltage through adaptive controller parameter adjustments.
- **At the control center level**, the new technologies could provide grid operators with effective emergency control strategies within seconds after the disturbances and extreme events under a stochastic environment, which is critical to assuring the resilience of the power grids. The resulting technology could provide a disruptive capability to independent system operators, regional transmission organizations, and power utilities to enable more efficient, resilient, and secure grid operation to prevent cascading failures and large-area blackouts.

5.5 Safety-Constraint Learning

Learning-based control has been demonstrated to be a powerful paradigm for learning optimal policies from experimental data (Tan et al. 2018). However, to find optimal policies, most learning-based control algorithms explore the whole action space, which may be harmful for real-world systems because some of the actions may violate the physical safety constraints of the systems at certain stages during the training. Often, it is not effective to resolve this safety issue during the training by simply adjusting the limits and boundaries of the action space because whether the physical constraints of the system will be violated is determined together by the state transition equations, current states, and the actions. Furthermore, the difficulty of interpreting the inner workings of many ML algorithms (notably in the case of DNNs), makes it challenging to make meaningful statements about the behavior of a system during the learning process, especially while the system has not yet converged to a suitable control policy. While this may not be a critical issue in a simulated reality, it can quickly become a limiting factor when attempting to put such an algorithm in control of a system in the physical world. As a consequence, learning-based control algorithms are rarely applied directly on safety-critical systems such as power grids in the real world.

Current efforts in policy meta-learning and transfer learning propose training an initial control policy in simulation and then carrying it over to the physical system (Christiano et al. 2016). While progress made in this direction is likely to reduce overall training time and increase the intelligence of the AI, it does not eliminate the risk of catastrophic system misbehavior. State-of-the-art NN policies have been shown to be vulnerable to small changes between training and testing conditions which inevitably arise between simulated and real systems (Huang et al. 2017b). Guaranteeing the correct behavior of simulation-trained schemes in the real world thus remains an important active and hot research area.

Safety-constraint learning explored learning algorithms that explicitly consider safety, which is defined in terms of safety guarantees under a stochastic environment (Berkenkamp et al. 2017) (Fisac et al. 2018). Safety-constraint learning algorithms are typically designed and archived by combing model-based control-theoretical analysis with data-driven Bayesian inference to construct and maintain high-probability guarantees around an arbitrary learning-based control algorithm. Drawing on Hamilton-Jacobi robust optimal control techniques, the safety-constraint learning defines a least-restrictive supervisory control law, which allows the system to freely execute its learning-based policy almost everywhere but imposes a computed action at states where it is deemed critical for safety. The safety analysis is refined through Bayesian inference in light of newly gathered evidence, thereby both avoiding excessive conservativeness and improving reliability by rapidly imposing the computed safe actions when confidence in model-based guarantees decreases because of unexpected observations.

5.6 Other Opportunities

Numerous opportunities await exploration in the application of AI/ML to power systems. Building advanced AI models is at the forefront and promises enhanced system intelligence. Implementing self-validation mechanisms, integrating human-in-the-loop approaches, and incorporating physics-aware ML techniques can greatly augment model robustness and reliability. Embracing GCNs opens doors to novel application patterns, facilitating complex grid analyses. Balancing speed and accuracy, especially in time-constrained scenarios, offers the potential to employ surrogate models and initially favors faster insights and gradual refining precision. ML-driven optimization, federated learning, and the synergy of the Internet of Things with ML presents avenues for smarter grid management. The concept of digital twins (mirroring real-world systems for precise modeling and control) holds immense potential for enhancing power system performance and resilience.

5.7 Challenges

Besides all the opportunities listed above, there are still many challenges in the application of AI/ML to power systems. Some challenge examples include handling large datasets, especially in scenarios involving extreme or unforeseen events. The sensitivity of data, particularly in the transition from development to deployment, poses a significant hurdle. Ensuring data formatting and compatibility across diverse sources is crucial. A strategic perspective and a clear roadmap are lacking, as utilities acknowledge the importance of AI/ML but await compelling results before committing more resources. Synergy among various domains becomes imperative. The interpretability of ML methods and their results raises concerns. Moreover, integrating domain knowledge and physics representation into existing ML frameworks remains a persistent challenge in this dynamic field.

The major challenges for applying AI/ML technologies to power systems can be summarized as follows:

1. **Data Quality and Availability:** the effectiveness of AI/ML models is heavily reliant on the quality and availability of data. The variety, volume, and recency of data used in training, validating, and continual learning of AI models are vital in determining their effectiveness and adaptability. Utilizing diverse data sources can unlock potent insights, yet it also resents challenges related to the data compatibility and the sharing of information between organizations. Consideration must be given to data ownership and privacy attached to the data. In power systems, obtaining comprehensive and accurate data, especially from diverse sources, can be challenging. Assuring data integrity and accessibility remains a key hurdle.
2. **Domain Knowledge Incorporation:** incorporating domain knowledge into scientific ML involves interdisciplinary collaboration between experts in ML and power systems. It requires a deep understanding of both the underlying science and ML techniques. Translating power system knowledge into actionable features or input representations for ML models can be complex.

3. **Explainability and Trust:** the inherent complexity of AI/ML algorithms can present challenges in generating interpretable and understandable conclusions, as well as gaining insights from ML prediction to improve confidence in the results. Establishing trust among stakeholders requires efforts to enhance the transparency and interpretability of these systems.
4. **Robustness**: developing stable and robust scientific ML methods to assure outcomes are unduly sensitive to disturbance in training data and model selection. This includes handling various configurations and uncertainties in power systems and being resilient to changes in training data and model selection. Achieving robustness requires rigorous testing and validation.
5. **Interoperability and Standardization:** power systems often involve a variety of equipment and technologies from different manufacturers. Achieving interoperability and standardization across these diverse components to enable seamless integration of AI/ML solutions poses a significant challenge.
6. **Automation:** automating machine learning (ML) applications effectively within the power systems involves utilizing data-intensive scientific ML techniques to automate scientific inference and data analysis tasks. Key factors include reliably identifying and sampling signals, patterns, and structures within complex, high-dimensional, noisy, and uncertain input data.
7. **Human–Machine Interactions:** human-machine interactions are critical for the adoption and acceptance of AI/ML techniques in the power industry. This involves defining clear roles, interfaces, and workflows for human operators and machines, ensuring the acquisition of high-quality data and high-fidelity models to enhance system resilience and responsiveness, and addressing human factors.
8. **Regulatory and Ethical Considerations:** the deployment of AI/ML in power systems raises regulatory and ethical questions. Assuring compliance with regulatory frameworks, addressing potential biases in algorithms, and navigating ethical considerations related to privacy are critical aspects that must be carefully managed.

Within this report, a multitude of opportunities and challenges have been discussed. Its purpose extends beyond documentation; it stands as a technical resource, aiding researchers intrigued by AI/ML applications in power systems in acquiring fundamental knowledge and comprehending both the present landscape and forthcoming hurdles. The continued advancement of AI/ML technologies will play a pivotal role in enhancing power system operation, management, optimization, and control. This aligns perfectly with the mission to advance clean energy solutions.

In conclusion, the journey towards leveraging AI/ML for power system applications is marked by both promising opportunities and complex challenges. Strategic approaches that address data issues, interoperability concerns, transparency, and ethical considerations will be instrumental in realizing the transformative potential of AI/ML in shaping the future of power systems.

6.0 References

Ahmad, A., N. Javaid, M. Guizani, N. Alrajeh, and Z. A. Khan. 2017. "An Accurate and Fast Converging Short-Term Load Forecasting Model for Industrial Applications in a Smart Grid." *IEEE Transactions on Industrial Informatics* 13 (5): 2587–2596. https://doi.org/10.1109/TII.2016.2638322.

Barbeiro, P. N. P., J. Krstulovic, H. Teixeira, J. Pereira, F. J. Soares, and J. P. Iria. 2014. "State Estimation in Distribution Smart Grids Using Autoencoders." In *Proceedings of the 2014 IEEE 8th International Power Engineering and Optimization Conference (PEOCO2014)*, pp. 358–363. https://doi.org/10.1109/PEOCO.2014.6814454.

Bengio, Y., A. Courville, and P. Vincent. 2013. "Representation Learning: A Review and New Perspectives." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 35 (8): 1798–1828. https://doi.org/10.1109/TPAMI.2013.50.

Berkenkamp, F., M. Turchetta, A. Schoelling, and A. Krause. 2017. "Safe Model-Based Reinforcement Learning with Stability Guarantees." In *Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17)*. pp. 908–919.

Bilionis, I., and N. Zabaras. 2012. "Multidimensional Adaptive Relevance Vector Machines for Uncertainty Quantification." *SIAM Journal on Scientific Computing* 34: B881–B908. https://doi.org/10.1137/120861345.

Blundell, C., J. Cornebise, K. Kavukcuoglu, and D. Wierstra. 2015. "Weight Uncertainty in Neural Networks." In *Proceedings of the 32nd International Conference on International Conference on Machine Learning (ICML'15)*. Vol. 37, pp. 1613–1622.

Cai, Y., T. Huang, E. Bompard, Y. Cao, and Y. Li. 2017. "Self-Sustainable Community of Electricity Prosumers in the Emerging Distribution System." *IEEE Transactions on Smart Grid* 8 (5): 2207–2216. https://doi.org/10.1109/TSG.2016.2518241.

Chen, P., N. Zabaras, and I. Bilionis. 2015. "Uncertainty Propagation Using Infinite Mixture of Gaussian Processes and Variational Bayesian Inference." *Journal of Computational Physics* 284: 291–333. https://doi.org/10.1016/j.jcp.2014.12.028.

Chen, Y., T. Yin, R. Huang, X. Fan, and Q. Huang. 2019. "Big Data Analytic for Cascading Failure Analysis." 2019 IEEE International Conference on Big Data (Big Data), Los Angeles, CA. pp. 1625–1630. https://doi.org/10.1109/BigData47090.2019.9005593.

Chen, Y., T. Jiang, M. Heleno, A. Moreira, and Y. R. Gel. 2022. "Evaluating Distribution System Reliability with Hyperstructures Graph Convolutional Nets." arXiv:2211.07645.

Christiano, P., Z. Shah, I. Mordatch, J. Schneider, T. Blackwell, J. Tobin, P. Abbeel, and W. Zaremba. 2016. "Transfer from Simulation to Real World through Learning Deep Inverse Dynamics Model." arXiv:1610.03518.

Copeland, M. 2016. "What's the Difference Between Artificial Intelligence, Machine Learning and Deep Learning?" NVIDIA. Last Modified July 29, 2016. Accessed February 22, 2024. https://blogs.nvidia.com/blog/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/.

Cui, Q., K. El-Arroudi, and G. Joos. 2017. "An Effective Feature Extraction Method in Pattern Recognition Based High Impedance Fault Detection." 19th International Conference on Intelligent System Application to Power Systems (ISAP), San Antonio, TX, September 17–20, 2017. https://doi.org/10.1109/ISAP.2017.8071380.

Dai, H., Z. Kozareva, B. Dai, A. Smola, and L. Song. 2018. "Learning Steady-States of Iterative Algorithms over Graphs." In *Proceedings of the 35th International Conference on Machine Learning*. pp. 1106–1114.

de Freitas, J. T., and F. G. F. Coelho. 2021. "Fault Localization Method for Power Distribution Systems Based on Gated Graph Neural Networks." *Electrical Engineering* 103 (5): 2259–2266. https://doi.org/10.1007/s00202-021-01223-7.

Del Angel, A., M. Glavic, and L. Wehenkel. 2003. "Using Artificial Neural Networks to Estimate Rotor Angles and Speeds from Phasor Measurements." In *Proceedings of Intelligent Systems Applications to Power Systems (ISAP)*, Lemnos, Greece.

Devlin, J., M.-W. Chang, K. Lee, and K. Toutanova. 2018. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv:1810.04805.

Dinesh, C., S. Makonin, and I. V. Bajic. 2019. "Residential Power Forecasting Using Load Identification and Graph Spectral Clustering." *IEEE Transactions on Circuits and Systems II: Express Briefs* 66 (11): 1900–1904. https://doi.org/10.1109/TCSII.2019.2891704.

Dong, J., M. Mandich, Y. Zhao, Y. Liu, S. You, Y. Liu, and H. Zhang. 2023. "AI-Based Faster-Than-Real-Time Stability Assessment of Large Power Systems with Applications on WECC System." *Energies* 16 (3): 1401. https://doi.org/10.3390/en16031401.

Du, Y., F. Li, J. Li, and T. Zheng. 2019. "Achieving 100x Acceleration for N-1 Contingency Screening with Uncertain Scenarios Using Deep Convolutional Neural Network." *IEEE Transactions on Power Systems* 34 (4): 3303–3305. https://doi.org/10.1109/TPWRS.2019.2914860.

El Sallab, A., M. Abdou, E. Perot, and S. Yogamani. 2017. "Deep Reinforcement Learning Framework for Autonomous Driving." arXiv:1704.02532.

Erhan, D., Y. Bengio, A. Courville, P.-A. Manzagol, P. Vincent, and S. Bengio. 2010. "Why Does Unsupervised Pre-training Help Deep Learning?" *Journal of Machine Learning Research* 11 (19): 625–660. https://www.jmlr.org/papers/v11/erhan10a.html.

Fan, J., S. Rao, G. Muniraju, C. Tepedelenlioglu, and A. Spanias. 2020. "Fault Classification in Photovoltaic Arrays Using Graph Signal Processing." In *2020 IEEE Conference on Industrial Cyber Physical Systems (ICPS)*. Vol. 1, pp. 315–319. https://doi.org/10.1109/ICPS48405.2020.9274763.

Fan, X., X. Li, E. L. Barrett, Q. Huang, J. G. O'Brien, R. Huang, Z. Hou, and R. Diao. 2021. Transformative Remedial Action Scheme Tool (TRAST). US Patent 16,435,352.

Feinberg, E. A., and D. Genethliou. 2005. "Load Forecasting." In *Applied Mathematics for Restructured Electric Power Systems: Optimization, Control, and Computational Intelligence*, edited by J. H. Chow, F. F. Wu, and J. Momoh, 269–285. New York City: Springer.

