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## REVIEW

# Data-driven operation of the resilient electric grid: A case of COVID-19

 H. Noorazar | A. Srivastava  | S. Pannala | Sajjan K Sadanandan 

School of Electrical Engineering and Computer Science, Washington State University, Pullman, Washington, USA  
(Email: [sajan.sadanandan@wsu.edu](mailto:sajan.sadanandan@wsu.edu))

**Correspondence**

A. Srivastava, The School of Electrical Engineering and Computer Science, Washington State University, Pullman, Washington, 99164, USA and West Virginia University, Morgantown, WV, 26505, USA.  
Email: [anurag.srivastava@mail.wvu.edu](mailto:anurag.srivastava@mail.wvu.edu)

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**Abstract**

Electrical energy is a vital part of modern life, and expectations for grid resilience to allow a continuous and reliable energy supply has tremendously increased even during adverse events (e.g. Ukraine cyberattack, Hurricane Maria). The global pandemic COVID-19 has raised the electric energy reliability risk due to potential workforce disruptions, supply chain interruptions, and increased possible cybersecurity threats. Additionally, the pandemic introduces a significant degree of uncertainty to the grid operation in the presence of other challenges including aging power grids, high proliferation of distributed generation, market mechanism, and active distribution network. This situation increases the need for measures for the resiliency of power grids to mitigate the impact of the pandemic as well as simultaneous extreme events including cyberattacks and adverse weather events. Solutions to manage such an adverse scenario will be multi-fold: (a) emergency planning and organisational support, (b) following safety protocol, (c) utilising enhanced automation and sensing for situational awareness, and (d) integration of advanced technologies and data points for ML-driven enhanced decision support. Enhanced digitalisation and automation resulted in better network visibility at various levels, including generation, transmission, and distribution. These data or information can be employed to take advantage of advanced machine learning techniques for automation and increased power grid resilience. In this paper, the resilience of power grids in the face of pandemics is explored and various machine learning tools that can be helpful to augment human operators are discussed by: (a) reviewing the impact of COVID-19 on power grid operations and actions taken by operators/organisations to minimise the impact of COVID-19, and (b) presenting recently developed tools and concepts of machine learning and artificial intelligence that can be applied to increase the resiliency of power systems in normal and extreme scenarios such as the COVID-19 pandemic.

## 1 | INTRODUCTION

Electricity is essential for daily life, and the electric power industry is the backbone of the country's economy. Interruption in the flow of energy will lead to catastrophic impacts on other critical infrastructure, like the inability to manufacture essential needs and the hindrance of healthcare systems. The consequences are far-reaching and impactful. Consistent supply of electricity is a matter of national security: during the COVID-19 pandemic, "the Department of Homeland Security listed power

plants, dams, nuclear reactors, communications, and transportation systems as critical infrastructure." [4, 5].

Power grids are actively generating and are continuously being monitored and maintained to provide reliable energy for each customer. The transmission ecosystem is under constant monitoring to assess the condition of the system and to execute appropriate actions if needed. Figure 1 shows the operation and control layout of existing power grids.

Distribution control room operators must monitor grid load and coordinate with field crews during routine maintenance and

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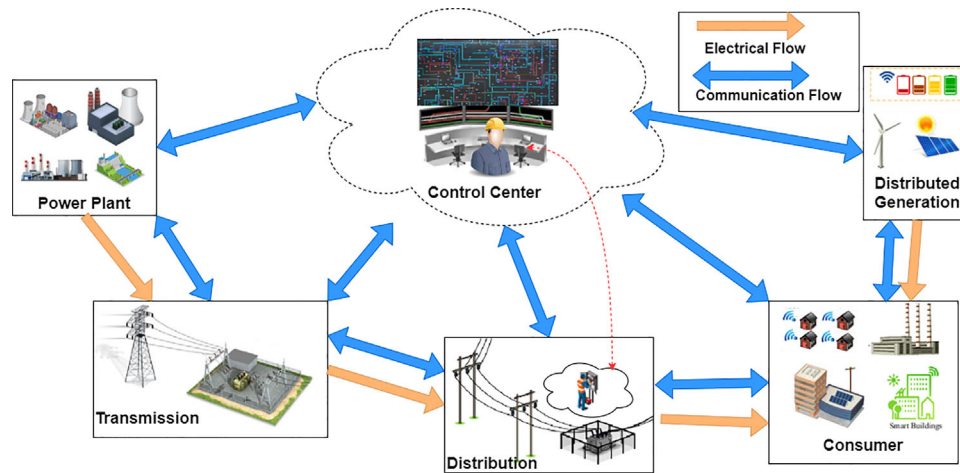


FIGURE 1 Overview of the power system operation and control

unexpected events [6] to restore power whenever abnormal circumstances cause outages.

## 1.1 | Background

Having robust contingency plans in the case of emergencies is vital. The energy and utility sector in the U.S. is well planned and designed to withstand disasters and emergencies. Still, “since 1980, there have been 246 weather and climate disasters exceeding \$1.6 trillion in remediation” [7]. Contingency planning has also improved and has been reshaped by pandemics of the past [8]. Examples of such experiences are the Black Death, the 1918 Spanish Flu, the influenza pandemics of 1957 and 1968, the SARS outbreak in the mid-2000s, and the 2009 H1N1 influenza. Nevertheless, the novel situations caused by COVID-19, with its fast spread and high transmissibility rate, have significantly affected the utility industry. Most of the contingency and backup plans are designed for physical assets and do not consider the health of employees [9]. We emphasise the fact that most, if not all, of the literature studying the resilience of power grid systems focuses its analysis on extreme weather conditions or cyberattacks that threaten the physical components of a power grid. To date, extant literature on the human aspects of power grid resiliency is very poor. For example, Jufri et al. [2] explore definitions of resiliency, grid exposure, and grid vulnerability in their review paper. All of the resources explored by [2] focus on extreme weather events as low-probability high-impact events. Building barriers and walls to protect physical assets against flood is discussed in the literature and technical reports [10, 11]. However, the human side of power systems is taken for granted. COVID-19 has impacted operators, forcing them to work remotely or be quarantined, and consequently, utility operations have been affected. Simmons and Stiles [12] and Terry [13] compare characteristics of COVID-19 and the 1918 Flu and the potential problems that can occur today due to coupled infrastructure, and authors from [14]

recounts painful lessons and what can be learned from the 1918 Flu pandemic. In addition to the pandemics mentioned in previous paragraphs, electrical disturbances caused by weather have increased over the past several decades [15]. It is estimated that power outages have cost the United States economy \$18–\$33 billion between 2003 and 2012 [16]. The average cost for each weather event totals roughly \$150,000, and 50 events could happen every year, resulting in losses of \$3 million annually [17]. On a smaller scale, EPB Electric Power in Chattanooga, TN, estimated that the annual cost of power outages to the community is approximately \$100 million. By deploying automated switching and smart meters, they saved about \$1.5 million in operational savings during the July 2012 wind storm [18]. According to EPRI, “severe droughts in recent years have sharply reduced hydropower capacity in the West and Southeast (U.S.) by 50%” [19]. According to the survey by IBM, proactive data-driven solutions can save a significant amount each year. Natural disasters are local (both in time and space); however, the COVID-19 pandemic spreads with people at high rates. Furthermore, it is not yet known whether a person can get infected multiple times [20, 21]. Preliminary studies suggest antibodies may last only a few weeks or months [22, 23]. If one can get infected more than once, then the severity of the problem would be magnified. System operators are highly skilled, and the expertise of an experienced grid operator is significant. Hence, the replacement of the workforce is challenging in case of any loss.

## 1.2 | Motivation

Due to the novelty of the pandemic and the lack of identifying the symptoms prematurely, operators of a control center became affected, and consequently, a power generation unit was shutdown [24]. Subsequently, all members of the electric power industry are actively updating their plans/guidelines in response to the ever-changing impacts of COVID-19. The

Electricity Subsector Coordinating Council (ESCC) is releasing and updating its resource guides, including recommendations for decision-makers of industry [25], and the North American Reliability Corporation (NERC) is providing (and updating) its planning recommendations [26]. To cope with unforeseen events such as pandemics and/or other natural disasters, we need to utilise all the available tools. Eliminating or reducing manual interventions will ensure resilient and reliable grid operations during normal situations, in extreme natural events, and under scenarios such as the COVID-19 pandemic. The reduction of manual interventions will help utility field crew reduce their exposure to people who could be either symptomatic or asymptomatic carriers of the virus. These tools not only help in pandemic situations but also are helpful in general and under normal conditions. The power grid management has evolved with the invention and advances in computer technologies [27] but is still behind and has not fully integrated newly developed research methods. Data analytics and machine learning (ML) tools can play a significant role in formulating effective solutions and strategies for managing natural events [28]. Moreover, as power systems become more complex, human operators must work in various situations and may encounter different types of emergencies [29]. More than two decades ago, in 1998, Bilke stated, “trends in the electric utility industry have increased the chances and costs of errors by power system operators” [30]. Using more sensors leads to the collection of more data. Consequently, the analysis of such vast data is beyond the cognitive capabilities of humans [31], and more tools for assisting the operators are needed [31–33]. Innovative technologies can improve operator knowledge of the state of the power system and thus make more efficient and reliable operation possible [34]. Decentralisation of power systems, shifting towards smart grids and consequently more complicated systems, and a scarcity of expert operators all mean new technologies and automation must assist human operators in their larger roles. Not only will machine learning be essential on the micro-level to perform some of the system operators’ tasks but, on the macro level, new technologies are needed for decision-makers to make better informed decisions in the case of disasters [7].

### 1.3 | Contributions

Most of the recent COVID-19-related papers and reports have focused on statistics in the reduction of power usage and change of demand patterns [35, 36]. Some of these papers rushed to analyse the change of pattern of power consumption. Baroah and Duzgun. [36] claims COVID-19 does not solely cause the change in demand pattern. While these COVID-19-related papers report on impacts on load-demand, economy, and implementation strategies to deal with difficulties of the pandemic [37], the main goal of this paper is to recommend technical strategies that are not integrated into the industry to date, and these techniques will have a far-reaching impact if the industry adopts them. Increasing the resiliency of power grids helps utility companies to deal with situations such as COVID-19 along with other

**TABLE 1** High impact, low probability events

Classification of events	Examples
Physical, manmade	Riots, vandalism, war [42–45]
Physical, natural	Hurricane, earthquake, storms [46–48]
Cyber	Phishing, data injection [49–52]
Non-physical, natural	COVID-19, Spanish flu

natural events. Resiliency usually is defined under high-impact low-probability weather events that impact physical assets of power grids. The COVID-19 pandemic has affected power grids indirectly by impacting operators. It is shown [38] that early restrictions on travel are effective, and late restrictions (when the outbreak is widespread) are less effective. Thus, implementing statistical learning approaches enhances the resiliency of microgrids by reducing the number of onsite operators.

Winter began in the Northern Hemisphere, and the importance of power systems’ resiliency cannot be overstated. In 2020, We have already seen a flood on May 19th and 20th, in Midland County, Michigan [39], as well as a Cyclone hurricane in India and Bangladesh, on May 20, present adverse impacts on the power transmission system [40]. The scope of our paper does not consider an analysis of natural disasters. While planning, operating, and restoring strategies in response to natural disasters are discussed in a typical review paper (first three rows of Table 1), we only discuss the methods relevant to pandemic scenarios (last two rows of Table 1). These models increase the resiliency of the power grid by decreasing the dependency on operators and increasing the automation. These methods significantly improve the non-physical problems that have mostly been ignored in the past. Reference [41] reviews some of the ideas related to human resource resilience.

The originality and motivation for our paper compared to other review papers lies in the fact that we focus on reviewing challenges of power grids under pandemics and offer potential approaches to counteract them. Thus, comparing different ML-based models (e.g. performance of the models) against each other is beyond scope of this paper. In this paper we provide an overview of data-driven methods that leads to the augmentation of human roles in operating power grids, which consequently will be beneficial in cases such as the COVID-19 pandemic. Contributions of this paper include:

1. Analysed impact of COVID-19 on power grid operations and actions being taken by operators/organisations to minimise the impact of COVID-19.
2. Analysed concept of resiliency and key differences with other existing concepts for the power grid
3. Reviewed some of the recent ML-based methodologies developed for increasing power systems’ resiliency that are relevant under the pandemic scenario and in general.