Finn, C., P. Abbeel, and S. Levine. 2017. “Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks.” arXiv:1703.03400.

Fisac, J., A. Akametalu, M. Zeilinger, S. Kaynama, J. Gillula, and C. J. Tomlin. 2018. “A General Safety Framework for Learning-Based Control in Uncertain Robotic Systems.” arXiv:1705.01292.

Gallicchio, C., and A. Micheli. 2010. “Graph Echo State Networks.” In *The 2010 International Joint Conference on Neural Networks (IJCNN)*. pp. 1–8. https://doi.org/10.1109/IJCNN.2010.5596796.

Gao, W., R. Fan, R. Huang, Q. Huang, Y. Du, W. Qiao, S. Wang, and D. W. Gao. 2022. “Improving DFIG Performance under Fault Scenarios through Evolutionary Reinforcement Learning Based Control.” *IET Generation, Transmission &. Distribution* 16 (19): 3825–3836. https://doi.org/10.1049/gtd2.12563.

Garcia, D. R., B. Poudel, A. Bidram, and M. J. Reno. 2022. “Substation-Level Circuit Topology Estimation Using Machine Learning.” In *2022 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, pp. 1–6. https://doi.org/10.1109/ISGT50606.2022.9817500.

Gillis, J. M., and W. G. Morsi. 2017. “Non-intrusive Load Monitoring Using Semi-supervised Machine Learning and Wavelet Design.” *IEEE Transactions on Smart Grid* 8 (6): 2648–2655. https://doi.org/10.1109/TSG.2016.2532885.

Goodfellow, I., J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. 2014. “Generative Adversarial Nets.” In *Proceedings of the 28th Annual International Conference on Neural Information Processing Systems*, Vol. 2, pp. 2672–2680.

Goodfellow, I., Y. Bengio, and A. Courville. 2016. *Deep Learning*. Cambridge, MA: MIT Press.

Granell, R., C. J. Axon, and D. C. H. Wallom. 2016. “Impact of Raw Data Temporal Resolution Using Selected Clustering Methods on Residential Electricity Load Profiles.” *IEEE Transactions on Power Systems* 30 (6): 3217–3224. https://doi.org/10.1109/TPWRS.2014.2377213.

Graves, A. 2011. “Practical Variational Inference for Neural Networks.” In *Advances in Neural Information Processing Systems*, pp. 2348–2356.

Guddanti, K. P., Y. Weng, A. Marot, B. Donnot, and P. Panciatici. 2022. “Graph Neural Networks for Voltage Stability Margins with Topology Flexibilities.” *IEEE Open Access Journal of Power and Energy* 10: 73–85. https://doi.org/10.1109/OAJPE.2022.3223962.

Hastie, T., R. Tibshirani, and J. Friedman. 2001. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York City: Springer.

He, Q., J. Si, and D. J. Tylavsky. 2000. “Prediction of Top-Oil Temperature for Transformers Using Neural Networks.” *IEEE Transactions on Power Delivery* 15 (4): 1205–1211. https://doi.org/10.1109/61.891504.

He, K. M., X. Y. Zhang, S. Q. Ren, and J. Sun. 2016. "Deep Residual Learning for Image Recognition." In *Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770–778. https://doi.org/10.1109/CVPR.2016.90.

Henao, N., K. Agbossou, S. Kelouwani, Y. Dubé, and M. Fournier. 2017. "Approach in Nonintrusive Type I Load Monitoring Using Subtractive Clustering." *IEEE Transactions on Smart Grid* 8 (2): 812–821. https://doi.org/10.1109/TSG.2015.2462719.

Hinton, G., L. Deng, D. Yu, G. E. Dahl, A. Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T. N. Sainath, and B. Kingsbury. 2012. "Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups." *IEEE Signal Processing Magazine* 29 (6): 82–97. https://doi.org/10.1109/MSP.2012.2205597.

Hospedales, T., A. Antoniou, P. Micaelli, and A. Storkey. 2021. "Meta-learning in Neural Networks: A Survey." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 44 (9): 5149–5169. https://doi.org/10.1109/TPAMI.2021.3079209.

Hossain, R. R., Q. Huang, and R. Huang. 2021. "Graph Convolutional Network-Based Topology Embedded Deep Reinforcement Learning for Voltage Stability Control." *IEEE Transactions on Power Systems* 36 (5): 4848–4851. https://doi.org/10.1109/TPWRS.2021.3084469.

Hou, Z., J. Follum, P. Etingov, F. Tuffner, D. Kosterev, and G. Matthews. 2018. "Machine Learning of Factors Influencing Damping and Frequency of Dominant Inter-area Modes in the WECC Interconnect." 2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Boise, ID, 2018, pp. 1–6. https://doi.org/10.1109/PMAPS.2018.8440361.

Hu, C., G. Lin, B. Wang, M. Yue, and J. Xin. 2022. "Post-Fault Power Grid Voltage Prediction via 1D-CNN with Spatial Coupling." 2022 5th International Conference on Artificial Intelligence for Industries (AI4I), Laguna Hills, CA, 2022, pp. 35–37, https://doi.org/10.1109/AI4I54798.2022.00016.

Huang, G., L. Zhuang, L. Van Der Maaten, and K. Q. Weinberger. 2017a. "Densely Connected Convolutional Networks." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2261–2269. https://doi.org/10.1109/CVPR.2017.243.

Huang, S., N. Papernot, I. Goodfellow, Y. Duan, and P. Abbeel. 2017b. "Adversarial Attacks on Neural Network Policies." ICLR Workshop, arXiv:1702.02284.

Huang, J., L. Guan, Y. Su, H. Yao, M. Guo, and Z. Zhong. 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.

Huang, R., W. Gao, R. Fan, and Q. Huang. 2022a. "Damping Inter-area Oscillation Using Reinforcement Learning Controlled TCSC." *IET Generation, Transmission & Distribution* 16 (11): 2265–2275. https://doi.org/10.1049/gtd2.12441.

Huang, R., Y. Chen, T. Yin, X. Li, A. Li, J. Tan, W. Yu, Y. Liu, and Q. Huang. 2022b. "Accelerated Derivative-Free Deep Reinforcement Learning for Large-Scale Grid Emergency Voltage Control." *IEEE Transactions on Power Systems* 37 (1): 14–25. https://doi.org/10.1109/TPWRS.2021.3095179.

Ioffe, S., and C. Szegedy. 2015. “Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift.” Proceedings of the 32nd International Conference on Machine Learning, Vol. 37, pp. 448–456.

Jain, T., L. Srivastava, and S. Singh. 2003. “Fast Voltage Contingency Screening Using Radial Basis Function Neural Network.” *IEEE Transactions on Power Systems* 18 (4): 1359–1366. https://doi.org/10.1109/TPWRS.2003.818607.

Jiang, H., X. Dai, D. W. Gao, J. J. Zhang, Y. Zhang, and E. Muljadi. 2016. “Spatial-Temporal Synchrophasor Data Characterization and Analytics in Smart Grid Fault Detection, Identification, and Impact Causal Analysis.” *IEEE Transactions on Smart Grid* 7 (5): 2525–1896. https://doi.org/10.1109/TSG.2016.2552229.

Jones, C. B., A. Summers, and M. J. Reno. 2021. “Machine Learning Embedded in Distribution Network Relays to Classify and Locate Faults.” 2021 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, February 16-18, 2021. https://doi.org/10.1109/ISGT49243.2021.9372247.

Jouppi N. P., C. Young, N. Patil, D. Patterson, G. Agrawal, R. Bajwa, S. Bates, S. Bhatia, N. Boden, A. Borchers, R. Boyle, P. Cantin, C. Chao, C. Clark, J. Coriell, M. Daley, M. Dau, J. Dean, B. Gelb, T. V. Ghaemmaghami, R. Gottipati, W. Gulland, R. Hagmann, C. R. Ho, D. Hogberg, J. Hu, R. Hundt, D. Hurt, J. Ibarz, A. Jaffey, A. Jaworski, A. Kaplan, H. Khaitan, D. Killebrew, A. Koch, N. Kumar, S. Lacy, J. Laudon, J. Law, D. Le, C. Leary, Z. Liu, K. Lucke, A. Lundin, G. MacKean, A. Maggiore, M. Mahony, K. Miller, R. Nagarajan, R. Narayanaswami, R. Ni, K. Nix, T. Norrie, M. Omernick, N. Penukonda, A. Phelps, J. Ross, M. Ross, A. Salek, E. Samadiani, C. Severn, G. Sizikov, M. Snelham, J. Souter, D. Steinberg, A. Swing, M. Tan, G. Thorson, B. Tian, H. Toma, E. Tuttle, V. Vasudevan, R. Walter, W. Wang, E. Wilcox, and D. H. Yoon. 2017. “In-Datacenter Performance Analysis of a Tensor Processing Unit.” In *Proceedings of the 44th Annual International Symposium on Computer Architecture (ISCA '17)*. Association for Computing Machinery, New York, NY, pp. 1–12. https://doi.org/10.1145/3079856.3080246.

Kalyani, S., and K. Swarup. 2011. “Static Security Evaluation in Power Systems using Multi-Class SVM with Different Parameter Selection Methods.” *International Journal of Machine Learning and Cybernetics* 1 (2): 193–198. https://doi.org/10.7763/IJMLC.2011.V1.28.

Karimi, A. M., Y. Wu, M. Koyutürk, and R. French. 2021. “Spatiotemporal Graph Neural Network for Performance Prediction of Photovoltaic Power Systems.” In *Proceedings of the AAAI Conference on Artificial Intelligence*, pp. 15323–15330. https://doi.org/10.1609/aaai.v35i17.17799.

Keogh, E., and A. Mueen. 2011. “Curse of Dimensionality.” In *Encyclopedia of Machine Learning*, edited by C. Sammut and G. I. Webb, pp. 257–258. New York City: Springer.

Khazeiynasab, S. R., J. Zhao, I. Batarseh, and B. Tan. 2022a. “Power Plant Model Parameter Calibration Using Conditional Variational Autoencoder.” *IEEE Transactions on Power Systems* 37 (2): 1642–1652. https://doi.org/10.1109/TPWRS.2021.3107515.

Khazeiynasab, S. R., J. Zhao, and N. Duan. 2022b. “WECC Composite Load Model Parameter Identification Using Deep Learning Approach.” 2022 IEEE Power & Energy Society General Meeting (PESGM), Denver, CO, July 17–21, 2022. https://doi.org/10.1109/PESGM48719.2022.9916921.

Khodayar, M., O. Kaynak, and M. E. Khodayar. 2017. “Rough Deep Neural Architecture for Short-Term Wind Speed Forecasting,” *IEEE Transactions on Industrial Informatics* 13 (6): 2770–2779. https://doi.org/10.1109/TII.2017.2730846.

Khorasgani, H., A. Hasanzadeh, A. Farahat, and C. Gupta. 2019. “Fault Detection and Isolation in Industrial Networks Using Graph Convolutional Neural Networks.” In *2019 IEEE International Conference on Prognostics and Health Management (ICPHM)*, pp. 1–7. https://doi.org/10.1109/ICPHM.2019.8819403.

Kipf, T. N., and M. Welling. 2016. “Semi-supervised Classification with Graph Convolutional Networks.” arXiv:1609.02907.

Kong, W., Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu, and Y. Zhang. 2019. “Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network.” *IEEE Transactions on Smart Grid* 10 (1): 841–851. https://doi.org/10.1109/TSG.2017.2753802.

Kumar, V., L. Gleyzer, A. Kahana, K. Shukla, and G. E. Karniadakis. 2023. “MyCrunchGPT: A chatGPT Assisted Framework for Scientific Machine Learning.” arXiv:2306.15551.

Kurup, A. R., M. Martínez–Ramón, A. Summers, A. Bidram, and M. J. Reno. 2021. “Deep Learning Based Circuit Topology Estimation and Fault Classification in Distribution Systems.” 2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), October 18–21, 2021. https://doi.org/10.1109/ISGTEurope52324.2021.9640097.

Lai, L. 1998. “Object-Oriented Analysis, Design and Development of Artificial Neural Networks.” In *Intelligent System Applications in Power Engineering*, QA76.618L35, pp. 1–35.

LeCun, Y., Y. Bengio, and G. Hinton. 2015. “Deep Learning.” *Nature* 521 (7553): 436–444. https://doi.org/10.1038/nature14539.

Li, R., F. Li, and N. D. Smith. 2016. “Multi-resolution Load Profile Clustering for Smart Metering Data.” *IEEE Transactions on Power Systems* 31 (6): 4473–4482. https://doi.org/10.1109/TPWRS.2016.2536781.

Li, Y., Y. Wen, D. Tao, and K. Guan. 2019. “Transforming Cooling Optimization for Green Data Center via Deep Reinforcement Learning.” *IEEE Transactions on Cybernetics* 50 (5): 2002–2013. https://doi.org/10.1109/TCYB.2019.2927410.

Li, X., X. Fan, H. Ren, Z. Hou, Q. Huang, S. Wang, and O. Ciniglio. 2019. “Data-Driven Feature Analysis in Control Design for Series-Compensated Transmission Systems.” *IEEE Transactions on Power Systems* 34 (4): 3297–3299. https://doi.org/10.1109/TPWRS.2019.2912711.

Liao W., D. Yang, Y. Wang, and X. Ren. 2020. “Fault Diagnosis of Power Transformers Using Graph Convolutional Network.” *CSEE Journal of Power and Energy Systems* 7 (2): 241–249. https://doi.org/10.17775/CSEEJPES.2020.04120.

Liu, D., L. Zeng, C. Li, K. Ma Y. Chen, and Y. Cao. 2018. “A Distributed Short-Term Load Forecasting Method Based on Local Weather Information.” *IEEE System Journal* 12 (1): 208–215. https://doi.org/10.1109/JSYST.2016.2594208.

Luo, Y., C. Lu, L. Zhu, and J. Song. 2021. "Data-Driven Short-Term Voltage Stability Assessment Based on Spatial-Temporal Graph Convolutional Network." *International Journal of Electrical Power & Energy Systems* 130: 106753. https://doi.org/10.1016/j.ijepes.2020.106753.