4. Suggested integrating some of the recently developed tools or concepts in ML and AI with industry practices. These approaches can increase the resiliency of power systems in general and in extreme scenarios such as the COVID-19 pandemic.
5. Presented an example case study for COVID-19 with the real-time resiliency management tool (RT-RMT) developed by our team that uses real-time data for optimal crew routing and restoration process after a power outage during the COVID-19 pandemic.

The rest of the paper is organised as follows. In Section 2, a quick review of existing power grid operations is presented. Next, in Section 3 impact of COVID-19 pandemic on power grid operations is analysed. Afterward, Section 4 investigates possible and employed practices to manage and combat the pandemic effects in normal operations, followed by ML applications for increasing resiliency of power systems in the future. In Section 5, we discuss some research directions that can be explored further in the future. Finally, we present our conclusions in Section 6.

## 2 | EXISTING POWER GRID OPERATIONAL PRACTICE

Power systems require a level of centralised planning and operation to ensure system reliability.

### 2.1 | Normal operation

The electric power system is built to handle periodic equipment failures, primarily by isolating faulty zones whenever any problems occur. The control room is the brain of a power grid, responsible for the reliability and security of the network. These operations in the power system are a combination of automated control and actions that require direct human intervention. System operators at control centers carry out many of these centralised tasks, including short-term monitoring, analysis, and control.

#### 2.1.1 | SCADA: Data acquisition and control

Supervisory control and data acquisition (SCADA) helps in achieving situational awareness and effective decision making. SCADA is a system of software and hardware elements responsible for gathering, monitoring, and processing real-time data. SCADA acquires measurement information related to voltage, current, and frequency, circuit breakers status, monitoring active and reactive power flow etc. Collecting, processing, and displaying real-time data allows operators to analyse the data via human-machine interface and enables them to take proper actions remotely from the control center. Currently, the presence of operators in control centers is necessary 24 h a day. Operators utilise the energy management system and distribu-

tion management system to monitor the state of the system such as the balance between generation and demand, fault signals, thermal loading of feeders etc.

#### 2.1.2 | Control center: Situational awareness and decision making

Situational awareness means being constantly aware of the state of power station or grid conditions. It is a significant contributor to successful control room operations. Observing the early signs of the system approaching a vulnerable state requires a wide-area view and analytics to recognise conditions. Situational awareness is vital to ensuring coordinated responses among operators within large organisations [53]. Situational awareness gained through SCADA and utilising sensors such as a smart meter, phasor measurement unit (PMU), and data acquired through the communication system provides an opportunity to develop continuous monitoring of the system [52].

Table 2 presents current challenges faced by electrical power systems where ML approaches can alleviate these problems and help operators in different tasks with decision support tools. Research methodologies have been developed to battle these challenges but are not yet integrated into the systems. Primarily, these approaches will reduce dependency on human operators, which is helpful in situations such as the COVID-19 pandemic.

### 2.2 | Contingent operation: Power outage and restoration

Power outage, restoration, and assessment management plan vary between expected contingency and emergency operations. The following section will discuss the preparation for events and restoration efforts during these two modes of operations.

#### 2.2.1 | Planning and training for normal expected contingency

In normal expected contingency operation, utilities prepare for all sorts of circumstances ranging from small storms, winter snow and ice storms, cyclones, insufficient resources of generation, shortage of fuel reserves, accidents, cyberattacks etc. There are several activities that utilities perform during regular operation to prepare for events in advance:

- Operators and field crews perform exercises and drills to prepare for various incidents.
- Modernising physical infrastructure to make it less vulnerable to physical or cyber events.
- Utilities complete contingency planning to ensure they can maintain supply even if one or more system components go offline.

**TABLE 2** Challenges for the power grid operation and control in extreme events

Field	Challenge	Opportunity (developed methods)	Refs.
Control center	Fault detection due to incomplete and conflicting alarms.	Data-driven based on mixed integer linear programming.	[54]
	Increasing number of measurement devices increases the number of alarms causing analysis and situational awareness more challenging.	Real-time event detection using synchrophasor data, and ensemble methodology that includes maximum likelihood estimation, DBSCAN, and decision trees.	[55]
	Fault section estimation.	Neural networks	[56–59]
	Classifying the observed anomalies of instrument transformers into different types of malfunctions, failures, or degradation.	A pipeline consisting of three steps; maximum likelihood estimation, DBSCAN and a decision logic diagram.	[60]
Office Staff	Classifying the customer ticket texts/calls.	Natural language processing, text analytics, recurrent neural networks.	[61]
Transmission protection systems	Detecting root cause of failures in transmission protection systems. Failure to do so causes propagation of faults, consequently resulting in multiple conflicting alarms.	Anomaly detection using an ensemble of ML approaches.	[62]
System protection - cyber security	Monitoring and detecting malicious activity in transmission protection systems.	Anomaly detection pipeline that includes long-term short-term memory (LSTM) networks, semi-supervised deep learning algorithms, and ridge regression.	[52]
	Classifying malicious data and possible cyberattacks.	Several ML algorithms such as random forests and support vector machine.	[50]
	Detecting anomalies and false data injection.	Gaussian mixture model is used to solve the problem.	[63]
	Detecting intrusions in smart grids.	Support vector machine and artificial immune system.	[51]

- Utilities perform regular vegetation management, which includes the cutting or trimming of plants, bushes, and other foliage that could be too near electric infrastructure, preventing potential damage to equipment during storms.
- Utilities regularly examine resources, noting deterioration and required repairs or replacements.

### 2.2.2 | Planning and resilient operation for emergency

During emergency operation mode, utilities coordinate with control room operators and crews to re-establish power supplies as fast as possible. If the event is known beforehand, then utility planning will be in two phases, pre-event and post-event.

#### Pre-event process:

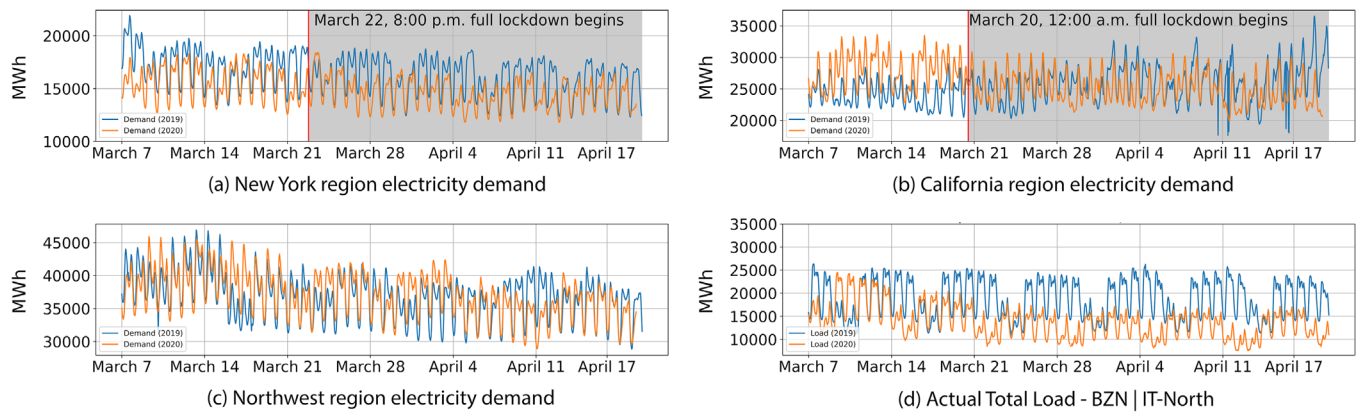
- Utilities create different leads for different functions (e.g. damage, restoration, vegetation management, overall communications).
- Utilities review critical infrastructure in the area.
- Utilities identify resources, including crews, backup generators, and other equipment, as well as mutual assistance available to respond to emergencies.
- Utilities employ advanced tools to anticipate extreme events and to prepare the system to have minimal impact.

#### Post-event process:

- Utilities perform a destruction estimation of lines and substations.
- Utilities eliminate all hazardous situations, such as downed live wires or other potentially life-threatening situations.
- Utilities restore power plant and transmission lines that carry maximum power to the distribution system whenever damaged.
- Utilities prioritise restoring power to critical infrastructure such as hospitals, police, and fire stations before individual homes and small businesses.
- Utilities employ advanced resiliency tools to optimise and recover after extreme events.

## 3 | IMPACT OF COVID-19 ON THE POWER GRID OPERATION

Edison Electric Institute in their 2020 report [64], states that “it is predicted that a large percentage of a company’s employees (up to 40%) could be out sick, quarantined, or might stay home to care for sick family members.” Moreover, certain nuclear facilities have operated marginally at low capacity due to remote operations and the challenges presented by delayed maintenance work, all of which impacts the timely operation of such facilities. Furthermore, COVID-19 is expected to delay



**FIGURE 2** COVID-19 impact on demand behaviour in three regions in the US and in Northern Italy (March 7–April 19)

project developments and impact renewable auctions due to supply chain delays. The pandemic has forced the NERC to delay implementation of several reliability standards [65, 66], some of which are cybersecurity measures. The pandemic has forced utilities to operate with skeleton crews, providing more opportunities for cyberattackers [25]. Three infected IT security engineers at a nuclear power plant were quarantined for 14 days [24], increasing the threat to normal operations. State of the art technologies in AI and ML can aid in reducing humans' direct involvement with oversight, maintenance, and failure detection [62].

These unusual low demand caused by the pandemic could be leveraged to cause frequency instabilities in power grids by compromising IoT-connected high-wattage loads [67]. Consequently, the researchers propose [67] a methodology to explore the possibility of load-changing attacks, modelling of such activity, and analysis that evaluates the impact of their modelled attack. For increased security against cyberattacks, extra measurements must be taken (see ref. [52]).

COVID-19 impacted power demand, mostly when lockdown periods went into effect. Electric Power Research Institute (EPRI) reported the change of pattern of load in Italy, Spain, and the U.S. [68]. Load impacts in the U.S. were also reported in [12, 69, 70]. The lockdowns reduced power consumption. However, the contribution of renewable energy production went up. The change in power consumption pattern and uncertainties in demand put pressure on operators. Zhong et al. [71] review some of the implications of such drastic change; uncertainty on demand and supply makes the power balance and voltage regulation challenging, financial implications are explored, and maintenance difficulties under the pandemic are discussed.

Figure 2 compares the power consumption in 2020 and 2019 in various regions of the U.S. and Italy when the pandemic became widespread, and lockdowns began. The data for the U.S. is obtained from Energy Information. The data for Italy is obtained from ENTSO-E Transparency [72]. The lockdown started on March 19 [73] in the state of California. The demand in California was higher before the lockdown began in 2020 compared to 2019. However, after the lockdown, it dropped below that of 2019 by a small amount. The Northwest region

includes several states; therefore, there was no uniform date for the beginning of lockdowns in the region, and no clear change of pattern is seen in the Northwest. In the state of New York, lockdown started on March 22 [74]. Here, demand in 2020 was less than demand in 2019, even before the lockdown period began. This difference might indicate that other factors (beyond COVID-19) might be involved in the difference between consumption loads of 2020 and 2019. The change of consumption power before and after the lockdown in India led India's Power System Operation Corporation to match the new demand by decreasing coal-based generations [75]. Impact of the pandemic on load and generation in China is discussed by Lu et al. [76]. Not all of the implications were negative. A positive impact of COVID-19 on power grid operation was observed in New York [77]; "larger ramp rates are observed less frequently after the pandemic in 2020 than in 2019, meaning hourly demand is changing more slowly. From the point of view of grid operation, that is a positive change."

Neural networks can be used for short-term load forecasting. Badri et al. [78] compare neural networks against fuzzy logic in the context of short-term load forecasting and reports on superiority of neural networks. Additionally, Dudek [79] compares different neural networks against each other for the same goal. The authors have to admit a rapid change in behaviour of power consumption as a result of lockdowns. Thus, a lack of sufficient data for ML-approaches will be a challenge.