Maas, A. L., A. Y. Hannun, and A. Y. Ng. 2013. "Rectifier Nonlinearities Improve Neural Network Acoustic Models." In *Proceedings of the 30th International Conference on Machine Learning (ICML-13)*, pp. 3–11.

Manitsas, E., R. Singh, B. C. Pal, and G. Strbac. 2012. "Distribution System State Estimation Using an Artificial Neural Network Approach for Pseudo Measurement Modeling." *IEEE Transactions on Power Systems* 27 (4): 1888–1896. https://doi.org/10.1109/TPWRS.2012.2187804.

Manohar, M., E. Koley, and S. Ghosh. 2019. "Enhancing Resilience of PV-fed Microgrid by Improved Relaying and Differentiating between Inverter Faults and Distribution Line Faults." *International Journal of Electrical Power & Energy Systems* 108: 271–279. https://doi.org/10.1016/j.ijepes.2019.01.015.

Matos, M. A., N. D. Hatziargriou, and J. A. Pecas Lopes. 2000. "Multicontingency Steady State Security Evaluation Using Fuzzy Clustering Techniques." *IEEE Transactions on Power Systems* 15 (1): 177–183. https://doi.org/10.1109/59.852118.

Micheli, A., D. Sona, and A. Sperduti. 2004. "Contextual Processing of Structured Data by Recursive Cascade Correlation." *IEEE Transactions on Neural Networks* 15 (6): 1396–1410. https://doi.org/10.1109/tnn.2004.837783.

Mnih, V., K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller. 2013. "Playing Atari with Deep Reinforcement Learning." arXiv:1312.5602.

Morris, M. R., J. Sohl-dickstein, N. Fiedel, T. Warkentin, A. Dafoe, A. Faust, C. Farabet, and S. Legg. 2023 "Levels of AGI: Operationalizing Progress on the Path to AGI." arXiv:2311.02462.

Moya, C., S. Zhang, G. Lin, and M. Yue. 2023a. "DeepONet-Grid-UQ: A Trustworthy Deep Operator Framework for Predicting the Power Grid's Post-Fault Trajectories." *Neurocomputing* 535: 166–182. https://doi.org/10.1016/j.neucom.2023.03.015.

Moya, C., G. Lin, T. Zhao, and M. Yue. 2023b. "On Approximating the Dynamic Response of Synchronous Generators via Operator Learning: A Step Towards Building Deep Operator-Based Power Grid Simulators." Submitted to *IEEE Transactions on Neural Networks and Learning Systems*, January 29, 2023: arXiv:2301.12538.

Munshi, A. A., and Y. A.-R. I. Mohamed. 2018. "Extracting and Defining Flexibility of Residential Electrical Vehicle Charging Loads." *IEEE Transactions on Industrial Informatics* 14 (2): 448–461. https://doi.org/10.1109/TII.2017.2724559.

Murphy, K. P. 2012. *Machine Learning: A Probabilistic Perspective*. Cambridge, MA: MIT Press.

Nair, V., and G. E. Hinton. 2010. "Rectified Linear Units Improve Restricted Boltzmann Machines." In *Proceedings of the 27th International Conference on Machine Learning (ICML-10)*, pp. 807–814.

Najm, H. N. 2009. "Uncertainty Quantification and Polynomial Chaos Techniques in Computational Fluid Dynamics." *Annual Review of Fluid Mechanics* 41: 35–52. https://doi.org/10.1146/annurev.fluid.010908.165248.

Nandanoori, S. P., S. Guan, S. Kundu, S. Pal, K. Agarwal, Y. Wu, and S. Choudhury. 2022. "Graph Neural Network and Koopman Models for Learning Networked Dynamics: A Comparative Study on Power Grid Transients Prediction." *IEEE Access* 10: 32337–32349. https://doi.org/10.1109/ACCESS.2022.3160710.

Nazaripouya, H., Y. Wang, P. Chu, H. R. Pota, and R. Gadh. 2016. "Univariate Time Series Prediction of Solar Power Using a Hybrid Wavelet-ARMA-NARX Prediction Method." IEEE/PES Transmission and Distribution Conference and Exposition, Dallas, TX, May 3–5, 2016. https://doi.org/10.1109/TDC.2016.7519959.

Ng, A. Y., and M. I. Jordan. 2002. "On Discriminative vs. Generative Classifiers: A Comparison of Logistic Regression and Naive Bayes." In *Advances in Neural Information Processing Systems*, pp. 841–848.

Ojetola, S. T., M. J. Reno, J. Flicker, D. Bauer, and D. Stoltzfuz. 2022. "Testing Machine Learned Fault Detection and Classification on a DC Microgrid." 2022 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), New Orleans, LA, April 24–28, 2022. https://doi.org/10.1109/ISGT50606.2022.9817517.

Owerko, D., F. Gama, and A. Ribeiro. 2018. "Predicting Power Outages Using Graph Neural Networks." In *2018 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*. Anaheim, CA, November 26–29, 2018, pp. 743–747.

Pan, H., X. He, S. Tang, and F. Meng. 2018. "An Improved Bearing Fault Diagnosis Method Using One-Dimensional CNN and LSTM." *Strojniški vestnik - Journal of Mechanical Engineering,* 64 (7–8): 443–452. https://doi.org/10.5545/sv-jme.2018.5249.

Peherstorfer, B., K. Willcox, and M. Gunzburger. 2018. "Survey of Multifidelity Methods in Uncertainty Propagation, Inference, and Optimization." *SIAM Review*, 60 (3): 550–591. https://doi.org/10.1137/16M1082469.

Poudel, B. P., A. Bidram, M. J. Reno, and A. Summers. 2022. "Zonal Machine Learning-Based Protection for Distribution Systems." *IEEE Access* 10: 66634–66645. https://doi.org/10.1109/access.2022.3184865.

Qin, J., and N. Yu. 2023. "Reconfigure Distribution Network with Physics-Informed Graph Neural Network." University of California Riverside.

Rasmussen, C. E., and C. K. I. Williams. 2006. *Gaussian Processes for Machine Learning*. Vol. 2, No. 3. Cambridge, MA: MIT Press.

Rezende, D. J., S. Mohamed, and D. Wierstra. 2014. "Stochastic Backpropagation and Variational Inference in Deep Latent Gaussian Models." arXiv:1401.4082.

Roberts, C., J. D. Lara, R. Henriquez-Auba, M. Bossart, R. Anantharaman, C. Rackauckas, B.-M. Hodge, and D. S. Callaway. 2022. "Continuous-Time Echo State Networks for Predicting

Power System Dynamics." *Electric Power Systems Research* 212: 108562. https://doi.org/10.1016/j.epsr.2022.108562.

Rumelhart, D. E., G. E. Hinton, and R. J. Williams. 1986. "Learning Representations by Back-propagating Errors." *Nature* 323 (6088): 533–536. https://doi.org/10.1038/323533a0.

Sa Da Costa, J. M. G. 1982. "Application of Pattern Recognition to Transient Security Assessment in Power Systems." PhD thesis, Control Systems Centre, Institute of Science and Technology, University of Manchester.

Sandryhaila, A., and J. M. F. Moura. 2013. "Discrete Signal Processing on Graphs." *IEEE Transactions on Signal Processing* 61 (7): 1644–1656. https://doi.org/10.1109/TSP.2013.2238935.

Scarselli, F., M. Gori, A. C. Tsoi, M. Hagenbuchner, and G. Monfardini, 2008. "The Graph Neural Network Model." *IEEE Transactions on Neural Networks* 20 (1): 61–80. https://doi.org/10.1109/TNN.2008.2005605.

Schmidhuber, J., and S. Hochreiter. 1997. "Long Short-Term Memory." *Neural Computation* 9 (8): 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735.

Shuman, D. I., S. K. Narang, P. Frossard, A. Ortega, and P. Vandergheynst. 2013. "The Emerging Field of Signal Processing on Graphs: Extending High-Dimensional Data Analysis to Networks and Other Irregular Domains." *IEEE Signal Processing Magazine* 30 (3): 83–98. https://doi.org/10.1109/MSP.2012.2235192.

Shi, H., M. Xu, and R. Li. 2018. "Deep Learning for Household Load Forecasting – A Novel Pooling Deep RNN." *IEEE Transactions on Smart Grid* 9 (5): 5271–5280. https://doi.org/10.1109/TSG.2017.2686012.

Shi, X., and Y. L. Zhu. 2015. "The Application of Deep Neural Network in Power Transformer Fault Diagnosis." (in Chinese) *Electric Power Construction* 36 (12): 116–122.

Silver, D., A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. van den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, S. Dieleman, D. Grewe, J. Nham, N. Kalchbrenner, I. Sutskever, T. Lillicrap, M. Leach, K. Kavukcuoglu, T. Graepel, and D. Hassabis. 2016. "Mastering the Game of Go with Deep Neural Networks and Tree Search." *Nature* 529 (7587): 484–489. https://doi.org/10.1038/nature16961.

Singh, S., and A. Majumdar. 2018. "Deep Sparse Coding for Non-intrusive Load Monitoring." *IEEE Transactions on Smart Grid* 9 (5): 4669–4678. https://doi.org/10.1109/TSG.2017.2666220.

Sobajic, D. J., and Y.-H. Pao. 1989. "Artificial Neural-Net Based Dynamic Security Assessment for Electric Power Systems." *IEEE Transactions on Power Systems* 4 (1): 220–228. https://doi.org/10.1109/59.32481.

Sperduti, A., and A. Starita. 1997. "Supervised Neural Networks for the Classification of Structures." *IEEE Transactions on Neural Networks* 8 (3): 714–735. https://doi.org/10.1109/72.572108.

Srivastava, N., G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. 2014. “Dropout: A Simple Way to Prevent Neural Networks from Overfitting.” *The Journal of Machine Learning Research* 15 (56): 1929–1958.

Su, T., J. Zhao, and X. Chen. 2024. “Deep Sigma Point Processes-Assisted Chance-Constrained Power System Transient Stability Preventive Control.” *IEEE Transactions on Power Systems* 39 (1): 1965–1978. https://doi.org/10.1109/TPWRS.2023.3270800.

Sun, K., S. Likhate, V. Vittal, V. S. Kolluri, and S. Mandal. 2007. “An Online Dynamic Security Assessment Scheme Using Phasor Measurements and Decision Trees.” *IEEE Transactions on Power Systems* 22 (4): 1935–1943. https://doi.org/10.1109/TPWRS.2007.908476.

Sun, L., T. Liu, D. Wang, C. Huang, and Y. Xie. 2022. “Deep Learning Method Based on Graph Neural Network for Performance Prediction of Supercritical CO_2 Power Systems.” *Applied Energy* 324: 119739. https://doi.org/10.1016/j.apenergy.2022.119739.

Sun, Y., C. Moya, G. Lin, and M. Yue. 2023. “DeepGraphONet: A Deep Graph Operator Network to Learn and Zero-Shot Transfer the Dynamic Response of Networked Systems.” *IEEE Systems Journal* 17 (3) 4360–4370. https://doi.org/10.1109/JSYST.2023.3298884.

Sutton, R. S., and A. G. Barto. 2018. *Reinforcement Learning: An Introduction*. Cambridge, MA: MIT Press.

Tan, J., T. Zhang, E. Coumans, A. Iscen, Y. Bai, D. Hafner, S. Bohez, and V. Vanhoucke. 2018. “Sim-to-Real: Learning Agile Locomotion for Quadruped Robots.” arXiv:1804.10332.

Tan, B., J. Zhao, T. Su, Q. Huang, Y. Zhang, and H. Zhang. 2022. “Explainable Bayesian Neural Network for Probabilistic Transient Stability Analysis Considering Wind Energy.” 2022 IEEE Power & Energy Society General Meeting (PESGM), Denver, CO, July 17–21, 2022. https://doi.org/10.1109/PESGM48719.2022.9916892.

Tripathy, R. K., and I. Bilionis. 2018. “Deep UQ: Learning Deep Neural Network Surrogate Models for High Dimensional Uncertainty Quantification.” *Journal of Computational Physics* 375: 565–588. https://doi.org/10.1016/j.jcp.2018.08.036.

Verzi, S., R. Guttromson, and A. Sorensen. 2022. “Using Reinforcement Learning to Increase Grid Security under Contingency Conditions.” 2022 IEEE Kansas Power and Energy Conference (KPEC), Manhattan, KS, April 25–26, 2022. https://doi.org/10.1109/KPEC54747.2022.9814746.

Wang, Y., Q. Chen, C. Kang, Q. Xia, and M. Luo. 2017. “Sparse and Redundant Representation-Based Smart Meter Data Compression and Pattern Extraction.” *IEEE Transactions on Power Systems* 32 (3): 2142–2151. https://doi.org/10.1109/TPWRS.2016.2604389.

Wehenkel, L., T. Van Cutsem, and M. Ribbens-Pavella. 1989. “An Artificial Intelligence Framework for Online Transient Stability Assessment of Power Systems.” *IEEE Transactions on Power Systems* 4 (2): 789–800. https://doi.org/10.1109/59.193853.

Wehenkel, L., M. Pavella, E. Euxibie, and B. Heilbronn. 1994. “Decision Tree Based Transient Stability Method a Case Study.” *IEEE Transactions on Power Systems* 9 (1): 459–469. https://doi.org/10.1109/59.317577.

Wu, Y., M. Schuster, Z. Chen, Q. V. Le, M. Norouzi, W. Macherey, M. Krikun, Y. Cao, Q. Gao, K. Macherey, J. Klingner, A. Shah, M. Johnson, X. Liu, Ł. Kaiser, S. Gouws, Y. Kato, T. Kudo, H. Kazawa, K. Stevens, G. Kurian, N. Patil, W. Wang, C. Young, J. Smith, J. Riesa, A. Rudnick, O. Vinyals, G. Corrado, M. Hughes, and J. Dean. 2016. “Google’s Neural Machine Translation System: Bridging the Gap between Human and Machine Translation.” arXiv:1609.08144.