Ruan et al. [80] have made an ensemble model to predict electricity consumption in NYISO in 2020 if COVID-19 were absent. They trained 800 neural network models, selecting the top 25% models with the lowest error. For certain selected days in April, they showed that electricity consumption was much lower than predicted by the model. Table 3 presents reduction of power consumption in different countries in 2020 compared to 2019. The reduction of electricity usage translates into a reduction of the system's resilience. Furthermore, most of the reduction of demand results from a reduction of electricity usage by large segments such as industrial and commercial organisations. These customers form a large segment of normal electricity demand, and their lack of stability translates into a reduction of stability in power grid operations.

**TABLE 3** Comparison of demand in different regions and time periods

Country	Demand reduction	Time Window	Refs.
USA	5.4%	Week of April 6, 2020 compared to the same time in 2019	[83]
NYISO (USA)	9% reduction in peak demand	March 2020 compared to 5-year average values	[37]
CAISO (USA)	5%-8% load reduction in weekdays	Since statewide shutdown on March 20 compared to 2019.	[84]
Europe	27%	The first week in February to the end of March in 2020 compared to 2019.	[85]
France, Germany, Italy, Spain, and Netherlands.	10%	The first week in February to the end of March in 2020 compared to 2019.	[85]
India	30%	Since full national lockdown on March 24.	[86]

In the U.K., The consumption of the transmission system kept falling week after week; “compared to the week of March ninth, total electricity demand fell by 13% in the week of March 23rd, by 14% in the week of March 30th, and by 24% in the week starting April sixth.” [81]. Europe went through a significant reduction (27%) during lockdowns. Even after the easing of lockdowns in June, the demand was still 10% less than that of 2019 [82].

Some interesting results, such as the impact of social distancing on electricity consumption can be found in [80].

To prevent the spread of the virus, operators and technicians have had to change their normal operations. Different solutions have been proposed by experts. The followings are some examples of the pandemic’s impacts and potential mitigations to consider.

- Minimising the number of onsite staff and working remotely if possible [25, 87].
- Using main and backup control rooms at different times and/or with separate operators [88].
- Regularly sterilising control center facilities during the day [25, 89].
- Changing shift duration and cycles [88].
- Limiting common equipment usage.
- Cancelling face-to-face meetings and direct interactions [90, 91].
- Limiting the number of field technicians in each vehicle and ensuring technicians carry personal protective equipment.
- Closing all non-critical common areas, such as exercise rooms or even cafeterias.

## 4 | SOLUTIONS FOR MINIMISING IMPACT OF COVID-19

The COVID-19 pandemic has changed usual operations at different levels. Recently, the Federal Energy Regulatory Commission (FERC) and NERC produced industry guidelines to reduce the impact of COVID-19 [92], and a comprehensive guide is given by [93].

### 4.1 | Actions being taken by grid operators

Operators are taking different actions to minimise the spread and impact of SARS-CoV-2 while attending their jobs and maintaining the power stations. Below is a list of some of these strategies.

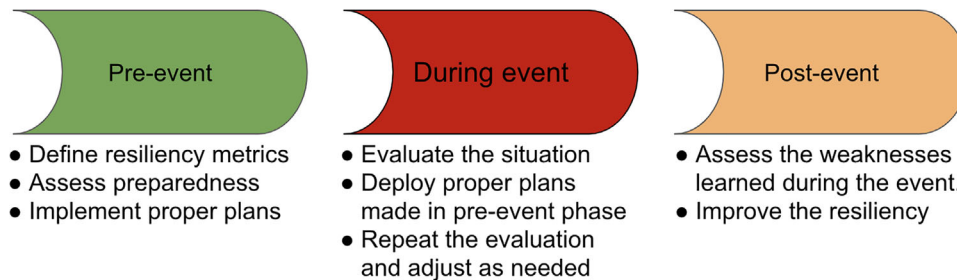
- Back-up control centers are activated, key workers are isolated, and deep cleaning has become routine [94].
- Food and other supplies are stored at the generating station (Utah’s Intermountain Power Plant) [95].
- Operators are preparing for the worst-case scenario; “we could operate the plant with a skeleton crew for an extended period of time” (Utah’s Intermountain Power Plant). An example is shown in Figure 3 provided by ref. [88], demonstrating New York’s power grid control operation working with only essential operators.
- Employees are telecommuting. (Southern California Edison, NYPA)
- Rotating personnel between power line repair teams is kept to a minimum (Southern California Edison) [95].
- Non-critical planned maintenance is being postponed (Southern California Edison).
- Critical workers are isolated (American Gas Assn.). In fact, “some sequestration is underway in certain areas, with employees and contractors living on-site at power plants and other facilities. It is critical that sequestered employees who are in close quarters be tested before and during sequestration” [24].
- Regular health screenings are being performed, as well as deep cleanings of control rooms to keep the coronavirus out (NYPA) [96].
- Splitting control center operators between the main and backup control center to limit contact (PJM) [96].

### 4.2 | Enabling grid resiliency

Other than the usual operational paradigm to focus on reliability, security, restoration, and emergency planning, energy suppliers need to invest in resiliency to bounce back from extreme



**FIGURE 3** Control center normal operations are impacted by COVID-19. power systems are operating with minimal number of staff onsite



**FIGURE 4** Multi-temporal resilience framework

events. Resiliency is a multidimensional concept. Jufri et al. [2] state that resiliency “involves multidisciplinary knowledge, such as power system, civil and structure, geography, computer science, probability, and meteorology and climatology.” Consequently, several definitions are available. Even for one aspect of resiliency, several definitions have been put forward, and there is no consensus in a given community. Definitions for a given aspect are not mutually exclusive and may overlap [97]. Table 4 provides some of the definitions of resiliency from different perspectives and/or in different domains, as well as for some closely related topics. For more details please see [97, 98].

As mentioned before, most of the effort on resiliency is focused on physical assets. In this paper, however, we are dealing with disease, which adds a different dimension to the problem: health. Consequently, the organisational domain becomes relevant, and a definition of resiliency for this aspect is presented in Table 4. By implementing ML approaches, the resiliency of a power system—as a group/society/organisation—is increased as organisational responsiveness is shifted from humans to machines.

In general, the resiliency of a power grid is defined as “the ability to withstand and fast recovery from deliberate attacks, accidents, or naturally occurring threats or incidents” [102]. For a system to be resilient, it needs to have a robust damage prevention plan in place, and a system designed for adaptation and fast

recovery in case of any damage. Temporally there are 3 stages to make, keep, and improve the system’s resiliency (Figure 4) pre-, during, and post-event actions are needed.

Extreme events cause a limited or complete blackout in the power grid. A complete blackout occurs with a low probability as a result of multiple interrelated contingencies; operators rarely anticipate that. If pandemics such as COVID-19 coincide with extreme weather events, then the problem escalates to a whole other level where the consequences are extremely high for at least two reasons. The first reason is that the COVID-19 regulations and limitations themselves increase difficulties on power grid operators. For example, fewer technicians are available to fix failures, while there are more opportunities for cyberattackers. The second reason is that hospitals (a very specific example is ventilators) depend on electricity [103]: “... electric power is not just important for the overall functioning of the facility, it is critical for direct patient care.” Automation and ML can aid in different ways to increase the resiliency of networks. For example, ML can help evaluate the risk of failure and consequently with the scheduling of timely maintenance [104]. Resiliency has to be implemented at multiple levels, though, as different incidents threaten the system e.g. a blizzard vs. human error.

Different approaches that can enhance the resiliency of power grid are discussed here.

**TABLE 4** Definitions of resilience and other coupled/interrelated concepts

Concept	Definition	Refs.
Resiliency	Ability to harden the power system against—and quickly recover from high-impact, low-frequency events. Resiliency consists of damage prevention, system recovery, and survivability.	[99]
Damage prevention (as a part of resiliency)	Damage prevention is self-explanatory. It is related to predicting and hardening the power systems against high-impact, low-frequency events.	[99]
System recovery (as a part of resiliency)	Going back to normal operations after occurrence of high-impact, low-frequency events.	[99]
Survivability (as a part of resiliency)	Ability to maintain some basic level of power to consumers when complete access to their normal power sources is not possible.	[99]
Resiliency	“Measure of a system’s ability to absorb continuous and unpredictable change and still maintain its vital functions.”	[97]
Resiliency in organisational domains	“Ability of an organisation to absorb strain and improve functioning despite the presence of adversity.”	[97]
Reliability	“The degree to which the performance of the elements of [the electrical] system results in power being delivered to consumers within accepted standards and in the amount desired.”	[100]
Flexibility	“The inherent capability to modify a current direction to accommodate and successfully adapt to changes in the environment.”	[101]

#### 4.2.1 | Challenges and opportunities with integration of microgrids and DERs

Although rigorous efforts and suitable solutions to strengthen the resiliency of the power grid are continuously evolving, the operator still needs to deal with challenging conditions due to unprecedented or adverse events. With the increased deployment of DERs and microgrids, the reliability and resiliency of the power grid can significantly be enhanced [105]. By reconfiguration of the network, DERs can be used to serve critical loads when the utility grid or a centralised generation unit is not available [106]. Similar to DERs, microgrids could operate independently or in connection with the distribution network [107, 108]. Furthermore, a microgrid can be used to pick up critical loads outside its boundary to increase the resiliency of power grids in case of extreme events [109]. Consequently, smart grids and distributed renewable energy systems can be a solution in the future [75] to alleviate problems imposed by pandemics.

Despite the fact that microgrids increase the resiliency of power systems, they face their own challenges. Machine learning provides solutions in the microgrid ecosystem as well. For example, Lin et al. [110] combine neural networks and support vector machine for state recognition in microgrids. Their algorithm is used to increase reliability of operation by changing the

protective settings and the network topology based on the system’s state. To learn more about these challenges (e.g. physical or cyber threats) please see Mishra et al. [111]. Table 5 provides a summary of some of these challenges and some of the methodologies developed by researchers to overcome the difficulties.

#### 4.2.2 | Operational practice for human operators

Operational practice guidelines and decision-making tools help the operator to apply the best plan to minimise the impact of an event, but mainly for known and analysed events. Effective proactive strategies with quantified measures in terms of resiliency metric can lead to substantial improvement in resilient power distribution grids [116–118, 119, 120]. Training for extreme events will be important. Further, any advancement in automatic decision-making tools based on data processing and analysis will ease the operator in handling these events [121]. An automatic emergency control action plan can be developed based on previous incidents and can be suggested to operators or used as an emergency automated operation. Distancing employees and scheduling operating cycles for minimal interactions with others during health hazards like COVID-19 stops escalation of impact to employees, specifically to critical personnel of utility companies, such as control center operators and field crews.

#### 4.2.3 | Organisational support

Organisational support plays a major role in a resilient grid operation, especially given that multiple organisations and interests impact grid operations—federal, state, and city governmental bodies, FERC, NERC, public utility commissions, vendors, service providers, technical committees, standard development organisations, researchers, and, of course, consumers. With proper support and guidelines from regulation authorities and federal energy agencies, utility companies could accelerate the deployment of advanced grid technologies to perform remote operations and increase the level of automation with sufficient personnel involvement. Organisations need to develop policy, proactive or corrective action plans against extreme weather (Tsunamis, Hurricanes, Tornadoes etc.) and outbreaks (COVID-19, Ebola etc.). As the grid is highly susceptible to cyber threats during these kinds of events, robust communication infrastructures and adaptive action plans must be implemented. During outbreak events, automated alarm and text messaging of outages, faults, equipment failures, and malfunctioning to crew engineers and field inspectors should be deployed to reduce the spread of infection and loss of crew. Automated routing of field personnel to equipment maintenance and replacement with minimal customer or human interaction can ensure continuous power supply. Moreover, optimal placement of inventory and crew by organisation greatly diminishes power delivery interruptions. Further, mutual coordination and personnel exchange between organisations operating in the same region could establish a more resilient and robust grid.

**TABLE 5** Examples of challenges and opportunities with integration of microgrids

Component	Challenge	Opportunity (developed methods)	Refs.
System Protection - Cyber Security	Detect and stop cyber attacks in wireless sensor networks in microgrids with different ownership.	Detecting anomaly based on the lower and upper bound estimation method to predict optimal intervals over the smart meter readings at electric consumers. They make use of the combinatorial concept of prediction intervals to solve the instability issues arising from the NNs.	[112]
Utility grid connected microgrids	Microgrids with distributed generation increase resiliency of power systems in case of any faults. Microgrids and using ML in their routine operations gives time and space to operators to fix the damaged components.	A NN is developed to provide cooperative voltage regulation for a microgrid that can be applied locally in a privacy preserving way.	[113]
	Enhancing protection for modernisation of distribution system against faults.	A NN and support vector machine is used for state recognition and state diagnosis.	[114]
Fault detection	Detecting events in each of the distributed stations.	Modified ensemble of bagged decision trees with an added boosting method	[115]

#### 4.2.4 | Redundancy and automation

Restoration is a key functionality of an advanced distribution management system (ADMS) for keeping the lights on after an outage. Redundancy plays a vital role in the restoration process, and spare inventory and parallel lines act as major attributes thereof. Outage management systems (OMS) can identify faulted sections using information received from trouble calls or field inspectors and dispatch crews to mend damaged equipment [15]. An increased number of multiple power flow paths in the network permits the load to be supplied through alternate pathways [34]. Modern grid technologies—automatic metering infrastructure (AMI), micro-phasor measurement units (microPMU), intelligent electronic devices (IED), fault indicators, remote terminal units (RTUs), digital relays and circuit breakers, data analytical tools—provide enhanced observability and controllability of distribution networks [15, 122]. Field devices can be used to automate the power grid through ML techniques. For example, predicting the probability of failure of a feeder switch can help prevention of outages. In the case of COVID-19, redundancy of spare devices and automation will help in faster restoration.

#### 4.3 | Future ML-based tools and resiliency

The need for increasing system resiliency has been heightened by several recent natural events and their dramatic impacts. But natural disasters are just one major cause of high-impact outages [123]. An example of this kind is human-caused outages applicable in the COVID-19 case. Making operators work longer hours or sequestering them to live on-site at power plants will increase the rate of human error. With increasing complexity, the tasks of human operators become even more challenging. Unlike a self-driving car, a fully automated scenario without human intervention is not possible due to complexity of the power grid. ML-based tools could help to minimise strain on over-burdened operators and hence minimise the chance of

human error. We review the potential of statistical learning and recently developed techniques to mitigate potential power grid challenges as outlined here.

##### 4.3.1 | ML and natural disasters

Gupta et al. [124] employ a probabilistic framework and support vector machine to predict cascading failure and provide early warning in case of any future events to increase resiliency. Eskandarpour and Khodaei [125] develop an ML-based prediction method to determine the potential outage of power grid components in response to an imminent hurricane. The decision boundary of the classifier is obtained via logistic regression to predict the number of failed components and failure duration. Predicting the state of a system after a hurricane is investigated in [126] using a support vector machine-based model to categorise power grid components into two classes—damaged and operational. Guikema [127] uses regression and data mining techniques to estimate the number of poles that need to be replaced after a hurricane event. Glavic et al. [128] and Huang et al. [129] explore the application of reinforcement learning in power system emergency control dynamics to alleviate current practices. In one interesting article, Maharjan et al. [130] combine DERs and support vector machines to improve the resiliency of power grids during natural disasters. They consider a scenario in which different load needs are categorised to prioritise life threatening cases (e.g. a kidney dialysis machine is more important than a fridge) and ensure power availability for the most necessary items during outages.

ML and demand forecasting. The demand drop and change of consumption pattern due to lockdowns lead to forecasting error. If the forecast predictions of demand are higher or lower than the actual demand, then energy prices will be affected [131]. The forecast error of PJM (a regional transmission organisation in the US) went up to 3% on average during the COVID-19 period [131]. Similarly, Benatia [132] reports that load forecast errors have gone up to 300% in

New York and over-forecasting has occurred continuously during the first 4 weeks of the lockdown. On the contrary, Ruan et al. [133] claims in the US market the demand forecasting error is small; “Although the pandemic has posed new challenge for demand forecasting, the overall impact has been rather limited—even under the influence of COVID-19, the prediction errors are still within a tolerable range.” Since daily forecasts are reliant on historical data, the errors in predictions have been inevitable. However, as more data are collected the prediction methods improve. Buechler et al. [134] investigated 27 European countries and California and reported that it took 3 to 5 weeks to correct the week-ahead forecasts errors. The problems imposed by the pandemic gave rise to the boom of new approaches to minimise the error under such a scenario. Buechler et al. [134] propose a hybrid approach (that includes regression and clustering) to estimate demand change based on weather condition, region-specific data for electricity consumption, and government restrictions. To minimise the impact of the pandemic on the performance of the forecasting model, Alasali et al. [135] build a rolling stochastic auto-regressive integrated moving average with exogenous model. Another interesting approach, mentioned earlier in Section 3 is proposed by Ruan [80] that predicts power consumption by training 800 NNs. In another interesting approach, Chen et al. [136] use mobility as a measure of economic activities to complement forecasting algorithms. The novelty of their approach lies in the fact that they use a transfer learning scheme to overcome data shortage.

ML methods are trained with the historical data. As such, a sudden drop in demand can be mistaken by ML as a cyberattack. This is a real challenge both for operators to deal with and for implemented ML algorithms. However, currently, load-changing attacks are not a real problem: “Although currently hypothetical, due to the low penetration rates of IoT-controllable high-wattage loads and DERs, load-changing attacks are projected to become a ‘real’ threat in the near future as the number of controlled DERs and loads is anticipated to grow exponentially” [137]. Therefore, the sudden drop in load demand was not expected to be a cyberattack. Some of the research attempts to address load-changing attacks through formulating the problem mathematically are [67, 137]. Ospina et al. [67] discuss the feasibility of load-changing attack during the COVID-19 pandemic. ML approaches for detecting cyberattacks are discussed in the next part of our paper and some references are provided in [137]. However, distinguishing the sudden drop in demand due to COVID-19 and cyberattack is a challenge that needs to be addressed.

#### 4.3.2 | ML and cyberattacks

Traditionally, cyberattacks are labelled as low-probability events. However, as more IoT and DERs are integrated into the power systems the rate of attacks is increasing. Hence, these events could be labelled as high-probability events. Hink et al. [50] explore several ML algorithms—such as random forests and support vector machine—to classify “malicious data and possible

cyberattacks” to help operators in normal and emergency situations. Foroutan and Salmasi [63] investigate a Gaussian mixture model for detecting anomalies and compare their model against some other models for false data injection. Zhang et al. [51] examine a distributed intrusion detection system embedded at each level of the smart grid—the home area networks, neighbourhood area networks, and wide area networks using the support vector machine and artificial immune system.

Protection systems are an essential part of the system, yet, they are prone to external influences. Multiple alarms reported in the control center could be a result of the faults or failures in the protection system (unexpected operation). Ahmed et al. [52] develop a ML technique to monitor transmission protection systems and detect malicious activity using long short-term memory (LSTM). These data are also utilised for failure diagnosis. Finally, a model to find the root causes of the observed events assisted by the cyber log data from the protection devices are developed. Anomaly detection in PMUs is further discussed in [62] to detect the root cause of the failure in the transmission protection system, and it is shown that ensemble models are superior to stand-alone methods.

Two relatively recent approaches for detecting anomalies are employing variational autoencoders (VAEs) and generative adversarial networks (GANs). A variational autoencoder represents the input data by extracting new features that can remove noise and redundant information [138], which can also be used for dimensionality reduction. It has been used in a variety of applications. For example, Biswas et al. [139] use VAE in the context of detecting faults in transmission networks. Zheng and Gu [140] use the VAE for detecting anomalies in power system forecasting. Takiddin et al. [141] propose anomaly detections based on variational autoencoders in the context of cyberattacks. They compare the result of two VAE based architectures; a fully-connected VAE and long-short-term-memory (LSTM) VAE architecture. Yang et al. [142] propose another architecture that combines the supervised adversarial variational autoencoder with regularisation and deep neural network for detecting intrusions. Yao et al. [138] also uses VAE to extract new variables for the purpose of anomaly detection in the context of network intrusion field using the KDD CUP 99 dataset and reports on good performance of using VAE. Other examples of attack/intrusion detection using VAEs are [143–145]. The generative adversarial networks (GANs) was introduced by Goodfellow et al. [146]. In this framework two models are trained; “a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G”. The two models compete against each other, hence the name. In Goodfellow et al.’s own words “The generative model can be thought of as analogous to a team of counterfeiters, trying to produce fake currency and use it without detection, while the discriminative model is analogous to the police, trying to detect the counterfeit currency.” The GANs approach is used for detecting cyberattacks as well as other fault detection applications. For example, Liu et al. [147] and Adiban et al. [148] use GAN framework to detect fault in wind turbine systems. Zhang et al. [149] employ a GAN approach for detecting false data injection from

cybersecurity perspective. Similarly, Ying et al. [150] generates attack samples using a GAN network and train a deep neural network to detect cyberattacks.

### 4.3.3 | ML-based tools to supplement operators

ML can help the operators in a variety of ways. For example, it can be used to classify the customer ticket texts into different categories [61] such as serious or non-serious events. Natural language processing and/or recurrent neural networks can be used to analyse customers' trouble calls to pinpoint the location of the faulty equipment as opposed to operators taking the calls. By automating this process, interaction among operators will be minimised as needed in the case of COVID-19.

For dispatchers and operators to manage a power grid correctly and efficiently, they need to understand the dynamics and the current state of the grid. Using alarms generated by SCADA is one of their tools. The rate of alarm generation can be reduced significantly (98%) by using an intelligent alarm processing system, which is a tremendous improvement for operators and dispatchers [151]. Interventions like these are critical, especially in emergencies, since the long work shifts and high levels of stress that occur over times of emergency (such as COVID-19) make operators even more prone to mistakes [152]. Furthermore, ML can be utilised to classify the alarms and hence reduce the workload of operators. Employing ML can help to identify multiple events associated with a set of reported alarms, consequently reducing the operators' cognitive burden.

### 4.3.4 | ML and hidden failures

Hidden failures are typically overlooked in the research community. We briefly touch on some of the existing concepts here.

Hidden failures are the failures in protection systems that remain undetected when the power system is working normally. Hidden failures can also happen in software system supporting power grid operation and control, which are not continuously monitored and difficult to detect. Hence, they are called hidden failures. Hidden failures are either uncovered, if another event occurs in the system [153] or during maintenance/checks by engineers/ technicians [154]; "Most of the hidden failures can be traced to protection system maintenance issues" [154]. They are known as a key contributor to cascading outages [155–157]. COVID-19 pandemic delayed the regular maintenance schedules, as mentioned before, and consequently, the probability of hidden failures goes up. Hidden failures reduce the systems' reliability, and advanced techniques can detect such failures [155]. Detecting hidden failures will prevent cascading failures that increase the reliability of the system and reduces the cost (financial and time) of repairs.

Jung et al. [158] propose an agent-based method for monitoring hidden failures of protective devices. Salfner and Malek [159] use pattern recognition for online failure prediction. Using ML approaches to predict/locate hidden failures to perform timely maintenance can improve the reliability of the power grids. Fur-

thermore, employing ML approaches will help detect and isolate the failed relays or circuit breakers to possibly prevent the cascading effect. There are many opportunities to explore this area, which has been mainly overlooked in the past.

## 4.4 | A case study for resiliency management tool with NLP

A real-time resiliency management tool (RT-RMT) is a unique tool developed by the authors' team. It provides the resiliency score of any power system network by considering the various factors such as power generation, critical and non-critical loads, threat type, and impact model including available backup resources, inventory, field crew, and inspection team, and weather information [160]. This tool also encompasses geospatial information of the power grid, and assesses an infrastructure condition to compute resilience scores during the propagation stages of natural threats. Three stages of events, pre-, during, and post-event, are considered to provide resiliency scores for each stage by taking relevant influencing factors into account. The real-time resiliency score is computed every 15 min using the information acquired through communication channels from different devices (e.g. SCADA, PLC, RTUs) in the distribution system. It can be deployed along with a commercial distribution management system software. RT-RMT provides real-time operational topology or configuration on a live tracking map shown in Figure 5. Further, it displays the connection between different nodes of the network and routing over the GIS layer. It can be adapted to analyse the impact of health hazards (e.g. COVID-19) and can effectively minimise its influence on the electrical distribution system operations.