Wu, W., and M. Peng. 2017. “A Data Mining Approach Combining K-Means Clustering with Bagging Neural Network for Short-Term Wind Power Forecasting.” *IEEE Internet of Things Journal* 4 (4): 979–986. https://doi.org/10.1109/JIOT.2017.2677578.

Yan, R., G. Geng, Q. Jiang, and Y. Li. 2019. “Fast Transient Stability Batch Assessment Using Cascaded Convolutional Neural Networks.” *IEEE Transactions on Power Systems* 34 (4): 2802–2813. https://doi.org/10.1109/TPWRS.2019.2895592.

Ye, K., J. Zhao, N. Duan, and Y. Zhang. 2023. “Physics-Informed Sparse Gaussian Process for Probabilistic Stability Analysis of Large-Scale Power System with Dynamic PVs and Loads.” *IEEE Transactions on Power Systems* 38 (3): 2868–2879. https://doi.org/10.1109/TPWRS.2022.3188182

Yu, J. J. Q., D. J. Hill, A. Y. S. Lam, J. Gu, and V. O. K. Li. 2018. “Intelligent Time-Adaptive Transient Stability Assessment System.” *IEEE Transactions on Power Systems* 33 (1): 1049–1058. https://doi.org/10.1109/TPWRS.2017.2707501.

Yu, J. J. Q., D. J. Hill, V. O. K. Li, and Y. Hou. 2019. “Synchrophasor Recovery and Prediction: A Graph-Based Deep Learning Approach.” *IEEE Internet of Things Journal* 6 (5): 7348–7359. https://doi.org/10.1109/JIOT.2019.2899395.

Yu, M., Z. Zhang, X. Li, J. Yu, J. Gao, Z. Liu, B. You, X. Zheng, and R. Yu. 2020. “Superposition Graph Neural Network for Offshore Wind Power Prediction.” *Future Generation Computer Systems* 113: 145–157. https://doi.org/10.1016/j.future.2020.06.024.

Zamzam, A. S., X. Fu, and N. D. Sidiropoulos. 2019. “Data-Driven Learning Based Optimization for Distribution System State Estimation.” *IEEE Transactions on Power Systems* 34 (6): 4796–4805. https://doi.org/10.1109/TPWRS.2019.2909150.

Zamzam, A. S. and N. D. Sidiropoulos. 2019. “Physics-Aware Neural Networks for Distribution System State Estimation.” arXiv:1903.09669.

Zhang, Y., T. Huang, and E. F. Bompard. 2018. “Big Data Analytics in Smart Grids: A Review.” *Energy Informatics* 1: 8. https://doi.org/10.1186/s42162-018-0007-5.

Zhang, L., G. Wang, and G. B. Giannakis. 2019. “Real-Time Power System State Estimation and Forecasting via Deep Unrolled Neural Networks.” *IEEE Transactions on Signal Processing* 67 (15): 4069–4077. https://doi.org/10.1109/TSP.2019.2926023.

Zhang, Y., J. Liu, F. Qiu, T. Hong, and R. Yao. 2022. "Deep Active Learning for Solvability Prediction in Power Systems." *Journal of Modern Power Systems and Clean Energy* 10 (6): 1773–1777. https://doi.org/10.35833/MPCE.2021.000424.

Zhang, Y., M. Yue, and J. Wang. 2023. "Off-Policy Deep Reinforcement Learning with Automatic Entropy Adjustment for Adaptive Online Grid Emergency Control." *Electric Power Systems Research* 217: 109136. https://doi.org/10.1016/j.epsr.2023.109136.

Zhao, Z., G. Xu, Y. Qi, N. Liu, and T. Zhang. 2016. "Multi-patch Deep Features for Power Line Insulator Status Classification from Aerial Images." 2016 International Joint Conference on Neural Networks (IJCNN), Vancouver, BC, Canada, July 24–29, 2016, pp. 3187–3194, https://doi.org/10.1109/IJCNN.2016.7727606.

Zhao, T., Z. Zhou, Y. Zhang, P. Ling, and Y. Tian. 2017. "Spatio-Temporal Analysis and Forecasting of Distributed PV Systems Diffusion: A Case Study of Shanghai Using a Data-Driven Approach." *IEEE Access* 5: 5135–5148. https://doi.org/10.1109/ACCESS.2017.2694009.

Zhao, R., R. Yan, Z. Chen, K. Mao, P. Wang, and R. Gao. 2019. "Deep Learning and Its Applications to Machine Health Monitoring." *Mechanical Systems and Signal Processing* 115: 213–237. https://doi.org/10.1016/j.ymssp.2018.05.050.

Zhao, Y., S. You, M. Mandich, L. Zhu, C. Zhang, H. Li, Y. Su, C. Zeng, Y. Zhao, Y. Liu, H. Jiang, H. Yuan, Y. Zhang, and J. Tan. 2021. "Deep Learning-Based Adaptive Remedial Action Scheme with Security Margin for Renewable-Dominated Power Grids." *Energies* 14 (20): 6563. https://doi.org/10.3390/en14206563.

Zhao, T., M. Yue, and J. Wang. 2022. "Structure-Informed Graph Learning of Networked Dependencies for Online Prediction of Power System Transient Dynamics." *IEEE Transactions on Power Systems* 37 (6): 4885–4895. https://doi.org/10.1109/TPWRS.2022.3153328.

Zhao, T., M. Yue, and J. Wang. 2023. "Deep-Learning-Based Koopman Modeling for Online Control Synthesis of Nonlinear Power System Transient Dynamics." *IEEE Transactions on Industrial Informatics* 19 (10): 10444–10453. https://doi.org/10.1109/TII.2023.3240939.

Zheng, Y., C. Hu, G. Lin, M. Yue, B. Wang, and J. Xin. 2022. "GLassoformer: A Query-Sparse Transformer for Post-Fault Power Grid Voltage Prediction." ICASSP 2022 – 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Singapore, May 23–27, 2002. https://doi.org/10.1109/ICASSP43922.2022.9747394.

Zhong, Z., L. Guan, Y. Su, J. Yu, J. Huang, and M. Guo. 2022. "A Method of Multivariate Short-Term Voltage Stability Assessment Based on Heterogeneous Graph Attention Deep Network," *International Journal of Electrical Power & Energy Systems* 136: 107648. https://doi.org/10.1016/j.ijepes.2021.107648.

Zhou, Y., Q. Guo, H. Sun, Z. Yu, J. Wu, and L. Hao. 2019. "A Novel Data-Driven Approach for Transient Stability Prediction of Power Systems Considering the Operational Variability." *International Journal of Electrical Power & Energy Systems* 107: 379–394. https://doi.org/10.1016/j.ijepes.2018.11.031.

Appendix A – DOE-OE AGM Program AI/ML Project Portfolio

1. **Learning to Adapt and Control for Complex Power Systems**

   Principle Investigator (PI): Dr. Shaobu Wang, Pacific Northwest National Laboratory (PNNL)

   Abstract: The objective of the proposal is to develop a robust AI-based online controller parameter optimization and adaption (AOCPO) and adaption framework for enhancing the resilience of power systems with increasing uncertainties and dynamics. The proposed AOCPO framework will be implemented and validated for controlling utility-scale renewable equipment/assets to adaptively ride through system faults and provide frequency/reactive grid services, which can significantly increase the security and reliability of modern power grids.

   Partners: Google, University of Nebraska-Lincoln, University of Denver, Clemson University

2. ***PowerDrone:* Adaptive Steering of Power Systems for Resilient Operation Under Adversarial Conditions**

   PI: Dr. Sutanay Choudhury, PNNL

   Abstract: The *PowerDrone* project developed AI methods to defend cyber-physical systems, such as power grid from cyberattacks. We studied how attackers can disrupt a cyber-physical system through subtle manipulation of the sensor measurements. The *PowerDrone* project developed scalable methods that detect data-driven attacks and recommend changes to the cyber-physical system configuration to improve robustness in the face of an ongoing attack.

3. **Adaptive RAS/SPS System Settings for Improving Grid Reliability and Asset Utilization Through Predictive Simulation and Controls**

   PI: Dr. Xiaoyuan Fan, PNNL

   Abstract: This project aims to demonstrate the value of calculating Remedial Action Scheme (RAS) parameters in an adaptive way (both statistical methods and data-driven learning methods) and the impact of the DOE-OE AGM program on industry planning and operation practices. The team is working closely with the power industry, including PacifiCorp, Peak Reliability, Idaho Power, WECC Modeling and Validation Work Group (MVWG), and is taking full advantage of PNNL's parallel computing techniques around commercial software platforms (e.g., Siemens PTI PSS/E) to perform massive computations for full WECC network considering RAS models and real-time snapshots.

   Partners: PacifiCorp, Idaho Power Company, Peak Reliability (former WECC Reliability Coordinator)

4. **Big Data Analytics for Cascading Analysis, Prevention, and Restoration**

   PI: Dr. Yousu Chen, PNNL

   Abstract: The objective of this project is to develop big data analysis techniques for contingency analysis prevention, analysis, and restoration by leveraging existing capability to in-depth analysis of cascading electrical system failure output data. The developed methodologies can effectively assess the system's vulnerability level under contingencies and propose potential remediation and restoration strategies. Case studies conducted on the IEEE 118-bus system and a 563-bus system, along with comparisons against a commercial tool, validate the advantages of the developed big data approach: accurate prediction and faster and more effective corrective actions. These techniques hold promise for broader application across various power system scenarios.

5. **A Machine Learning Framework for DCAT to Assess Power Grid Security for Future Grid Planning**

   PI: Dr. Bharat Vyakaranam, PNNL

   Abstract: This project is to develop a framework using advanced machine learning techniques to be integrated with Dynamic Contingency Analysis Tool (DCAT) database module to assess impacts of extreme contingencies in future grid scenarios on cascading failures. The aim of this work is to assess the security of future grid by developing advanced machine learning methods for analyzing the diverse scenarios, which are not part of the present system and help the power system engineers to perform numerous planning studies. Adding advanced machine learning to DCAT simulations will enable to enhance analytics of large volumes of results and direct the selection of scenarios.

6. **Advanced Computational Algorithms for Power System Restoration**

   PI: Dr. Feng Qiu, Argonne National Laboratory (ANL)

   Abstract: Restoring electricity service after a disruption is a critical capability for power system reliability and resilience. System restoration is an enormously complicated process, involving operations, and static/dynamic security, and it is becoming increasingly complex with the introduction of emerging technologies, such as renewable participation and energy storages. As a result, there is a paramount demand for advanced computational algorithms to solve the operation and planning problems in system restoration. AI/ML is investigated in this project to enhance modeling and computing capabilities. In the first work, the project team uses AI/ML for modeling dynamics-constrained optimization problems. In the restoration process, static and dynamic security must be considered simultaneously to assure the success of a restoration plan. Dynamic security (e.g., frequency or trajectory) is modeled by differential equations. Static security (e.g., power and voltage) on the other hand, is modeled by algebraic equations. Simultaneous consideration of both in a restoration optimization problem is extremely difficult. We use AI/ML to tackle this modeling challenge by first developing a DNN and train it with system dynamic simulations so that the NN captures/approximates frequency responses as a function of static status. Then, we transform the NN into an equivalent mixed-integer programming model so that it can be put into the optimization model. In this work, AI/ML offers a modeling technique that can turn highly nonlinear sophisticated constraints into a tractable formulation. In the second work, we use AI/ML to provide an edge computing solution for the distribution grids to make fast responses to disruptions. We utilize imitation learning (IL) to train response models that make quick decisions on distribution network reconfiguration when certain lines are in outages. The imitation learning guarantees a faster convergence rate compared with exploration-dominant reinforcement learning. In this work, AI/ML provides an alternative to solving a time-consuming mathematical optimization problem and makes a decision very quickly. In the third work, we use AI/ML to build neural-in-the-loop intelligent controllers for inverter-based resources to support frequency response during the restoration process. We develop a physics-constrained ML framework that guarantees closed-loop stability. We adopt a centralized training and decentralized execution paradigm so that the intelligent controllers can only use local measurements to achieve global performance collaboratively. In this work, AI/ML offers an end-to-end integration of disturbance estimation and online optimal control that achieves simultaneously adaptivity and real-time capability.

   Partners: Ohio State University

7. **Advanced Machine Learning and Optimization for Modeling and Mitigating Wildfire Threats in Transmission Operational and Long-Term Planning Under Climate Change**

   PI: Dr. Feng Qiu, ANL

   Abstract: Due to climate change, much of the continental U.S. will have significantly hotter and drier days, leading to more wildfire hazards which threaten the safety and reliability of the power grid. Unfortunately, the U.S. power industry is not well prepared and still predominantly relies on empirically calculated fire danger indices, which do not consider the full spectrum of factors and dynamic information and lead to ineffective mitigation actions. In this work, we will develop a set of actionable wildfire risk metrics and models by employing advanced statistics, ML, and stochastic processes to better understand and predict wildfire risks and incorporate them into risk mitigation models for grid operations and planning to reduce both wildfire risks and outages in the near and long term. AI/ML, specifically statistic learning, is used to model the wildfire risks and predict disruptions to solar energy production caused by wildfire smokes. Firstly, we develop a flexible spatiotemporal wildfire prediction framework using multi-modal time-series data, such as wildfire reports and weather. We predict the wildfire risk (the chance of a wildfire event) in real-time, considering historical events using discrete mutually exciting point process models, which was further enhanced with the flexible distribution-free time-series conformal prediction (CP) approach. Through extensive experiments using real wildfire data from California, we demonstrate the effectiveness of our methods and their flexibility and scalability in large regions. Secondly, since power delivery facilities is one causes of wildfires, we incorporate power delivery networks into the wildfire prediction model. We propose a new spatiotemporal point process that captures (i) the current effect on wildfire risks due to the key environmental covariate information; (ii) the cumulative long-term effects that explain how historical covariate information affect current wildfire risks; and (iii) the spatiotemporal dependency among different segments within the power delivery network. The experimentation with California wildfire data demonstrates the improvement over the traditional point process and a high accuracy. Thirdly, we are leveraging a physics-informed (advection-diffusion mechanics) statistical learning method to predict wildfire smoke propagation and quantify its impact on solar power production.