RT-RMT tool has four main windows; system information, resilience monitoring, decision support, and planning analysis. System information portrays physical assets (number of buses, transformers, fault indicators, protection devices, other equipment), and their ratings along with deployed location and current operating status. Resilience monitoring captures real-time resiliency score for the provided distribution system. This value will change subject to operating conditions (i.e. with variations in the generation, loads connected etc.). The decision support on RT-RMT helps the operator take appropriate actions suggested by the tool to boost the system's resiliency, including pre-, during, and post-event requirements as the event progresses through different stages. Planning and analysis of tool emphasises enhancing the resilience of system operation with system upgrades like adding distributed energy resources, increased energy reserve, fast communication technologies, sensors etc.

Two use cases are developed to evaluate the performance of the RT-RMT tool. The first use case focuses on the normal operation of the distribution system without any event. The evaluated resiliency score for a given operating condition is near to 0.9 as shown in Figure 5. The second use case includes the COVID-19 pandemic. It shows how RT-RMT will be adapted to help the operators address the problems with minimal impact on the electrical power supply and all the consumers. The data used in this scenario are obtained from John Hopkins'

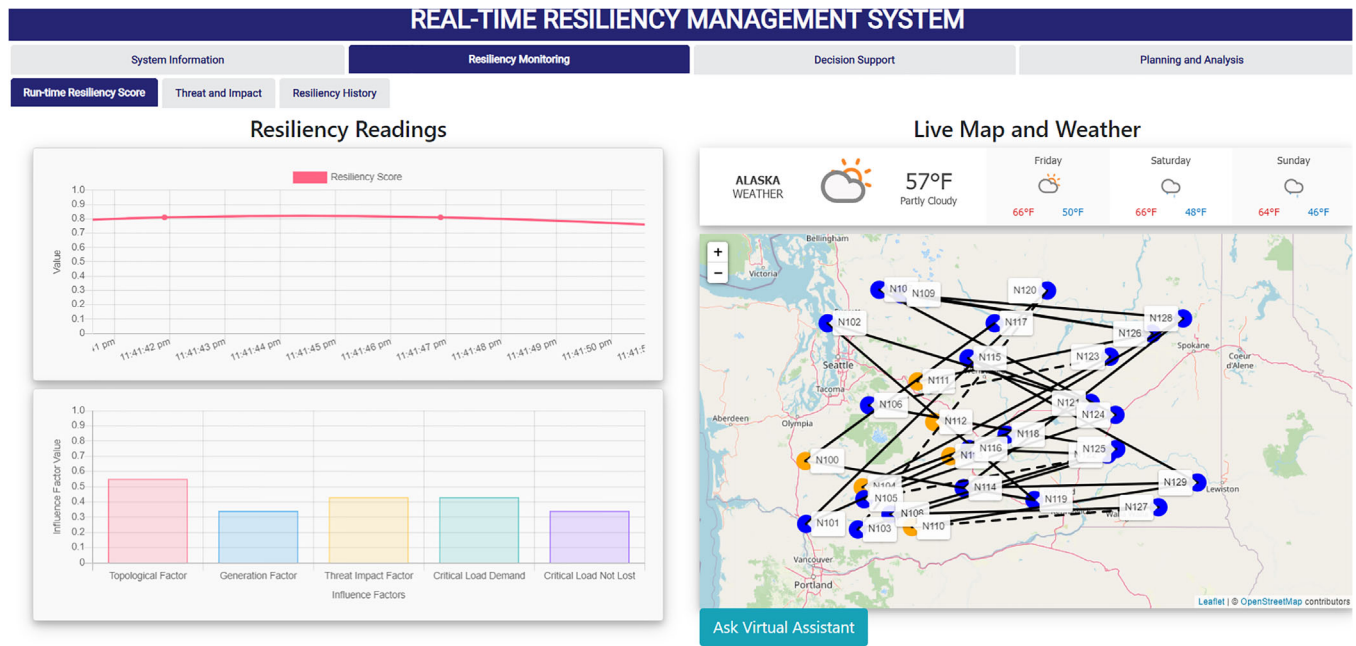


FIGURE 5 RT-RMT tool view: normal operating condition

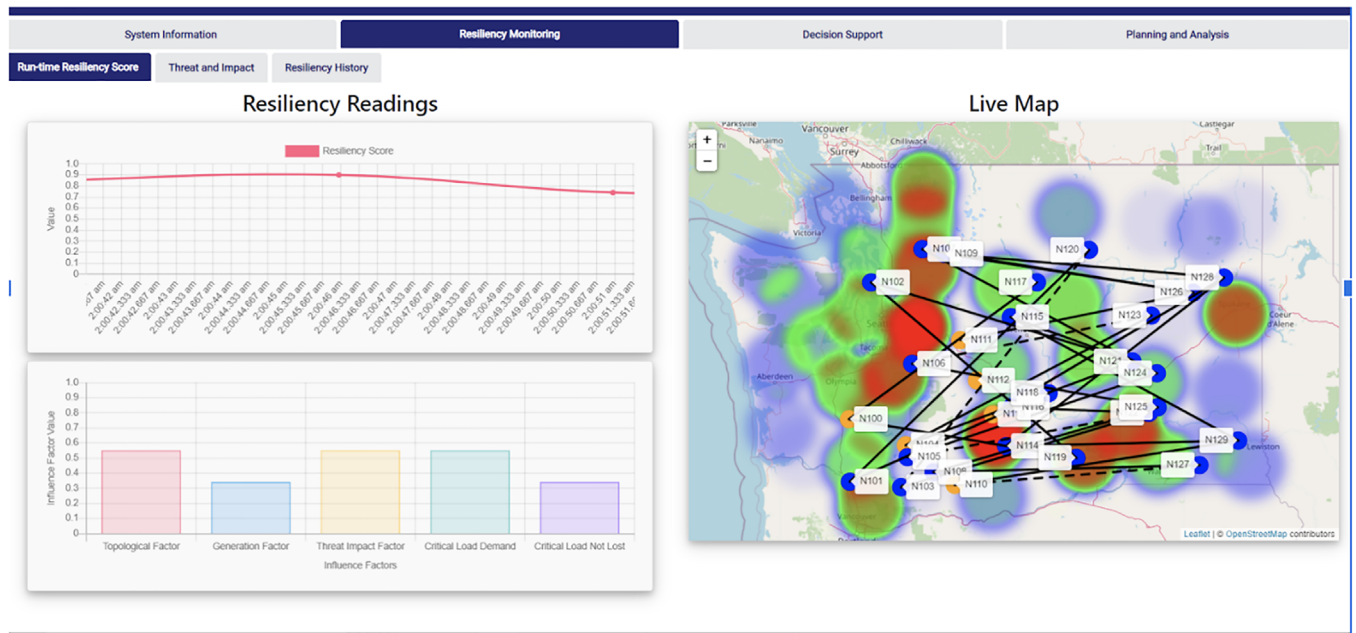


FIGURE 6 RT-RMT tool view: spread of COVID-19 cases across Washington state with blue being lowest and red being the highest number of cases

Coronavirus dataset [161] and are anonymised to avoid data privacy issues. Different regions with different intensities of COVID-19 cases are shown in different colours in Figure 6 over the distribution system in a live tracking map. This tool informs the operators (visually) about areas with high cases of COVID-19. Consequently, they can decide to change any scheduled maintenance plan or repair a failed equipment plan as needed. The operator may address the issues in regions with a low number of COVID cases, first with precautions. For example, by sending limited crew per vehicle. RT-RMT also optimises the

route to avoid the paths going through regions with a high number of cases to protect crew members against infection. The operator could also plan to send crew members at once in a day along with PPE kits to ensure minimal contact of humans. Further, effective reconfiguration of the network can also be performed in regions with high positive cases to restore the power after an outage or equipment failure so that electrical supply is still maintained without field crew inspection and replacement of faulty equipment. Detailed explanation is provided in the Section 4.4.1.

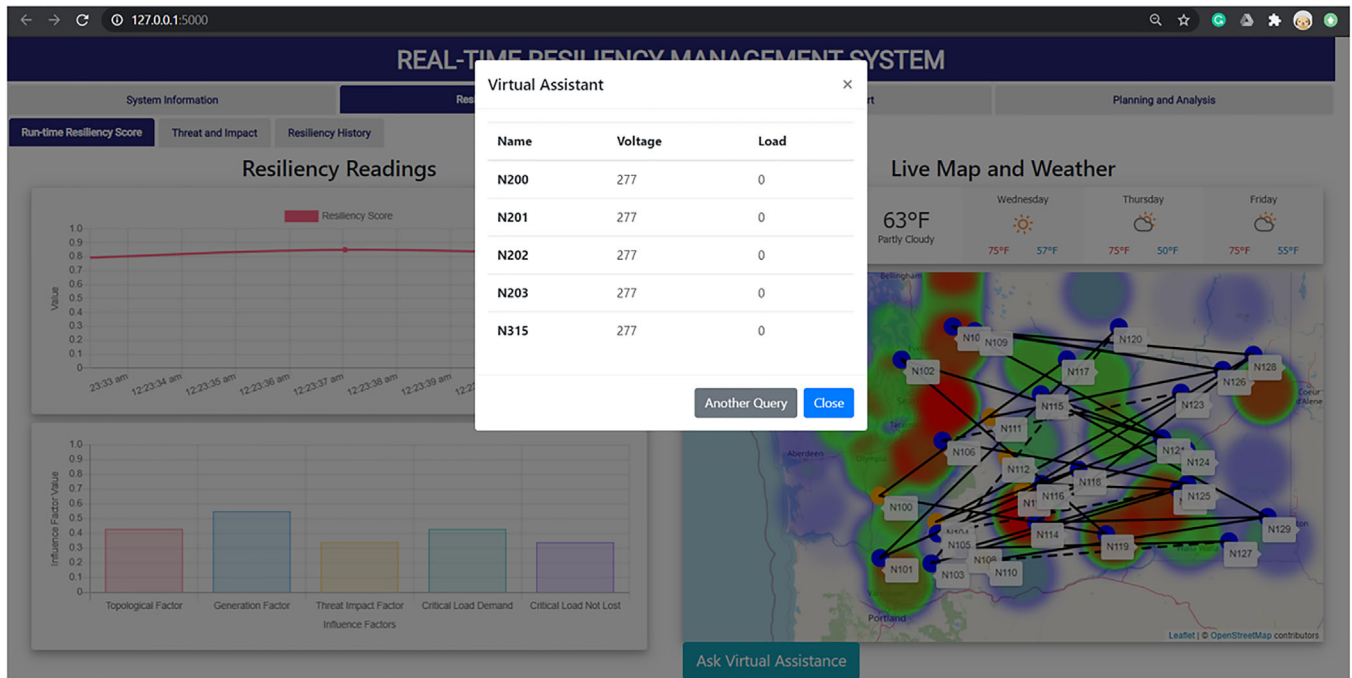


FIGURE 7 Virtual assistant demonstration on RT-RMT

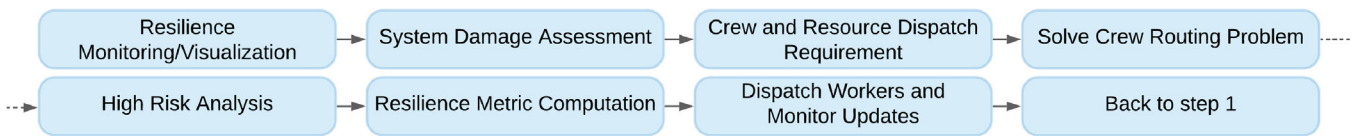


FIGURE 8 Safe crew-dispatch algorithm

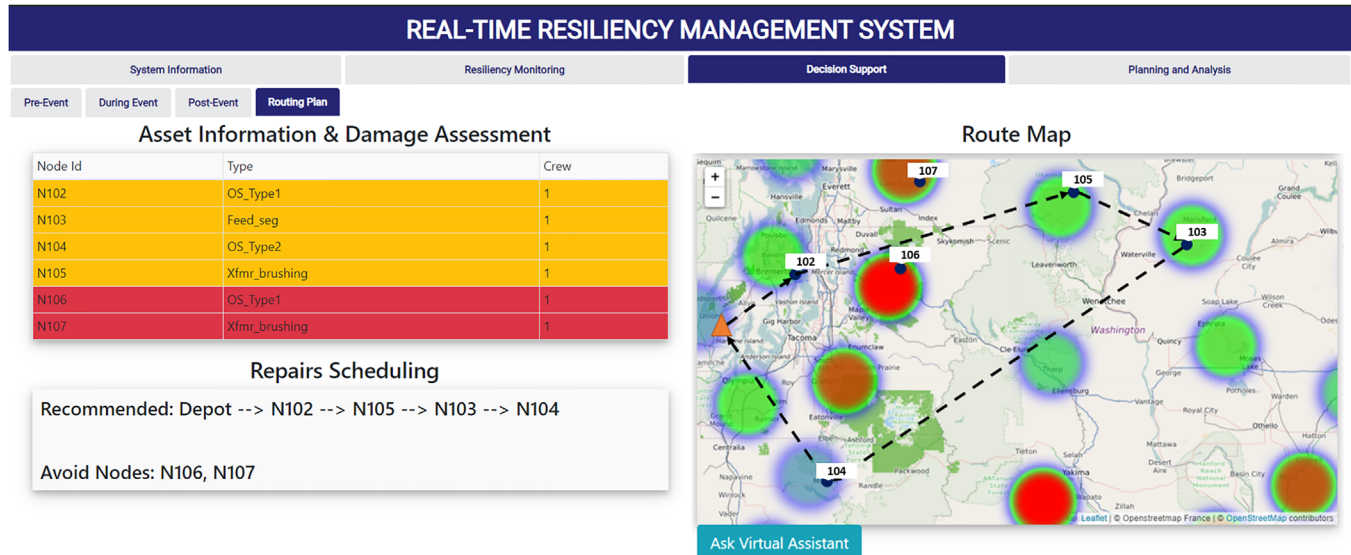
Digital query assistant is developed using natural language processing and plugged into the RT-RMT tool with the name “Ask Virtual Assistant” as shown in Figure 5. This can be used to dig the required information from the database where high data volumes from the power system network are stored. A virtual assistant will ease operator searches for necessary information during normal operating scenarios as well as emergency situations (such as outages, weather-related events, pandemics). The virtual assistant also lessens the cognitive burden on operators, reducing human errors in control decisions. A typical demonstration is showcased here by asking the query: “what node has the lowest voltage”? Results appear within a small window over the main screen as shown in Figure 7. This can be further enhanced with a virtual voice assistant—similar to Google and Apple applications—which helps the operator to locate necessary information.

#### 4.4.1 | Use case of RT-RMT for optimal crew routing during COVID-19 pandemic

The distribution test system is a 45-node simplified distribution network that is remote and with a large DERs support-

ing most of the operation, as shown in Figure 5. The dataset for the COVID-19 is derived from the CORD-19 (COVID-19 Open Research Dataset) presented by Wang et al. [162]. In normal operating conditions, the RT-RMT only supports operator actions while tracking the resiliency performance of the system. In the case of the COVID-19 pandemic, the authors developed a safe crew-routing algorithm, presented in Figure 8 that solves the crew routing problem for system repairs. It then filters the solution set for the crew route and schedules a path with the least risk of contracting COVID-19. The filtered solution set is then subject to a comparative analysis through the resiliency metrics to identify the most resilient crew route and is visualised in the RT-RMT live map for operator sign-off. The resiliency metric that captures the resiliency performance of the system after the extreme event has ended gathers the resiliency indicators that inform the rapidity of recovery for each restoration plan that is proposed by the operator [41].

A vector of recover resiliency indicators is formed ( $\mathbf{R} = [T_d, C_r, \tau, CL_r, SO]$ ) for each path. The indicator  $T_d$  represents the total down time,  $C_r$  represents the cost of repairs,  $\tau$  represents the topological resiliency coefficient that is based on graph-theoretical spectral metrics [116],  $CL_r$  represents the number of critical loads restored in the process, and SO is the



**FIGURE 9** Screen capture of RT-RMT showing the asset information with repair instructions, scheduling with no-go zones, and the routing on the map with crew-routing algorithm

number of switching operations. For each path, the vector  $\mathbf{R}$  is computed, and the analytical hierarchical process [119] is applied to find the composite resilience score. Resilience is maximally enabled when the operator selects a path with the highest resilience metric score.

A simple eight-node repair scenario is analysed in the test system from Figure 6. Once the RT-RMT obtains the damage assessment scenario, the resilience computation engine applies the routing algorithm to get the lowest weight route with the GIS, COVID-19 data, repair information, and scheduling requirements so that exposure of field crew to COVID-19 hotspots is avoided. Figure 6 shows the main operator screen with the resilience metrics calculations. The position of each node and relative proximity with COVID-19 hotspots are displayed on the tool UI (Figure 9). Three routes are analysed using the resilience metrics analysis, and the most resilient option that is also the safest is chosen. The safest route with avoided zones is shown in Figure 9.

## 5 | FUTURE WORK AND PATH FORWARD

The data needed for statistical learning can be divided into two parts: environmental data and power system data [163]. The ecological situation (e.g. precipitation, soil moisture, wind speed etc.) is not affected by the pandemic. Some parts of power systems data, such as component failures or the nature of cyberattacks, are not also affected by COVID-19. Hence, the rarity of COVID-19 affects neither the power system data nor the environmental data. Consequently, ML-approaches can be beneficial in pandemic situations. One challenge that needs to be addressed is finding efficient approaches to deal with sudden behaviour changes in energy consumption patterns in terms of short-term forecasting.

As reported by many resources such as [37], many control center experts had to work long hours, which leads to fatigue (as well as other problems), potentially resulting in human error. Implementing ML approaches can reduce the cognitive workload of humans in such cases.

Statistical learning techniques e.g. natural language processing, can be employed to analyse incoming calls of customers to pinpoint the location of failures in the power grid. Investing in the implementation of ML approaches is worthwhile to help customer operations and office staff by automatically detecting failed devices/locations, even without taking calls.

The IT staff were forced to work remotely which created opportunities for cyberattackers. Implementing ML approaches to detect suspicious changes in the power grid to protect against cyberattacks is beneficial to IT experts. Opinion dynamics have been studied for about 50 years; however, they have attracted a lot of attention recently [164, 165]. In the past few years, opinion dynamics are being used to thwart attacks on networks [166–168]. Therefore, combining ML and opinion dynamics is a potential future technique that could be applied to power grids to combat cyberattacks.

Utilising topological data analytics in anomaly detection in power grid studies are limited. Two examples of topological data analytics are [169, 170]. Topological data analytics in [170] is used to identify the divergent subpopulation in phenomics data throughout the growth period of plants. Such an approach might potentially detect the root cause of failures and early warning when equipment starts to behave abnormally. Moreover, Chen et al. [171] have designed an algorithm that reveals ML-algorithms' (such as recurrent neural networks) vulnerability to disturbance of input data. Attackers might manipulate the input data in order to affect the output of ML-algorithms. Chen et al. argue that current algorithms cannot detect such disturbances. Therefore, it would be worthwhile to investigate the approach of [170] to detect such disturbances. Furthermore, ML

is also being explored for cyber situational awareness [172] and needs more development in the future.

The existence of large amounts of data (e.g. collected by PMUs) is both a gift and a curse. From a hardware point of view, there is a need to either build an infrastructure that can handle that amount of data or long-term collaborations with Microsoft's Azure or Amazon's AWS need to be established. From a software point of view, there are packages that implement some ML techniques to enable dealing with data at scale. However, there are some challenges: some of the implemented techniques are very costly in terms of storage and computations (e.g. iterative methods such as neural networks), or not all ML techniques are implemented in a given software/library. Zheng and Degnino [173] provide a detailed survey of available resources and challenges in this regard.

Finally, we remind the reader of a lack of contingency plans for human aspect of power systems. COVID-19 revealed the vulnerability of power systems being implicitly affected as a result of human operators' vulnerability. Thus, there is an important gap in our knowledge that needs to be addressed. Filling this gap will need financial and organisational support but will be beneficial long term. Regardless of the dearth of data on operator vulnerability, resiliency, and/or contingency plans for human assets, the implementation of data-driven approaches discussed in this paper will increase the resiliency of the power grids so that normal operations can continue smoothly under circumstances such as COVID-19. The presence of data-driven techniques can be considered a prevention strategy for any interruption—e.g. the decrease in working hours of operators or the reduction in the number of human operators on site.

Similar to protection plans for physical assets (e.g. water barriers for substations), there is a need to build similar protection plans for human assets. Similar concepts can be carried out for humans—e.g. building onsite amenities for humans to stay for long shifts.

## 6 | CONCLUSIONS

As observed over the last several years, the frequency and intensity of natural disasters and extreme events and their associated impact on the power grid have been increasing. Pandemics such as COVID-19 add to these challenges and push organisations to their limits. Driven by smart grid investment, the power grid is moving towards massive sensor deployment and automation. Enhanced digitalisation has resulted in the collection of so much data that it is beyond the capacity of human operators to analyse, use, and factor it into timely decisions when responding to extreme events.

In this paper, the impact of COVID-19 on power grid operations has been analysed. Actions being taken by operators/organisations to minimise the effects of COVID-19 has been discussed in detail. Solutions have been suggested for deploying recently developed tools and concepts in ML and AI that will increase the resiliency of power systems in general and in extreme scenarios such as the COVID-19 pandemic. Suggested tools can assist operators in taking control actions,

allowing collaborative machine–human interactions while using increased data integration from diverse sources in an intelligent manner. Data-driven ML and AI could benefit operators by helping with the systems' resiliency, decision making, and disaster management in smarter ways. For example, predicting disaster impact, anomaly detection, and overlapping the COVID-19 hotspots with electricity service maps helps control room operators restore the grid fast and effectively by considering all safety measures. A sample case study of data-driven RT-RMT tool is presented to demonstrate the usefulness of advanced tools to system operator in case of pandemic and for enhanced resiliency.

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## ORCID

A. Srivastava  <https://orcid.org/0000-0003-3518-8018>

Sajan K.Sadanandan  <https://orcid.org/0000-0002-9770-8771>

## REFERENCES

- Panteli, M., Mancarella, P.: Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies. *Electric Power Syst. Res.* 127, 259–270 (2015)
- Jufri, F. H., Widiuputra, V., Jung, J.: State-of-the-art review on power grid resilience to extreme weather events: Definitions, frameworks, quantitative assessment methodologies, and enhancement strategies. *Appl. Energy* 239, 1049–1065 (2019)
- Panteli, M., Mancarella, P.: The grid: Stronger, bigger, smarter?: Presenting a conceptual framework of power system resilience. *IEEE Power Energy Mag.* 13(3), 58–66 (2015)
- A guide to critical infrastructure security and resilience. <https://www.cisa.gov/sites/default/files/publications/Guide-Critical-Infrastructure-Security-Resilience-110819-508v2.pdf>. Accessed 30 Apr 2020
- Utility readiness during pandemic: Keeping the lights on despite COVID-19. <https://www.tdworld.com/disaster-response/article/21126119/utility-readiness-during-pandemic-keeping-the-lights-on-despite-covid19>. Accessed 30 Apr 2020]
- Stevens-Adams, S., et al.: Situation awareness and automation in the electric grid control room. *Procedia Manufacturing* 3, 5277–5284, (2015)
- Talley, J. W.: Disaster management in the digital age. *IBM J. Res. Develop.* 64(1/2), 1:1–1:5 (2020)
- <https://www.eenews.net/stories/1062615349>. Accessed 30 Apr 2020]
- The microbiological threat to the national power grid, advanced pandemic planning for utilities executives. <https://www.mcguirewoods.com/news-resources/publications/Roche-Energy-White-Paper.pdf>. Accessed 30 Apr 2020
- Hoffman, P. et al.: Hardening and resiliency: U.S. energy industry response to recent hurricane seasons. Office of Cybersecurity, Energy Security, and Emergency Response (2010). <https://www.oe.netl.doe.gov/docs/HR-Report-final-081710.pdf>
- Bogges, J. M., Becker, G. W. & Mitchell, M. K. : Storm flood hardening of electrical substations. In: 2014 IEEE PES T D Conf. Expo., pp. 1–5. IEEE, Piscataway, NJ (2014). <https://www.ieee-pes.org/presentations/td2014/td2014p-000564.pdf>