   Partners: South California Edison, University of Arkansas

8. **A Scalable Deep Learning Framework for Resilient Grid Operations Under Contingency Events in Power Systems**

   PI: Dr. Kibaek Kim (lead PI) and Mihai Anitescu, ANL

   Abstract: This project aims to develop a scalable deep learning framework that implements AI/ML algorithms for solving power system optimization problems under contingency. The main focus of this project is on the development and experiments of various AI/ML models and approaches that can provide good approximations of large-scale complex optimization problems in power system operations under uncertainty. In this research project, we have addressed critical challenges in power system operations, particularly focusing on optimization and contingency management. Firstly, we developed a GCN model to predict optimal load-shedding ratios that would prevent transmission lines from overloading under contingencies, like line tripping. By incorporating the power system network topology into the GCN model, we were able to outperform classical NN and linear regression models by an order of magnitude in IEEE test cases. This promises a robust, real-time solution to large-scale, nonlinear optimization challenges in power system operations. Secondly, we developed a RL approach to the Alternating Direction Method of Multipliers—a popular distributed optimization algorithm for solving alternating current OPF under contingency. By this novel integration of RL, we achieved a significant speedup for the solutions (up to 59%) to outperform existing methods. Moreover, our RL-based approach showed excellent generalizability, handling unseen loading schemes and losses effectively, thereby reducing the iterations by up to 50%. Together, these accomplishments serve as a proof-of-concept for the application of ML techniques to power systems, significantly accelerating computational efficiency and enhancing the system's adaptability to unforeseen events. The advancements in ML and distributed optimization algorithms for power systems have significant implications for DOE-OE. By achieving accelerated convergence in solving alternating current OPF problems, these methods enhance the operational efficiency and adaptability of large-scale electrical grids. This could lead to more robust, scalable, and responsive electricity systems which are crucial for addressing OE's goals in grid modernization and resilience. The capability to handle unseen scenarios further augments the system's resilience to contingencies, thereby advancing the OE's mission to secure and improve the nation's electrical infrastructure.

9. **A General Framework for AI-Accelerated Power Systems Optimization**

PI: Dr. Alinson S. Xavier, ANL

Abstract: New grid technologies, such as renewables, energy storage, and behind-the-meter DERs, have led to an exponential increase in the complexity of the mathematical models that the power industry relies on to maintain the reliability, resilience, and affordability of the power grid. To address this computational challenge, we developed a general framework for the next generation of hybrid power systems optimization tools combining classical optimization with AI to become increasingly more efficient over time. Unlike other approaches, we use AI to accelerate (instead of replace) existing state-of-the-art mixed-integer linear programming (MIP) solvers, which are widely used and trusted by the power industry. In past fiscal years, we have successfully developed multiple AI strategies to accelerate MIP performance, including AI-enhanced warm starts, lazy constraints, branching, and cutting planes. When applied to realistic, large-scale instances of the security constrained unit commitment problem, we demonstrated that these techniques could solve the problem 4–10x faster without deterioration to solution quality. To disseminate the proposed framework and methodologies, we implemented them and made them publicly available as an open-source software framework called *MIPLearn*. The framework supports multiple programming languages (Python, Julia), multiple modeling languages (Pyomo, Gurobipy, JuMP), multiple state-of-the-art MIP solvers (Gurobi, CPLEX, XPRESS), and can support existing power systems optimization tools developed at various national laboratories, including UnitCommitment.jl (ANL), EGRET (Sandia), PowerModels.jl (LANL), PowerSimulations.jl (NREL), and HIPPO (PNNL/MISO). Direct integration of MIPLearn with some of these tools is currently underway. Finally, the project has ongoing collaborations with industry (MISO, ISO-NE) and supports the ongoing IEEE Task Force on Large-Scale Power Systems Applications.

Partners: Georgia Institute of Technology

10. **Extreme Weather Outage Forecasting and Response Planning Through Advanced Learning and Optimization**

PI: Dr. Feng Qiu, ANL

Abstract: Adverse weather events can cause widespread power grid outages, which often lead to massive economic losses and a significant loss of lives in some cases. Being able to forecast and respond to power outages is a crucial capability for grid reliability and resilience. As the power grid spans large geographical areas with complex environmental and weather conditions, it is difficult to predict the impacts of an extreme weather event in terms of where, when, and how extensive the outages are, and how to enhance grid resilience against extreme weather. Existing approaches mostly use model-based studies for analyzing the weather impact on the power grid; but the validity of the underlying models is often questioned. In this work, we will leverage Argonne's in-house electricity outage data warehouse and develop a data-driven approach for electricity outage prediction—a set of advanced prediction models that combine stochastic processing, ML, and AI. In addition to prediction, we will also perform causal analysis and other statistic learning to investigate the impact factors (including natural and societal factors) on the resilience in a certain electricity service region. Furthermore, we will develop grid resilience enhancement optimization models to optimally upgrade grid infrastructure and reduce electricity outages during extreme weather events.

In this project, we developed an advanced outage prediction model that combines a DNN and a stochastic process (Hawk process) model. The NN captures complex impacts of over 100 weather variables, and the stochastic process provides a spatial-temporal model for outage processes. The prediction model has demonstrated its accuracy in outage forecasting. The output parameters in the model can be used to make insightful indications about grid resilience in different regions and against different types of weather events. One advantage of the hybrid model of NN and stochastic process is interpretability. The parameters in stochastic model can be interpreted with system resilience characteristics, such as vulnerability and recoverability. We have also enhanced the forecasting model so that the model does not require a full-scale weather information. For example, the only inputs the prediction model needs are the maximal temperature, wind speed, and precipitation. This simplification can greatly benefit disaster response planners. We also use statistical learning, such as causal analysis, to find the root cause of outages, including both natural factors (e.g., certain weather variables) and societal factors (e.g., incomes and racial groups).

Partners: Georgia Institute of Technology

11. **Weather Outage Prediction Model**

PI: Dr. Donatella Pasqualini, Los Alamos National Laboratory (LANL)

Abstract: The ability to predict electrical outages resulting from extreme events, such as hurricane-force winds and ice damage to electrical distribution networks, is key for mitigating the effects of these events. It is also a critical step in the analysis of cascading failures in critical or lifeline infrastructure networks that depend directly or indirectly on electrical power. While there is research currently underway to model power outages caused by specific severe weather, to date there is no comprehensive model to describe how hazardous weather events of different types impact the electrical grid. In addition, most of the existing models are customized for specific regions/power distribution systems and there is not a high-resolution model that can operate at a national scale. This project develops a ML model to identify weather events that may damage the power system and forecast the geographical distribution of power outages. The model will correlate climatic and weather-related variables with power outages. The proposed effort will build upon existing capabilities developed to support the Department of Homeland Security and the University of Connecticut. The final deliverable of this effort will be a support decision tool that utilities can use to forecast an area at risk for power outage induced by weather-related events.

Partners: University of Connecticut

12. Hybrid Learning Assisted Optimization Methods for Uncertainty Management and Corrective Control

PI: Dr. Sidhant Misra, LANL

Abstract: Uncertainty in power system operations is managed through both preventive and corrective means. Currently, preventive measures are incorporated in OPF by using pre-selected uncertainty scenarios, or through simplistic assumptions on the uncertainty distribution. Similarly, corrective control is either modeled as discrete generation dispatch rules following an N-1 contingency, or as an affine control policy (automatic generation control and automatic voltage regulators) to model the generation adjustment in response to real-time fluctuations from uncertainty sources. These approaches suffer from scalability and sub-optimality issues. The main technical bottleneck to assure accurate modeling, security, and optimality is that the resulting robust/stochastic optimization problems are very challenging to scale using traditional purely optimization-based methods. Inspired by the recent advances and success of ML techniques, we develop hybrid learning assisted optimization algorithms for these tasks. The hallmark of our approach is that ML is used to boost the performance of optimization algorithms, not replace them. The nature of power systems operations makes it highly suitable for application of ML techniques. For example, system models are known a priori and very seldomly change day-ahead load and renewable forecasts which are readily available; OPF problems are solved routinely and often with similar system conditions. All of these have made available plenty of training data for offline ML methods to be applied. This project focuses on the following directions for learning assisted optimization:

1. Formulation of the uncertainty aware OPF as an adjustable robust optimization problem that incorporates both preventive and corrective actions. This provides a flexible, yet powerful modeling framework that can accommodate both current practices as well as any advanced preventive and corrective controls that are developed.
2. Leveraging our results on constrained optimization using active-set learning to identify critical constraints in preventive robust optimization to significantly reduce computational complexity. Further, we will address a primary bottleneck to the scalability of the scenario-based approach to robust OPF by training ML methods that identify critical uncertainty scenarios. Crucially, both the aforementioned techniques are complementary and can be used concurrently. Further, these methods are compatible with current operational practices, since identifying critical transmission lines in the system and worst-case uncertainty scenarios are steps that are already currently used using ad-hoc techniques.

Learning efficient generation policies for corrective control occurs by using the fully adjustable OPF as the benchmark. The fully adjustable OPF—where all generators are allowed to react to the uncertainty realization—although impractical, is optimal both economically and in terms of enforcing security. Data from several runs of the fully adjustable OPF can be used to learn best response rules that generalize existing ones, such as linear voltage-dependent reactive power adjustment, while still remaining practical to assure the latter constraints will be included while learning the policies that (i) limit the number of generators and controllable resources that can participate in corrective control; and (ii) use limited centralized information and communication capabilities, thus restricting the generators to respond to local measurements, as an example.

13. Robust Real-Time Control, Monitoring, and Protection of Large-Scale Power Grids in Response to Extreme Events

PI: Dr. Yury Maximov, LANL

Abstract: The protection and emergency control system for the U.S. transmission grid is one of the most crucial points of U.S. national security. An emergency occurs when the power system is close to or beyond stability limits, which are quantified in terms of feasibility/security of voltage magnitudes, frequency, and active and reactive power transfer. Emergency control actions in principle are designed to move the power system from an insecure operating point to a secure operating point within desired timeframes to protect the system from cascading outages and blackouts.

Current operational paradigms for emergency control primarily rely on relay protection devices and automated schemes, such as under-voltage load shedding, that effectively restrict emergencies to local regions and prevent cascading outages. Many utilities implement RAS or SPS to improve system reliability and performance during maintenance scenarios or in extreme events. These schemes may significantly improve the system's response to failures and are believed to enable better integration of RESs. However, while the benefits of SPS have led to widespread adoption, the potentially deteriorating effects of mis-operation and unintended interference between different schemes can pose a serious risk to system operations.

This project designs real-time extreme event monitoring and identification methods and provides the computation and implementation of fast control actions in a similarly short time frame as the traditional special protection schemes, and revisits the way those systems are designed. Specifically, we will consider a context where increased uncertainty in the system state and more frequent extreme events (such as snowstorms and tornadoes) affecting grid topology and line parameters lead to greater demand and diversity in the required control actions. To develop advanced automatic control schemes protecting the system, we leverage a limited set of non-local measurements provided by high-fidelity sensors, such as PMUs, and draw on recent advances in robust, stochastic, and data-driven power system optimization and control.

Partners: Lawrence Livermore National Laboratory (LLNL), University of Wisconsin, Massachusetts Institute of Technology

14. Non-Linear Power System Optimization and Control Under Uncertainty

PI: Dr. Marc Vuffray, LANL

Abstract: Increasing penetration of renewable generation and demand-side penetration from DERs calls for operational planning methods that account for uncertainty. The goal of this project is to develop stochastic optimization tools that are able to accommodate more accurate power flow models. These methods need to be specifically designed to account for the nonlinearity of AC power equations and uncertainty at the same time while maintaining efficiency.

The first part of the approach deals with the primary challenge of finding scalable ways to integrate nonlinearity of the power flow physics and the effect of uncertainty into optimization. This involves investigation of several UQ methods that can be incorporated into an AC-OPF formulation.

The methods explored are (i) partial linearization that linearizes the effect of uncertainty while keeping the nonlinearity of the power flows for the nominal case; (ii) the Lassere's hierarchy that approximates probabilistic constraints with polynomials; and (iii) the polynomial chaos expansion that represents the effect of uncertainty as additional constraints in the optimization. Based on observations during the first year of the project, the polynomial chaos expansion has been identified as the most promising method in term of quality and scaling potentiality. Subsequent efforts have been devoted to making this approach scalable to large systems by taking advantage of network structure and the specifics of the power-flow physics.

The second technical approach attempts to accelerate real-time stochastic OPF by using ML tools to identify features of OPF that can be learned offline. Specifically, this approach creates a mapping between the realization of the uncertainty and the active set of constraints at optimality. This method ultimately aims at performing near real-time stochastic OPF and preliminary tests have been successful on DC-OPF.

The third part is dedicated to formulating inner approximations for a robust AC-OPF formulation. Special consideration is given to enforcing stability under uncertainty, which requires guaranteeing feasibility of the AC power flow equations themselves. The main technical tool is creating a convex restriction of the robust OPF in the form of an explicit set of convex quadratic constraints, which guarantees feasibility of both the power flow equations and the technical limits. An algorithm consisting of solving a sequence of convex optimization problems is designed to solve the robust AC-OPF problem. Experiments on test cases from the PGLib suite demonstrates the efficiency of the algorithm.

15. Autonomous Energy Grids: A New Paradigm to Enhance Resiliency, Security, and Reliability and Autonomous Energy Grids: A Unified Framework for Data-Driven Control and Optimization

PI: Dr. Chin-Yao Chang, National Renewable Energy Laboratory (NREL)

Abstract: The project focuses on control methodologies for the autonomous energy systems paradigm championed at NREL. Our objective is to establish an adaptable, scalable, and autonomously organized information and control architecture for the forthcoming power grid. This design will not only foster extensive integration of DERs but will also usher in monumental advancements in resiliency, security, and reliability.

Autonomous energy systems are poised to self-optimize instantaneously in a distributed manner, guaranteeing both economical and efficient performance. Concurrently, they inherently safeguard the power infrastructure against potential contingencies, communication disruptions, and cyber threats.