12. Simmons, M., Stiles, C.: 1918 flu sheds light on how COVID-19 could affect critical infrastructure. <https://www.hstoday.us/subject-matter-areas/infrastructure-security/1918-flu-sheds-light-on-how-COVID-19-could-affect-critical-infrastructure/>. Accessed 30 Apr 2020
13. Terry, M.: Compare: 1918 spanish influenza pandemic versus covid-19. <https://www.biospace.com/article/compare-1918-spanish-influenza-pandemic-versus-covid-19/>. Accessed 30 Apr 2020
14. Zeitz, J.: Rampant lies, fake cures and not enough beds: What the spanish flu debacle can teach us about coronavirus. <https://www.politico.com/news/magazine/2020/03/17/spanish-flu-lessons-coronavirus-133888>. Accessed 30 Apr 2020
15. Chen, J. W. C., Ton, D.: Modernizing distribution system restoration to achieve grid resiliency against extreme weather events: An integrated solution. *Proc. IEEE* 105(7), 1267–1288 (2017)
16. Economic benefits of increasing electric grid resilience to weather outages. [https://www.energy.gov/sites/prod/files/2013/08/f2/Grid%20Resiliency%20Report\\_FINAL.pdf](https://www.energy.gov/sites/prod/files/2013/08/f2/Grid%20Resiliency%20Report_FINAL.pdf). Accessed 30 Apr 2020
17. Rapid response: How outage prediction models help utilities get power back on quickly and save money after a storm. <https://www.ibm.com/downloads/cas/P80BZ0XX>. Accessed 30 Apr 2020
18. Electric grid security and resilience establishing a baseline for adversarial threats. <https://www.energy.gov/sites/prod/files/2017/01/f34/Electric%20Grid%20Security%20and%20Resilience--Establishing%20a%20Baseline%20for%20Adversarial%20Threats.pdf>. Accessed 30 Apr 2020
19. Electric power system resiliency, challenges and opportunities. <https://www.naseo.org/Data/Sites/1/resiliency-white-paper.pdf>. Accessed 30 Apr 2020
20. Coronavirus: Can you get COVID-19 twice or does it cause immunity? <https://www.independent.co.uk/life-style/health-and-families/coronavirus-immunity-reinfection-get-covid-19-twice-sick-spread-relapse-a9400691.html>. Accessed 07 Jul 2020
21. Can you get the COVID-19 coronavirus twice? <https://theconversation.com/can-you-get-the-covid-19-coronavirus-twice-137309>. Accessed 7 Jul 2020
22. Heidt, A.: Studies report rapid loss of COVID-19 antibodies. <https://www.the-scientist.com/news-opinion/studies-report-rapid-loss-of-covid-19-antibodies-67650>. Accessed 29 July 2020
23. Liu, T., et al.: Prevalence of IgG antibodies to SARS-CoV-2 in wuhan-implications for the ability to produce long-lasting protective antibodies against SARS-CoV-2. *medRxiv* 2020.06.13.20130252 (2020)
24. Ensuring energy reliability throughout the covid-19 pandemic: Testing and protecting mission-essential control center and generation facility personnel is fundamental. [https://www.electricitysubsector.org/-/media/Files/ESCC/Documents/ESCC\\_Mission\\_Essential\\_Workforce\\_2020.aspx?la=en&hash=7618009ED20A06A987105A0817A180202406AFDF](https://www.electricitysubsector.org/-/media/Files/ESCC/Documents/ESCC_Mission_Essential_Workforce_2020.aspx?la=en&hash=7618009ED20A06A987105A0817A180202406AFDF). Accessed 30 Apr 2020
25. Special report. pandemic preparedness and operational assessment: Spring 2020. [https://www.nerc.com/pa/rrm/bpsa/Alerts%20DL/NERC\\_Pandemic\\_Preparedness\\_and\\_Op\\_Assessment\\_Spring\\_2020.pdf](https://www.nerc.com/pa/rrm/bpsa/Alerts%20DL/NERC_Pandemic_Preparedness_and_Op_Assessment_Spring_2020.pdf). Accessed 30 Apr 2020
26. Shaker, M. S., et al.: COVID-19: Pandemic contingency planning for the allergy and immunology clinic. *J. Allergy Clin. Immunol.: In Pract.* 8(5), 1477–1488.e5 (2020)
27. Wu, K. M. F. F., Bose, A.: Power system control centers: Past, present, and future. *Proc. IEEE* 93(11), 1890–1908 (2005)
28. Utility outage prediction 2.0: Embracing advanced analytics & machine learning solutions. <https://www.ibm.com/downloads/cas/VO6DNBR3>. Accessed 30 Apr 2020
29. Bao, Y., et al.: Impact analysis of human factors on power system operation reliability. *J. Modern Power Syst. Clean Energy* 6(1), 27–39 (2018)
30. Bilke, T. A., Midwest, I.: Cause and prevention of human error in electric utility operations. Master's Thesis, Colorado State University (1998)
31. Prostejovsky, A. M., et al.: The future role of human operators in highly automated electric power systems. *Electric Power Syst. Res.* 175, 105883 (2019)
32. Guttromson, R. et al.: Human factors for situation assessment in power grid operations. *Pacific Northwest Nat. Lab. Rep.–PNNL16780* (2007) [https://www.pnnl.gov/main/publications/external/technical\\_reports/PNNL-16780.pdf](https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-16780.pdf)
33. Czarnowski, I., et al.: Complex power system status monitoring and evaluation using big data platform and machine learning algorithms: A review and a case study. *Complexity* 2018, 8496187 (2018)
34. The future of electric grid. <https://energy.mit.edu/wp-content/uploads/2011/12/MITEI-The-Future-of-the-Electric-Grid.pdf>. Accessed 30 Apr 2020
35. Covid-19 pandemic; challenges and opportunities in power systems. <https://smartgrid.ieee.org/newsletters/may-2020/covid-19-pandemic-challenges-and-opportunities-in-power-systems>. Accessed 30 Apr 2020
36. Barooh, P., Agdas, D.: The COVID-19 pandemic's impact on electricity demand and supply. <https://eprints.qut.edu.au/200965/>. Accessed 30 Apr 2020
37. Paaso, A., et al.: Sharing Knowledge on Electrical Energy Industry's First Response to COVID-19. IEEE, Piscataway, NJ (2020)
38. Kraemer, M. U., et al.: The effect of human mobility and control measures on the COVID-19 epidemic in china. *Science* 368(6490), 493–497 (2020)
39. Michigan puts \$175m price tag on flooding damage in midland county. <https://www.freep.com/story/news/local/michigan/2020/06/08/midland-flood-damage-major-disaster-whitmer/5321673002/>. Accessed 07 Jul 2020
40. After cyclone hits india and bangladesh, the waiting begins <https://www.nytimes.com/2020/05/20/world/asia/cyclone-amphan-india-bangladesh-map.html>. Accessed 07 Jul 2020
41. Kandaperumal, G., Srivastava, A. K.: Resilience of the electric distribution systems: concepts, classification, assessment, challenges, and research needs. *IET Smart Grid* 3(2), 133–143 (2020)
42. Arab, A., et al.: Electric power grid restoration considering disaster economics. *IEEE Access* 4, 639–649 (2016)
43. Krishnamurthy, V., Kwasinski, A.: Comparison of communication networks power resilience during man-made and natural disasters. In: 2018 IEEE Int. Telecommunication Energy Conf. (INTELEC), pp. 1–8. IEEE, Piscataway, NJ (2018)
44. Kwasinski, A., Krein, P. T.: Telecom power planning for natural and man-made disasters. In: INTELEC 07-29th Int. Telecommunication Energy Conf., pp. 216–222. IEEE, Piscataway, NJ (2007)
45. Council, N. R., et al.: *Terrorism Electric Power Delivery System*. National Academies Press, Washington, D.C. (2012)
46. Amirion, M., et al.: Metrics and quantitative framework for assessing microgrid resilience against windstorms. *Int. J. Elect. Power Energy Syst.* 104, 716–723 (2019)
47. Wang, Y., et al.: Research on resilience of power systems under natural disasters—a review. *IEEE Trans. Power Syst.* 31(2), 1604–1613 (2016)
48. Mohamed, M. A., et al.: Proactive resilience of power systems against natural disasters: A literature review. *IEEE Access* 7, 163778–163795 (2019)
49. Hossain, E., et al.: Application of big data and machine learning in smart grid, and associated security concerns: A review. *IEEE Access* 7, 13960–13988 (2019)
50. Borges Hink, R. C., et al.: Machine learning for power system disturbance and cyber-attack discrimination. In: 2014 Seventh Int. Symp. Resilient Control Syst. (ISRCs), pp. 1–8. IEEE, Piscataway, NJ (2014)
51. Zhang, Y., et al.: Distributed intrusion detection system in a multi-layer network architecture of smart grids. *IEEE Trans. Smart Grid* 2(4), 796–808 (2011)
52. Ahmed, A., et al.: Cyber physical security analytics for anomalies in transmission protection systems. In: 2018 IEEE Ind. Appl. Society Annu. Meeting (IAS), pp. 1–8. IEEE, Piscataway, NJ (2018)
53. Giri, J., et al.: The situation room: Control center analytics for enhanced situational awareness. *IEEE Power Energy Mag.* 10(5), 24–39 (2012)
54. Jiang, Y., Srivastava, A. K.: Data-driven event diagnosis in transmission systems with incomplete and conflicting alarms given sensor malfunctions. *IEEE Trans. Power Del.* 35(1), 214–225 (2020)
55. Pandey, S., Srivastava, A., Amidan, B.: A real time event detection, classification and localization using synchrophasor data. *IEEE Trans. Power Syst.* 35(6), 4421–4431 (2020)