Central to our approach are algorithms characterized by:

1. Data-driven decision-making: These algorithms keenly tap into real-time system behaviors to autonomously determine control actions.

2. Hierarchical-distributed control and data flow: this characteristic directly addresses challenges related to extensive data flow and system scalability.

Key innovations encompass:

- Feedback-based optimization algorithms: Leveraging real-time data as feedback ensures decisions mirror the immediate system status. By eliminating the necessity for extensive underlying power grid model details, we’ve achieved advanced practical readiness, ensuring adaptability to varied communication environments and assuring convergence with minimal assumptions.
- Privacy-preserved system identification and controls: Recognizing the reluctance of privately owned DERs to divulge data, we’ve introduced a system identification technique.

This ensures that DERs or their representative agents remain non-disclosive of local data. Simultaneously, every agent can discern how its localized controls influence system-wide states. Impressively, these algorithms dovetail perfectly with feedback-based optimization, as evidenced by encouraging simulation results in distribution system controls. Advancements towards integrating NN system models are ongoing.

- Online data-enabled predictive controls: Our pioneering predictive control algorithm is devoid of model dependency, relying solely on input-output data for control generation. Real-time data updates the behavioral system model, making the algorithm suitable for dynamically changing system applications.

Partners: University of California at San Diego, University of Colorado at Boulder, University of Minnesota

16. **Improving Distribution System Resiliency via Deep Reinforcement Learning**

    PI: Dr. Wesley Jones, NREL

    Abstract: Modern power systems require innovative algorithms that facilitate fast online decision-making and optimal sequential control to improve grid resilience after system failure due to extreme event(s). RL can learn, adapt, and optimize decision-making in uncertain and complex environments. Together with its capability to handle system stochasticity and nonlinearity, the offline trained optimal RL control policy largely improves real-time action-readiness, and thus is a promising candidate for enhancing grid resiliency. In this project, NREL will first create a modularized simulation framework with standard interface to the state-of-the-art RL learning platform. Then RL controllers will be trained using scalable RL algorithms on NREL's HPC system. Finally, RL controllers will be evaluated and the potential advantages over existing approaches will be investigated and concluded. Overall, the objective of this project is to 1) explore and identify RL approaches suitable for solving power system control problems; 2) investigate and demonstrate whether and how RL can outperform existing control methods for improving grid resiliency; and 3) discuss the general applicability of RL for solving control problems involving bulk power system in a scalable and flexible manner.

    Partners: Virginia Tech, University of California at Santa Cruz

17. **Virtual Operator Assistance**

    PI: Dr. Yilu Liu, Oak Ridge National Laboratory (ORNL)

    Abstract: This work is collaboration between NREL and ORNL to help operator decision-making. ORNL utilized AI to reduce large system dynamic simulation time from several minutes to a few milliseconds. This is done by offline simulation of a large number of conditions and trains the AI to produce results without simulations at all. The AI agent could find transient stability results for frequency nadir, short circuit clearing time, and small signal stability results reliably much faster than real time.

    Partners: NREL

18. **Mitigation of Cascading Outages by Multi-Layer Interaction Graph**

    PI: Dr. Srdjan Simunovic, ORNL

    Abstract: Objective of the project is to develop a multi-layer interaction graph operational model for the patterns of cascading outages based on interactions between the key components and their failures. Cascading outage is a major threat to grid operations, which usually involves a long chain of events, including faults, equipment failures, protection actions, and uncertainties in real-time operations. Grid operators need to be aware of possible cascading outage patterns in real time to take effective remedial actions. HPC-enabled power system simulations can enable fast simulation and analysis of detailed outage propagation and dynamics of the grid under potential for cascading outages. However, once cascading outages initiate and start propagating to wide areas, real-time mitigation can no longer rely on direct power system simulation due to a limited decision time available to operators.

Partners: University of Tennessee, Knoxville

19. **Adaptive Model Driven Protective Relay with AI/Machine Learning**

    PI: Dr. Matthew Reno, Sandia National Laboratories (SNL)

    Abstract: This project was a collaboration between ORNL and SNL to bring new aspects of ML into power system protection for increased system resilience. We integrated SNL's ML algorithms for improved system reliability and model accuracy with the ORNL model driven adaptive protection relay. Several aspects of ML-based adaptive protection were demonstrated. First, it was demonstrated that an ML module locally connected to the relay could do online learning of protection settings dispatched by the adaptive protection system. As the ML algorithm learned from historical settings, it could be used for model predictive look-ahead control, cybersecurity validation of settings received through the communication system, and a backup system in case the communication network went down. Second, it was demonstrated the ML could be trained using offline simulations of the system to identify faults, classify the type of fault, and determine the distance to the fault. The trained ML algorithm was then embedded into a relay to do purely ML-driven protective relaying. Hardware-in-the-loop tests showed that the ML-based relay was significantly faster than conventional overcurrent relays.

    Partners: ORNL

20. **Machine Learning for Grid Stability**

    PI: Mr. Ross Guttromson, SNL

    Abstract: Grid operating security studies are typically employed to establish operating boundaries, ensuring secure and stable operation for a range of operations under NERC guidelines. However, if these boundaries are violated, the existing system security margins will be largely unknown. As an alternative to the use of complex optimizations over dynamic conditions, this work employs the use of reinforcement-based ML to identify a sequence of secure state transitions which place the grid in a higher degree of operating security with greater static and dynamic stability margins. The approach requires the training of a ML agent to accomplish this task using modeled data and employs it as a decision support tool under severe, near-blackout conditions.

21. **Stability Preserving Adaptive Load Shedding with Energy Justice Aware Actuators**

    PI: Dr. Miguel Jimenez-Aparicio, SNL

    Abstract: For a power system to operate safely, certain critical signals, such as system frequency or voltages, must be maintained within defined safety bounds at all times. Under-frequency load shedding schemes (UFLS) can be used as a last resort to guarantee that the frequency never decreases beyond a defined threshold. However, UFLS are implemented as a blunt tool, disconnecting critical and noncritical load alike without consideration of unintended consequences to vulnerable communities. Moreover, UFLS is increasingly being used on less affluent communities that have limited access to DERs collocated with the loads. With the increase in penetration of distributed generation (DG), and use of the current infrastructure, it is not possible to disconnect the load while keeping the DG connected.

These limitations call for novel control strategies able to exploit the full capabilities of DERs and DGs.

This project aims to develop novel UFLS strategies, including ML techniques, that address these two key challenges by developing adaptive and decentralized strategies to be deployed on load shedding relays using only local information. To avoid unintended consequences that affect disadvantaged communities, load selection for control action will include functions that capture the effect of an action in the communities.

One of the UFLS strategies will be a data-driven approach using a RL model to effectively maintain frequency within bounds while minimizing the effect on disadvantages communities using loads as actuators. This model will be locally deployed on load shedding relays and will take into account local power and socioeconomic data.

22. **Scientific Machine Learning for Simulation and Control in Large-Scale Power Systems**

    PI: Dr. Duncan Callaway, Lawrence Berkeley National Laboratory (LBNL)

    Abstract: This project developed new tools at the intersection of SciML and power systems engineering. These tools will accelerate the simulation of power systems with high penetration of PECs, to assure that we can simulate these systems in near-real time. This acceleration will be achieved by 1) using SciML to develop accurate models of aggregations of PECs to reduce the number of equations we need to solve and 2) using SciML to improve the mathematical techniques we use for solving these equations.

    Partners: NREL, University of California, Berkeley, University of Colorado Boulder, Massachusetts Institute of Technology

23. **Risk-Controlled Expansion Planning in Distributed Resources (REPAIR)**

    PI: Dr. Miguel Heleno, LBNL

    Abstract: The Risk-controlled Expansion Planning with Distributed Resources (REPAIR), developed by Lawrence Berkeley National Laboratory, is an innovative model to support decisions around utility grid planning to prevent and mitigate the impact of outages caused by routine equipment failures (reliability) or by extreme events (resilience), such as storms, earthquakes, or wildfires that long-term interruption of service.

    Partners: ComEd, UT Dallas

24. **A Deep Learning Based Online Platform for Critical Anomaly Detection and Emergency Control to Enhance Grid Reliability and Resiliency**

    PI: Dr. Meng Yue, Brookhaven National Laboratory (BNL)

    Abstract: The objective of this study is to develop a data-driven, deep learning-based solution to prevent the propagation of cascading failures when the grid is challenged by unexpected contingencies or combinational contingencies under uncertain environments. The proposed end-to-end technology will be an online platform capable of evaluating and predicting grid conditions and selecting emergency control actions focused on load-shedding strategies and determination of timing and boundaries for splitting the grid into self-sustained islands, as needed, to mitigate the propagation of cascading failures. This can be considered an enhancement of the last line of defense to prevent a widespread blackout. Both load-shedding strategies and the determination of islanding boundaries require intensive computation and are currently performed in an offline environment. With the rapidly increasing penetration level of renewables, additional uncertainties are introduced into the grid operation, making the computation for grid control even more demanding and difficult.

Partners: Purdue University, Southern Methodist University, New York Power Authority

25. Hierarchical Machine Learning-Based Optimal Parameterization Scheme for WECC Composite Load Model Under All Disturbances

PI: Dr. Meng Yue, BNL

Abstract: Accurate load modeling is a key to characterizing the dynamic behaviors of power systems. In the past few years, the WECC Load Modeling Work Group under the WECC Modeling and Validation Subcommittee has been continuously developing a CLM representing the aggregation of various end-user load devices. In the WECC CLM, load devices are categorized based on the features and each category of the loads is represented by an aggregated model, which is expected to be sufficient to duplicate the aggregated behaviors by properly choosing the parameters. However, there is a lack of a systematic approach to tuning the CLM parameters and the CLM parameters carefully selected for one fault event cannot achieve satisfactory performance in another fault.

We propose to develop an optimal parameterization scheme for the WECC CLM based on a simulation approach assisted by a unique combination of state-of-the-art ML techniques, including IL and RL. The parameterization scheme will be used for thorough validation and benchmarking of the WECC CLM and for developing optimal parameters for the CLM to duplicate dynamic behaviors of the aggregated loads and the entire system under various disturbances and operating conditions of the grid. The same parameterization scheme will be extended for cases with incomplete information about the loads, (i.e., some parameters of the loads are unknown while some other information is becoming more and more available based on DOE's efforts). Additionally, we will propose an alternative approach to develop a library characterizing the basic load features that can be used to better build composite load models. Note that the focus of this study is on reproducing the post-contingency dynamic behaviors under various scenarios by optimizing the load model parameters, and the proposed generic approach differs from the existing studies that target only the specific event(s).

Partners: Southern Methodist University, WECC Modeling and Validation Subcommittee and PacifiCorp, New York Power Authority

26. Quantum Reinforcement Learning in Power System Operations

PI: Dr. Peng Zhang, BNL

Abstract: The objective of this study is to develop a QRL framework that can efficiently solve the computationally expensive control and optimization problems in power system operation and apply the developed QRL framework to topology control of the power grid as a case study. In this study, we propose to develop a QRL model that can solve the decision, control, and optimization problems in power system operation more efficiently. Previous QRL work was used in maze navigation problems and software-defined networking problems, such as the control of cognitive-radio systems. It was shown that the quantum deep RL agent can converge faster and more stably while using fewer model parameters. Such quantum advantage will improve the computation efficiency significantly in the power system operation.

Partners: Southern Methodist University

27. Load Sculptor (Robust Dynamic Load Modeling and Uncertainty Quantification)

PI: Dr. Nan Duan and Dr. Nai-Yuan Chiang, Lawrence Livermore National Laboratory (LLNL)

Abstract: Dynamic load models play a crucial role in facilitating utility operations by assisting in tasks, such as planning, stability assessment, and control. However, their development traditionally involves resource-intensive methodologies, often resulting in complex models that bear computational burdens and susceptibility to parameter uncertainties. To tackle these challenges, this project introduces a transformative approach to dynamic load modeling and uncertainty quantification.

This project encompasses two primary objectives. Firstly, it aims to construct surrogate load models that provide cost-effective alternatives for dynamic simulation and security assessments while maintaining the necessary accuracy levels. This endeavor seeks to streamline simulations and strengthen the assessment of system stability and security. Secondly, this project aims to establish robust load model parameter sets capable of representing a wide spectrum of operating conditions. It endeavors to quantify the impact of parameter uncertainties on simulation outcomes. This critical analysis addresses the potential pitfalls of parameter uncertainty, including misleading stability assessments, security vulnerabilities, and economic implications.

Through the innovative methodologies and advanced data-driven techniques, this project redefines dynamic load modeling. By improving accuracy, simplifying computational complexities, and addressing parameter uncertainties, this project empowers utilities with refined tools that enable more informed and effective decision-making in power system operations.

Partners: Mississippi State University, University of Connecticut, PJM, ISO-NE

28. **Hybrid Learning of Black-Box and White-Box Power System for Large-Scale Adaptive Optimization Under Uncertainty**

    PI: Dr. Xiao Chen, LLNL

    Abstract: This project focuses on the development of efficient computational frameworks for optimizing hybrid problems in power systems. These problems involve both known mathematical functions (“white-box”) and unknown or incomplete information (“black-box”). The project extends this hybrid framework by integrating adaptive surrogates with high-fidelity system models for multi-objective and chance-constrained optimization. The aim is to achieve optimal trade-offs between multiple objectives and data availability while effectively managing the risk of power grid failures.

    Partners: Virginia Tech, University of Connecticut

29. **Alternative Grid Operations**

    PI: Dr. Steve Bukowski, INL

    Abstract: Many challenges have been solved by the electric power industry in support of the national power grid over the last 120 years. However, if the same problem existed today would we solve it in a similar fashion with existing technology? This project is investigating power systems operations in the wake of resource transition from synchronous generation to inverter-based-resource generation, specifically in system protection. This project is leveraged ML in speech recognitions and the PSSN to develop a real-time environment a ML-algorithm to identify faults. Advanced Grid Operations (AGO) leverages the PSNN to process voltage and current waveform data in Real-Time to identify events and anomalies as they take place. The AGO team successfully demonstrated PARITY in the fault identification between a distribution relay (SEL-351) and the machine learning Protective Relay developed under this project. In this demonstration an RTDS was used to simulate distribution feeder while utilizing hardware-in-the-loop to interact both the distribution relay and the ML-relay. In the demonstration both relays identified faults created within RTDS correctly and timely.

The AGO project has shown that an AI approach to protection works a conventional power system relay in a side-by-side test. We are organizing to share our training dataset through the Grid Event Signature Library at ORNL. The first dataset is of simple bolted faults. We are working on a new dataset for motor starts. Motors starts can look similar to faults. Our next objective is to train the algorithm to distinguish between a fault and a motor start. Ultimately, AGO intends to train the AI relay algorithm on all events and anomalies that take place on the power grid.

This is particularly important in the context of renewable energy. Solar, battery storage and many forms of wind rely on inverters to convert the direct current (DC) produced by the renewable energy source to alternating current (AC) used on the power grid. Unfortunately, the inverters operate in such a way as to inhibit the ability of circuit breakers from operating correctly. This new approach to protection using the PSNN will overcome the challenges presented by inverter technologies..

Partners: New Mexico State University, Clemson University, Visgence

Appendix B – DOE-OE AGM Program AI/ML Publications

- Aghajan, A., J. Poveda, M. Jimenez-Aparicio, M. Ropp, "Adaptive Under-Frequency Load Shedding with Socio-Technical Criticality Functions," submitted to 2024 Kansas Power and Energy Conference (KPEC).

- Ahmed, A., Basumallik, S., Srivastava, A.K., Wu, Y. and Choudhury, S., 2023. "Federated Synchrophasor Data Prediction, Aggregation and Inference Using Deep Learning: A Case of Proactive Control for Short-Term Stability." *IEEE Transactions on Power Delivery*.

- Baros, S., C.-Y. Chang, G. Colon-Reyes, and A. Bernstein. 2022. "Online Data-Enabled Predictive Control." *Automatica* 138: 109926. https://doi.org/10.1016/j.automatica.2021.109926.

- Buason, P., S. Misra, and D. Molzahn, 2022. "A Data-driven Method for Locating Sensors and Selecting Alarm Thresholds to Identify Violations of Voltage Limits in Distribution Systems." arXiv:2210.09414.

- Buason, P., S. Misra, and D. Molzahn, 2022. "A Sample Based Approach for Computing Conservative Linear Power Flow Approximations." *Electric Power Systems Research*.

- Chen, Y., T. Jiang, M. Heleno, A. Moreira, and Y. R. Gel. 2022. "Evaluating Distribution System Reliability with Hyperstructures Graph Convolutional Nets." IEEE International Conference on Big Data (Big Data), Osaka, Japan, December 17–20, 2022. https://doi.org/10.1109/BigData55660.2022.10020715.

- Chen, Y., T. Yin, R. Huang, X. Fan, and Q. Huang. "Big Data Analytic for Cascading Failure Analysis," IEEE International Conference on Big Data (Big Data), Los Angeles, CA, December 9–12, 2019, pp. 1625–1630. https://doi.org/10.1109/BigData47090.2019.9005593.

- Cheolmin, K., K. Kim, P. Balaprakash, and M. Anitescu. 2019. "Graph Convolutional Neural Networks for Optimal Load Shedding under Line Contingency." 2019 IEEE Power & Energy Society General Meeting (PESGM), Atlanta, GA, August 4–8, 2019. https://doi.org/10.1109/PESGM40551.2019.8973468.

- Deka, D., and S. Misra. 2019. "Learning for DC-OPF: Classifying Active Sets Using Neural Nets." 2019 IEEE Milan PowerTech, Milan, Italy, June 23–27, 2019, pp. 1–6. https://doi.org/10.1109/PTC.2019.8810819.

- Duan, N., J. B. Zhao, B. Wang, S. Wang, "Discrete Empirical Interpolation Method based Dynamic Load Model Reduction," *IEEE Power and Energy Society General Meeting*, July 25-29, pp. 1-5, 2021.

- Fan, X., X. Li, E. L. Barrett, Q. Huang, J. G. O'Brien, R. Huang, Z. Hou, and R. Diao. 2021. Transformative Remedial Action Scheme Tool (TRAST). U.S. Patent No. 16,435,352.

- Gao, W., R. Fan, R. Huang, Q. Huang, Y. Du, W. Qiao, S. Wang, and D. W. Gao. 2022. "Improving DFIG Performance under Fault Scenarios through Evolutionary

Reinforcement Learning Based Control.” *IET Generation, Transmission &. Distribution* 16 (19): 3825–3836. https://doi.org/10.1049/gtd2.12563.

- Gao, W., R. Fan, W. Qiao, S. Wang, and D. W. Gao. 2023. “Fast Frequency Response Using Reinforcement Learning-Controlled Wind Turbines,” 2023 IEEE IAS Annual Meeting, Nashville, TN, October 29–November 2, 2023. https://doi.org/10.1109/IAS54024.2023.10406378.

- Girigoudar, K., and L. Roald, “Linearized Three-Phase Optimal Power Flow Models for Distribution Grids with Voltage Unbalance,” accepted to IEEE Conference on Decision and Control (CDC), Dec 2021.

- Gorka, J., T. Hsu, T, W. Li, Y. Maximov, and L. Roald. 2024. “Cascading Blackout Severity Prediction with Statistically-Augmented Graph Neural Networks.” *Power Systems Computations Conference, 2024 (accepted)*.

- Gu, X., S. S. Dey, Á. S. Xavier, and F. Qiu. 2022. “Exploiting Instance and Variable Similarity to Improve Learning-Enhanced Branching.” arXiv:2208.10028.

- Gupta, S., S. Misra, D. Deka, and V. Kekatos. 2022. “DNN-Based Policies for Chance-Constrained Stochastic AC-OPF.” *Electric Power Systems Research* 213: 108563. https://doi.org/10.1016/j.epsr.2022.108563.

- Guddanti K., B. Vyakaranam, K. Mahapatra, Z. Hou, P.V. Etingov, N.A. Samaan, and T.B. Nguyen, et al. 2023. "Dynamic Security Analysis Framework for Future Large Grids with High Renewable Penetrations." *IEEE Access* 11. PNNL-SA-174886. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=10021977

- Guddanti K., B. Vyakaranam, T.B. Nguyen, S. Kincic, P.V. Etingov, Q.H. Nguyen, and N.A. Samaan, et al. 2022. "Identification of Voltage Stability Critical Locations for Future Large Grids with Dynamics and High Renewable Mix." *IEEE Open Access Journal of Power and Energy*. PNNL-SA-178082. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=10217798

- Hu, Y., A. Mulawarman, Z. Cheng, A. Elandaloussi, A. Apostolov, A. Bidram, A. Rajapakse, C. Arbona, D. Sabin, J. Ponraj, J. Raymond, J. Blumschein, J. Pineros, M. Reno, N. Nair, R. Das, R. Fowler, S. Billaut, S. Brahma, S. Kamalasadan, V. Madani, Y. Liu, Y. Yin. “Practical Applications of Artificial Intelligence and Machine Learning in Power System Protection and Control,” IEEE Power System Relaying and Control Committee, PES-TR112, 2023.

- Huang, R., Y. Chen, T. Yin, X. Li, A. Li, J. Tan, W. Yu, Y. Liu, and Q. Huang. 2021. “Accelerated Derivative-Free Deep Reinforcement Learning for Large-Scale Grid Emergency Voltage Control.” *IEEE Transactions on Power Systems* 37 (1): 14-25. https://doi.org/10.1109/TPWRS.2021.3095179.

- Huang, R., W. Gao, R. Fan, and Q. Huang. 2022. “Damping Inter-area Oscillation Using Reinforcement Learning Controlled TCSC.” *IET Generation, Transmission &. Distribution* 16 (11): 2265–2275. https://doi.org/10.1049/gtd2.12441.

- Jimenez-Aparicio, M., J. Hernandez-Alvidrez, A. Y. Montoya, and M. J. Reno, "Embedded, Real-Time, and Distributed Traveling Wave Fault Location Method Using Graph Convolutional Neural Networks" *Energies*, 2022.

- Jimenez-Aparicio, M., J. Hernandez-Alvidrez, A. Y. Montoya, and M. J. Reno, "Micro Random Forest: A Local, High-Speed Implementation of a Machine-Learning Fault Location Method for Distribution Power Systems," IEEE PES General Meeting, 2023.

- Jimenez-Aparicio, M., T. Patel, M. J. Reno, J. Hernandez-Alvidrez. "Protection Analysis of a Traveling-Wave, Machine-Learning Protection Scheme for Distributions Systems With Variable Penetration of Solar PV." *IEEE Access*, 2023.

- Kamal, M., W. Li, D. Deka, and H. Mohsenian-Rad. 2022, May. "Physics-conditioned Generative Adversarial Networks for State Estimation in Active Power Distribution Systems with Low Observability." In 2022 International Conference on Smart Grid Synchronized Measurements and Analytics (SGSMA) (pp. 1-6). IEEE.

- Khazeiynasab, S., J. B. Zhao, I. Batarseh, B. Tan, "Power Plant Model Parameter Calibration Using Conditional Variational Autoencoder," *IEEE Trans. Power Systems*, vol. 37, no. 2, pp. 1642-1652, 2022.

- Khazeiynasab, S., J. B. Zhao, N. Duan, "WECC Composite Load Model Parameter Identification Using Deep Learning Approach," *IEEE Power and Energy Society General Meeting*, pp. 1-5, 2022.

- Kurup, A. R., A. Summers, A. Bidram, M. J. Reno, and M. Martinez-Ramon, "Ensemble Models for Circuit Topology Estimation, Fault Detection, and Classification in Distribution Systems." *Sustainable Energy, Grids and Networks*, 2023.

- Lee, D., K. Turitsyn, D. Molzahn, and L. Roald. "Robust AC Optimal Power Flow with Convex Restriction," *IEEE Transactions on Power Systems,* 2021.

- Li, W., and D. Deka. 2021. "PPGN: Physics-preserved Graph Networks for Real-time Fault Location in Distribution Systems with Limited Observation and Labels." *56th Hawaii International Conference on System Sciences (HICSS) 2023.*

- Li, W., D. Deka, R. Wang, and M. Paternina. 2023. "Physics-constrained Adversarial Training for Neural Networks in Stochastic Power Grids." *IEEE Transactions on Artificial Intelligence*.

- Li, X., X. Fan, H. Ren, Z. Hou, Q. Huang, S. Wang, and O. Ciniglio. 2019. "Data-Driven Feature Analysis in Control Design for Series-Compensated Transmission Systems." *IEEE Transactions on Power Systems* 34 (4): 3297–3299. https://doi.org/10.1109/TPWRS.2019.2912711.

- Lin, Y., J. Wang, and M. Yue, "Free-Form Dynamic Load Model Synthesis With Symbolic Regression Based on Sparse Dictionary Learning," in *IEEE Transactions on Power Systems*, vol. 39, no. 2, pp. 2438-2447, March 2024, doi: 10.1109/TPWRS.2023.3270139.

❖ Lukashevich, A., V. Gorchakov, P. Vorobev, D. Deka, and Y. Maximov. 2023. “Importance Sampling Approach to Chance-constrained dc Optimal Power Flow.” *IEEE Transactions on Control of Network Systems*.

❖ Métivier, D., M. Vuffray, and S. Misra. "Efficient Polynomial Chaos Expansion for Uncertainty Quantification in Power Systems." *Electric Power Systems Research* 189, 106791, June 2020

❖ Mezghani, I., S. Misra, and D. Deka. 2020. “Stochastic AC Optimal Power Flow: A Data-Driven Approach.” *Electric Power Systems Research* 189: 106567. https://doi.org/10.1016/j.epsr.2020.106567.

❖ Misra, S., L. Roald, and Y. Ng. 2020. “Learning for Constrained Optimization: Identifying Optimal Active Constraint Sets.” Under review in *IJOC*.

❖ Mitrovic, M., O. Kundacina, A. Lukashevich, S. Budennyy, P. Vorobev, V. Terzija, and D. Deka. 2023. “Gp cc-opf: Gaussian Process Based Optimization Tool for Chance-constrained Optimal Power Flow.” *Software Impacts*, *16*, 100489.

❖ Mitrovic, M., A. Lukashevich, P. Vorobev, V. Terzija, S. Budennyy, Y. Maximov, and D. Deka. 2023. “Data-driven Stochastic AC-OPF Using Gaussian Process Regression.” *International Journal of Electrical Power & Energy Systems*, *152*, 109249.

❖ Moya, C., S. Zhang, G. Lin, and M. Yue, “DeepONet-Grid-UQ: A Trustworthy Deep Operator Framework for Predicting the Power Grid's Post-Fault Trajectories,” *Neurocomputing*, Volume 535, May 2023.

❖ Mühlpfordt, T., L. Roald, V. Hagenmeyer, T. Faulwasser, and S. Misra. “Chance-Constrained AC Optimal Power Flow: A Polynomial Chaos Approach,” *IEEE Transactions on Power Systems*, Volume: 34, Issue: 6, Nov. 2019.

❖ Mühlpfordt, T., L. Roald, V. Hagenmeyer, T. Faulwasser, and S. Misra. “On Polynomial Real-Time Control Policies in Stochastic AC Optimal Power Flow,” accepted to Power System Computation Conference (PSCC), June 2020.

❖ Mukherjee, S., Nandanoori, S.P., Guan, S., Agarwal, K., Sinha, S., Kundu, S., Pal, S., Wu, Y., Vrabie, D.L. and Choudhury, S., 2022, December. “Learning Distributed Geometric Koopman Operator for Sparse Networked Dynamical Systems.” In *Learning on Graphs Conference* (pp. 45-1). PMLR.

❖ Nandanoori, S., S. Guan, S. Kundu, S. Pal, K. Agarwal, Y. Wu, and S. Choudhury. 2022. “Graph Neural Network and Koopman Models for Learning Networked Dynamics: A Comparative Study on Power Grid Transients Prediction.” *IEEE Access* 10: 32337–32349. https://doi.org/10.1109/ACCESS.2022.3160710.

❖ Nandanoori, S., S. Kundu, S. Pal, K. Agarwal, and S. Choudhury. 2020. “Model-Agnostic Algorithm for Real-Time Attack Identification in Power Grid Using Koopman Modes.” In IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (IEEE SmartGridComm 2020), Tempe, AZ, November 11–13, 2020, pp. 1–6.

- Nandanoori S., S. Kundu, S. Pal, S. Choudhury, and K. Agarwal. 2021. "Nominal and Adversarial Synthetic PMU Data for Standard IEEE Test Systems." (https://data.pnnl.gov/publication/grid_prediction)
- Nandanoori, S., S. Pal, S. Sinha, S. Kundu, K. Agarwal, and S. Choudhury. 2021. "Data-driven Distributed Learning of Multi-agent Systems: A Koopman Operator Approach." 2021 60th IEEE Conference on Decision and Control (CDC), Austin, TX, December 14-17, 2021, pp. 5059–5066. https://doi.org/10.1109/CDC45484.2021.9682872.
- Ng, Y., S. Misra, L. Roald, and S. Backhaus. 2018. "Statistical Learning for DC Optimal Power Flow," Power Systems Computation Conference (PSCC), Dublin, Ireland, June 11–15, 2018, pp. 1–7. https://doi.org/10.23919/PSCC.2018.8442859.
- Ojetola, S. T., and M. J. Reno, "Time Series Classification for Detecting Fault Location in a DC Microgrid," *IEEE PES Grid Edge Technologies Conference & Exposition*, 2023.
- Ojetola, S. T., M. J. Reno, J. Flicker, D. Bauer, and D. Stoltzfuz, "Testing Machine Learned Fault Detection and Classification on a DC Microgrid," *IEEE Innovative Smart Grid Technologies* (ISGT), 2022.
- Pareek, P., D. Deka, S. Misra, 2023. "Data-efficient Power Flow Learning for Network Contingencies." arXiv:2310.00763
- Pareek, P., D. Deka, S. Misra, 2023. "Graph Structured Kernel Design for Power Flow Learning Using Gaussian Processes." arXiv preprint arXiv:2308.07867.
- Paruthiyil, S., A. Bidram, and M. J. Reno, "A Physics-informed Learning Technique for Fault Location of DC Microgrids Using Traveling Waves," *IET Generation, Transmission, and Distribution*, 2022.
- Penne, M. et al. 2024. "Robust Disturbance Rejection Rotor Current Control of Doubly-Fed Induction Generators," in *IEEE Transactions on Industry Applications*, doi: 10.1109/TIA.2024.3352553.
- Poudel, B. P., A. Bidram, M. J. Reno, and A. Summers, "Zonal Machine Learning-based Protection for Distribution Systems." *IEEE Access*, 2022.
- Qin, C., K. Guddanti, B. Vyakaranam, T. Nguyen, K. Mahapatra, Q. Nguyen, Z. Hou, P. Etingov, and N. Samaan. "Critical Zone Identification Framework for Bulk Electric System Security Assessment," *International Journal of Electrical Power & Energy Systems*, Volume 155, Part B, 2024, 109542, ISSN 0142-0615, https://www.sciencedirect.com/science/article/pii/S0142061523005999.
- Roberts, C., J. D. Lara, R. Henriquez-Auba, M. Bossart, R. Anantharaman, C. Rackauckas, B.-M. Hodge, and D. S. Callaway. 2022. "Continuous-Time Echo State Networks for Predicting Power System Dynamics." *Electric Power Systems Research* 212: 108562. https://doi.org/10.1016/j.epsr.2022.108562.
- Summers, A., T. Patel, R. Matthews, and M. J. Reno, "Prediction of Relay Settings in an Adaptive Protection System," *IEEE Innovative Smart Grid Technologies* (ISGT), 2022.

- Sun, Y., X. Fan, Q. Huang, X. Li, R. Huang, T. Yin, and G. Lin. 2019. "Local Feature Sufficiency Exploration for Predicting Security-Constrained Generation Dispatch in Multi-area Power Systems." In 17th IEEE International Conference on Machine Learning and Applications, pp. 1283–1289. https://doi.org/10.1109/ICMLA.2018.00208.

- Sun, Y., C. Moya, G. Lin, and M. Yue, "DeepGraphONet: A Deep Graph Operator Network to Learn and Zero-Shot Transfer the Dynamic Response of Networked Systems," *IEEE Systems Journal*, vol. 17, no. 3, pp. 4360-4370, Sept. 2023, doi: 10.1109/JSYST.2023.3298884.

- Tan, B., J. B. Zhao, "Debiased Uncertainty Quantification Approach for Probabilistic Transient Stability Assessment," *IEEE Trans. Power Systems*, 2023.

- Tan, B., J. B. Zhao, Q. Huang, Y. Zhang, H. Zhang, "Explainable Bayesian Neural Network for Probabilistic Transient Stability Analysis Considering Wind Energy," *IEEE Power and Energy Society General Meeting*, pp. 1-5, 2022 (Best Paper Award).

- Tan, B., J. B. Zhao, W. Liu, N. Duan, "Interpretable Data-Driven Probabilistic Power System Load Margin Assessment with Uncertain Renewable Energy and Loads," IEEE PES ISGT Aisa, pp. 1-5, 2022 (Best Paper Award).

- Tan, B., J. B. Zhao, D. Nan, "Amortized Bayesian Parameter Estimation Approach for WECC Composite Load Model," *IEEE Trans. Power Systems*, 2023.

- Tong, S., J. Zhao, X. Chen, "Analytic Input Convex Neural Networks-based Model Predictive Control for Power System Transient Stability Enhancement," selected as one of the best conference papers for 2023 IEEE PES general meeting

- Tong, S., J. Zhao, X. Chen, "Deep Sigma Point Processes-Assisted Chance-Constrained Power System Transient Stability Preventive Control," *IEEE Transactions on Power Systems*, Early Access, pp. 1–13, 2023.

- Verzi, S., R. Guttromson, and A. Sorensen. "Using Reinforcement Learning to Increase Grid Security Under Contingency Conditions." In 2022 IEEE Kansas Power and Energy Conference (KPEC), pp. 1-4. IEEE, 2022.

- Verzi, S., R. Guttromson, A. Sorensen, and C. Jones. 2021. "AlphaGrid: Grid Stability Using Machine Learning State Space Navigation." (No. SAND2021-8290PE). Sandia National Lab.(SNL-NM), Albuquerque, NM (United States).

- Vyakaranam B., K. Mahapatra, X. Li, H. Wang, P.V. Etingov, Z. Hou, and Q.H. Nguyen, et al. 2021. "Novel Data-Driven Distributed Learning Framework for Solving AC Power Flow for Large Interconnected Systems." *IEEE Open Access Journal of Power and Energy* 8. PNNL-SA-158500. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9468991

- Vyakaranam B., Q.H. Nguyen, T.B. Nguyen, N.A. Samaan, and R. Huang. 2021. "Automated Tool to Create Chronological AC Power Flow Cases for Large Interconnected Systems." *IEEE Open Access Journal of Power and Energy* 8. PNNL-SA-157963. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9416491

- Wei, G., F. Qiu, and X. Liu. 2023. “A Convolutional Non-homogeneous Poisson Process Model to Quantify Wildfire Risk for Power Delivery Networks.” Finalist of Data Analytics & Information Systems (DAIS) Best Track Paper, 2023 IISE Annual Conference & Expo, New Orleans, LA, May 20–23, 2023.

- Weisser, T., L. Roald, and S. Misra. "Chance-constrained Optimization for Non-linear Network Flow Problems." 2018.

- Wilches-Bernal, F., M. Jiménez-Aparicio, and M. J. Reno, “Algorithm for Fast Fault Location and Classification Based on Mathematical Morphology and Machine Learning,” *IEEE Innovative Smart Grid Technologies* (ISGT), 2022.

- Wilches-Bernal, F., M. Jiménez-Aparicio, and M. J. Reno, “A Machine Learning-based Method using the Dynamic Mode Decomposition for Fault Location and Classification,” *IEEE Innovative Smart Grid Technologies* (ISGT), 2022.

- Xavier, Á. S., F. Qiu, and S. Ahmed. 2021. “Learning to Solve Large-Scale Security-Constrained Unit Commitment Problems.” *INFORMS Journal on Computing* 33 (2): 739–756. https://doi.org/10.1287/ijoc.2020.0976.

- Xu, C., Y. Xie, D. A. Zuniga Vazquez, R. Yao, and F. Qiu. 2023. “Spatio-temporal Wildfire Prediction Using Multi-modal Data.” *IEEE Journal on Selected Areas in Information Theory* 4: 302–313. https://doi.org/10.1109/JSAIT.2023.3276054.

- Xu, Y., M. Korkali, L. Mili, X. Chen, J. Valinejad, and Z. Zheng, “An Adaptive-Importance-Sampling-Enhanced Bayesian Approach for Topology Estimation in an Unbalanced Power Distribution System,” *IEEE Transactions on Power Systems*, vol. 37, no. 3, pp. 2220–2232, May 2022.

- Xu, Y., M. Korkali, L. Mili, J. Valinejad, T. Chen, and X. Chen, “An Iterative Response-Surface-Based Approach for Chance-Constrained AC Optimal Power Flow Considering Dependent Uncertainty,” *IEEE Transactions on Smart Grid,* vol. 12, no. 3, pp. 2696–2707, May 2021.

- Xu, Y., L. Mili, M. Korkali, X. Chen, J. Valinejad, and L. Peng, “A Surrogate-Enhanced Scheme in Decision Making under Uncertainty in Power Systems,” *Proceedings of the 2021 IEEE Power and Energy Society General Meeting (PESGM),* July 25-29, 2021 (virtual).

- Ye, K., J. B. Zhao, N. Duan, D. Maldonado, “Stochastic Power System Dynamic Simulation and Stability Assessment Considering Dynamics from Correlated Loads and PVs,” *IEEE Trans. Industry Applications*, vol. 58, no. 6, pp. 7764-7775, 2022.

- Ye, K., J. B. Zhao, N. Duan, D. Maldonado, “Uncertainty Quantification of Loads and Correlated PVs on Power System Dynamic Simulations,” IEEE IAS Industrial & Commercial Power System Asia, 2021 (Best Paper Award).

- Ye, K., J. B. Zhao, N. Duan, Y. Zhang, “Physics-Informed Sparse Gaussian Process for Probabilistic Stability Analysis of Large-Scale Power System with Dynamic PVs and Loads,” *IEEE Trans. Power Systems*, vol. 38, no. 3, pp. 2868-2879, 2023. (2023 IEEE PES Technical Committee Prize Paper Award)

- Zeng, S., A. Kody, Y. Kim, K. Kim, and D. K. Molzahn. 2022. "A Reinforcement Learning Approach to Parameter Selection for Distributed Optimal Power Flow." *Electric Power Systems Research* 212: 108546. https://doi.org/10.1016/j.epsr.2022.108546.

- Zhang, X., Y. Liu, J. Zhao, J. Liu, M. Korkali and X. Chen, "Short-circuit Current Constrained Unit Commitment and Transmission Switching Model for Improving Renewable Integration: An MILP formulation," *IET Generation, Transmission. Distribution,* vol. 16, no. 9, pp. 1743–1755, Feb 2022.

- Zhang, Y., C. Chen, G. Liu, T. Hong, and F. Qiu. 2021. "Approximating Trajectory Constraints with Machine Learning – Microgrid Islanding with Frequency Constraints." *IEEE Transactions on Power Systems* 36 (2): 1239–1249. https://doi.org/10.1109/TPWRS.2020.3015913.

- Zhang, Y., H. Cui, J. Liu, F. Qiu, T. Hong, R. Yao, and F. Li. 2022. "Encoding Frequency Constraints in Preventive Unit Commitment Using Deep Learning with Region-of-Interest Active Sampling." *IEEE Transactions on Power Systems* 37 (3): 1942–1955. https://doi.org/10.1109/TPWRS.2021.3110881.

- Zhang, Y., J. Liu, F. Qiu, T. Hong, and R. Yao. 2022. "Deep Active Learning for Solvability Prediction in Power Systems." *Journal of Modern Power Systems and Clean Energy* 10 (6): 1773–1777. https://doi.org/10.35833/MPCE.2021.000424.

- Zhang, Y., F. Qiu, T. Hong, Z. Wang, and F. Li. 2022. "Hybrid Imitation Learning for Real-Time Service Restoration in Resilient Distribution Systems." *IEEE Transactions on Industrial Informatics* 18 (3): 2089–2099. https://doi.org/10.1109/TII.2021.3078110.

- Zhang, Y., M. Yue, and J. Wang. "Off-policy Deep Reinforcement Learning with Automatic Entropy Adjustment for Adaptive Online Grid Emergency Control," *Electric Power System Research*, Volume 217, April 2023.

- Zhang, Y., M. Yue, J. Wang and S. Yoo, "Multi-Agent Graph-Attention Deep Reinforcement Learning for Post-Contingency Grid Emergency Voltage Control," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 3, pp. 3340-3350, March 2024, doi: 10.1109/TNNLS.2023.3341334.

- Zhao, T., M. Yue, and J. Wang, "Deep-Learning-Based Koopman Modeling for Online Control Synthesis of Nonlinear Power System Transient Dynamics," in *IEEE Transactions on Industrial Informatics*, vol. 19, no. 10, pp. 10444-10453, Oct. 2023, doi: 10.1109/TII.2023.3240939.

- Zhao, T., M. Yue, and J. Wang, "Structure-informed Graph Learning of Networked Dependencies for Online Prediction of Power System Transient Dynamics," in *IEEE Transactions on Power Systems*, Vol. 37, No. 6, November 2022.

- Zheng, X., J. Wang, and M. Yue, "A Fast Quantum Algorithm for Searching the Quasi-Optimal Solutions of Unit Commitment," accepted by *IEEE Power Engineering Letters*.