56. Cardoso, G., Rolim, J. G., Zurn, H. H.: Application of neural-network modules to electric power system fault section estimation. *IEEE Trans. Power Del.* 19(3), 1034–1041 (2004)
57. Wang, H., Butler, K. L.: Neural network modeling of distribution transformers with internal short circuit winding faults. In: *PICA 2001. Innov. Comput. Power - Electric Energy Meets Market. 22nd IEEE Power Eng. Soc. Int. Conf. Power Ind. Comput. Appl.*, pp. 122–127. IEEE, Piscataway, NJ (2001)
58. Reddy, A. S., Vijaykumar, M.: Neural network modeling of distribution transformer with internal winding faults using double fourier series. *Int. J. Comput. Sci. Appl.* 1(3), 160–163 (2008)
59. Ghanizadeh, A. J., Gharehpetian, G. B.: ANN and cross-correlation based features for discrimination between electrical and mechanical defects and their localization in transformer winding. *IEEE Trans. Dielectrics Elect. Insul.* 21(5), 2374–2382 (2014)
60. Cui, B., Srivastava, A. K., Banerjee, P.: Synchrophasor-based condition monitoring of instrument transformers using clustering approach. *IEEE Trans. Smart Grid* 11(3), 2688–2698 (2020)
61. Rudin, C., et al.: Analytics for power grid distribution reliability in New York City. *Interfaces* 44(4), 364–383 (2014)
62. Gholami, A., Srivastava, A. K., Pandey, S.: Data-driven failure diagnosis in transmission protection system with multiple events and data anomalies. *J. Modern Power Syst. Clean Energy* 7(4), 767–778 (2019)
63. Foroutan, S. A., Salmasi, F. R.: Detection of false data injection attacks against state estimation in smart grids based on a mixture gaussian distribution learning method. *IET Cyber-Phys. Syst.: Theory Appl.* 2(4), 161–171 (2017)
64. Electric companies & pandemic planning what you should know. <https://www.eei.org/issuesandpolicy/Documents/Electric%20Companies%20and%20Pandemics%20-%20What%20You%20Should%20Know.pdf>. Accessed 30 Apr 2020
65. FERC approves NERC's motion to defer implementation of seven reliability standards due to COVID-19. <https://www.nerc.com/news/Pages/NERC-Files-Motion-to-Defer-Implementation-of-Seven-Reliability-Standards-Due-to-COVID-19.aspx>. Accessed 30 Apr. 2020
66. Order granting deferred implementation of certain nerc reliability standard. <https://www.nerc.com/FilingsOrders/us/FERCOrdersRules/order%20granting%20motion%20to%20defer%20the%20implementation%20dates.pdf>. Accessed 30 Apr 2020
67. Ospina, J., et al.: On the feasibility of load-changing attacks in power systems during the COVID-19 pandemic. *IEEE Access* 9, 2545–2563 (2021)
68. Tuohy, A., et al.: Covid-19 bulk system impacts. <http://mydocs.epri.com/docs/public/covid19/3002018602R2.pdf>. Accessed 30 Apr 2020
69. COVID-19-related load impacts are being reported by several us grid operators. <https://www.spglobal.com/platts/en/market-insights/latest-news/electric-power/032320-COVID-19-related-load-impacts-are-being-reported-by-several-us-grid-operators>. Accessed 30 Apr 2020
70. Utilities beginning to see the load impacts of COVID-19 as economic shutdown widens. <https://www.utilitydive.com/news/utilities-are-beginning-to-see-the-load-impacts-of-COVID-19-as-economic-sh/574632>. Accessed 30 Apr 2020
71. Zhong, H., et al.: Implications of COVID-19 for the electricity industry: A comprehensive review. *CSEE J. Power Energy Syst.* 6(3), 489–495 (2020)
72. Entso-e transparency. <https://transparency.entsoe.eu/> (2020). Accessed 29 July 2020
73. Executive department of California, executive order n-33-20. <https://www.gov.ca.gov/wp-content/uploads/2020/03/3.19.20-attested-EO-N-33-20-COVID-19-HEALTH-ORDER.pdf>. Accessed 07 July 2020
74. <https://www.governor.ny.gov/news/governor-cuomo-signs-new-york-state-pause-executive-order>. Accessed 07 July 2020
75. Madurai Elavarasan, R., et al.: COVID-19: Impact analysis and recommendations for power sector operation. *Appl. Energy* 279, 115739 (2020)
76. Lu, Y., Zhou, R., Wang, J.: Analysis of power generation and load change under the influence of lockdown based on COVID-19 epidemic. In: *2020 AEIT Int. Annual Conf. (AEIT)*, pp. 1–6. IEEE, Piscataway, NJ (2020)
77. Agdas, D., Barooah, P.: Impact of the covid-19 pandemic on the u.s. electricity demand and supply: An early view from data. *IEEE Access* 8, 151523–151534 (2020)
78. Badri, A., Ameli, Z., Birjandi, A.: Application of artificial neural networks and fuzzy logic methods for short term load forecasting. *Energy Procedia* 14, 1883–1888 (2012)
79. Dudek, G.: Neural networks for pattern-based short-term load forecasting: A comparative study. *Neurocomputing* 205, 64–74 (2016)
80. Ruan, G., et al.: A cross-domain approach to analyzing the short-run impact of COVID-19 on the U.S. electricity sector. *Joule* 4(11), 2322–2337 (2020)
81. Abbas, H., Wen, J.: How is COVID-19 impacting the UK electricity system? <https://www.frontier-economics.com/uk/en/news-and-articles/articles/article-i7214-how-is-covid-19-impacting-the-uk-electricity-system/>. Accessed 13 Sept 2020
82. COVID-19 impact on electricity. <https://www.iea.org/reports/covid-19-impact-on-electricity/>. Accessed 13 Sept 2020
83. COVID-19: America hasn't used this little energy in 16 years. <https://www.weforum.org/agenda/2020/04/united-states-energy-electricity-power-coronavirus-covid19/>. Accessed 13 Sept 2020
84. California renewables curtailments surge as coronavirus cuts energy demand. <https://www.greentechmedia.com/articles/read/california-renewable-curtailments-spike-as-coronavirus-reduces-demand/>. Accessed 13 Sept 2020
85. Renewables achieve clean energy record as covid-19 hits demand. <https://www.renewableenergyworld.com/2020/04/06/renewables-achieve-clean-energy-record-as-covid-19-hits-demand/> (2020). Accessed 13 Sept 2020
86. 5 things to know about how coronavirus has hit global energy. <https://www.weforum.org/agenda/2020/05/covid19-energy-use-drop-crisis/>. Accessed 13 Sept 2020
87. Abnormal system. grid operators brace for the worst. <https://www.eenews.net/stories/1062955735/print>. Accessed 19 Apr 2021
88. We have never done this before. inside N.Y.'s grid lockdown. <https://www.eenews.net/stories/1062737239>. Accessed 30 Apr 2020]
89. America's electricity is safe from the coronavirus—for now. <https://www.wired.com/story/americas-electricity-is-safe-from-the-coronavirus-for-now>. Accessed 19 Apr 2021
90. Grid operators cancel travel, shift to remote meetings, as industry preps for broad coronavirus absenteeism. <https://www.utilitydive.com/news/gridoperators-cancel-travel-shift-to-remote-meetings-asindustry-preps-f/573988/>. Accessed 19 Apr 2021
91. Pjm coronavirus (COVID-19) information. <https://www.pjm.com/about-pjm/newsroom/info-connection>. Accessed 19 Apr 2021
92. FERC, NERC provide industry guidance to ensure grid reliability amid potential coronavirus impacts. <https://www.nerc.com/news/Headlines%20DL/FERC%20NERC%20031820%20final.pdf>. Accessed 30 Apr 2020
93. Assessing and mitigating the novel coronavirus (COVID-19), a resource guide - version 6. [https://www.electricitysubsector.org/-/media/Files/ESCC/Documents/ESCC\\_COVID\\_Resource\\_Guide\\_v2-03242020.ashx?la=en&hash=D3732CBFB46827AA0331277E8D5CBE0CC4DFC3BF](https://www.electricitysubsector.org/-/media/Files/ESCC/Documents/ESCC_COVID_Resource_Guide_v2-03242020.ashx?la=en&hash=D3732CBFB46827AA0331277E8D5CBE0CC4DFC3BF) (2020). Accessed 30 Apr 2020
94. Announcement grid operators well prepared for COVID-19, alert responses find. <https://www.nerc.com/news/Headlines%20DL/Alert%2027MAR20.pdf>. Accessed 30 Apr 2020
95. How power companies are keeping your lights on during the pandemic. <https://www.latimes.com/environment/story/2020-03-19/how-power-companies-are-keeping-your-lights-on-during-the-pandemic>. Accessed 30 Apr 2020
96. America's electricity is safe from the coronavirus—for now. <https://www.wired.com/story/americas-electricity-is-safe-from-the-coronavirus-for-now/> (2020). Accessed 30 Apr 2020
97. Hosseini, S., Barker, K., Ramirez-Marquez, J. E.: A review of definitions and measures of system resilience. *Rel. Eng. Syst. Saf.* 145(C), 47–61 (2016)
98. Bie, Z., et al.: Battling the extreme: A study on the power system resilience. *Proc. IEEE* 105(7), 1253–1266 (2017)

99. Electric power system resiliency, challenges and opportunities. <https://www.nasco.org/Data/Sites/1/resiliency-white-paper.pdf>. Accessed 07 Jul 2020
100. Hirst, E. & Kirby, B. : Bulk-power basics: Reliability and commerce. Consulting Electric-Ind. Restructuring, Oak Ridge, Tennessee pp. 1–40 (2000). <http://www.consultkirby.com/files/RAPBPBasics.pdf>
101. Robustness, flexibility and resilience. <http://www.husdal.com/2008/04/28/robustness-flexibility-and-resilience-in-the-supply-chain/#:~:text=Flexibility%20is%20the%20inherent%20capability,these%20changes%20despite%20severe%20impact>. Accessed 17 July 2020
102. Presidential policy directive (PPD) 21: Critical infrastructure security and resilience. <https://www.cisa.gov/sites/default/files/publications/PPD-21-Critical-Infrastructure-and-Resilience-508.pdf>. Accessed 30 Apr 2020
103. Michael Lewis, R. H.: Resilience and pandemics. [https://smartgrid.ieee.org/newsletters/may-2020/resilience-and-pandemics?utm\\_source=sg-monthly-may2020&utm\\_medium=email&utm\\_campaign=2020-enevletter](https://smartgrid.ieee.org/newsletters/may-2020/resilience-and-pandemics?utm_source=sg-monthly-may2020&utm_medium=email&utm_campaign=2020-enevletter) (2020). Accessed 7 July 2020 (2020)
104. Rudin, C., et al.: Machine learning for the new york city power grid. *IEEE Trans. Pattern Anal. Mach. Intell.* 34(2), 328–345 (2012)
105. Wu, R., Sansavini, G.: Integrating reliability and resilience to support the transition from passive distribution grids to islanding microgrids. *Appl. Energy* 272, 115254 (2020)
106. Improving electric grid reliability and resilience: Lessons learned from superstorm sandy and other extreme events. [https://www.gridwise.org/documents/ImprovingElectricGridReliabilityandResilience\\_6\\_6\\_13webFINAL.pdf](https://www.gridwise.org/documents/ImprovingElectricGridReliabilityandResilience_6_6_13webFINAL.pdf). Accessed 30 Apr 2020
107. Mirsaedi, S., et al.: An analytical literature review of the available techniques for the protection of micro-grids. *Int. J. Elect. Power & Energy Syst.* 58, 300–306 (2014)
108. Li, Z., et al.: Networked microgrids for enhancing the power system resilience. *Proc. IEEE* 105(7), 1289–1310 (2017)
109. Liu, X., et al.: Microgrids for enhancing the power grid resilience in extreme conditions. *IEEE Trans. Smart Grid* 8(2), 589–597 (2017)
110. Lin, H., et al.: Adaptive protection combined with machine learning for microgrids. *IET Gener., Transmiss. Distribution* 13(6), 770–779 (2019)
111. Mishra, S., et al.: Microgrid resilience: A holistic approach for assessing threats, identifying vulnerabilities, and designing corresponding mitigation strategies. *Appl. Energy* 264, 114726 (2020)
112. Abdollah, K., Su, W., Jin, T.: A machine learning based cyber attack detection model for wireless sensor networks in microgrids. *IEEE Trans. Ind. Inform.* 17(1), 650–658 (2020)
113. Kolluri, R. R., de Hoog, J.: Adaptive control using machine learning for distributed storage in microgrids. In: *Proc. Eleventh ACM Int. Conf. Future Energy Syst.* pp. 509–515, ACM Press, New York (2020)
114. Lin, H., et al.: Adaptive protection combined with machine learning for microgrids. *IET Gener., Transmiss. Distribution* 13(6), 770–779 (2019)
115. Al Karim, M., Currie, J., Lie, T.: Dynamic event detection using a distributed feature selection based machine learning approach in a self-healing microgrid. *IEEE Trans. Power Syst.* 33(5), 4706–4718 (2018)
116. Chanda, S., Srivastava, A. K.: Defining and enabling resiliency of electric distribution systems with multiple microgrids. *IEEE Trans. Smart Grid* 7(6), 2859–2868 (2016)
117. Venkataramanan, V., Hahn, A., Srivastava, A.: Cyphyr: a cyber-physical analysis tool for measuring and enabling resiliency in microgrids. *IET Cyber-Phys. Syst.: Theory Appl.* 4(4), 313–321 (2019)
118. Venkataramanan, V., Hahn, A., Srivastava, A.: CPSAM: Cyber-physical security assessment metric for monitoring microgrid resiliency. *IEEE Trans. Smart Grid* 11(2), 1055–1065 (2020)
119. Diahovchenko, I., Kandaperumal, G., Srivastava, A.: Distribution power system resiliency improvement using distributed generation and automated switching. In: *2019 IEEE sixth Int. Conf. Energy Smart Syst. (ESS)*, pp. 126–131. IEEE, Piscataway, NJ (2019)
120. Pandey, S., et al.: Resiliency-driven proactive distribution system reconfiguration with synchrophasor data. *IEEE Trans. Power Syst.* 35(4), 2748–2758 (2020)
121. Madani, V., et al.: Ieee psrsc report on global industry experiences with system integrity protection schemes (SIPS). *IEEE Trans. Power Del.* 25(4), 2143–2155 (2010)
122. Smart grid investments improve grid reliability, resilience, and storm responses. <https://www.energy.gov/sites/prod/files/2014/12/f19/SG-ImprovesRestoration-Nov2014.pdf>. Accessed 30 Apr 2020
123. Madani, V., Novosel, D.: Getting a grip on the grid. *IEEE Spectr.* 42(12), 42–47 (2005)
124. Gupta, S., et al.: Support-vector-machine-based proactive cascade prediction in smart grid using probabilistic framework. *IEEE Trans. Ind. Electr.* 62(4), 2478–2486 (2015).
125. Eskandarpour, R., Khodaei, A.: Machine learning based power grid outage prediction in response to extreme events. *IEEE Trans. Power Syst.* 32(4), 3315–3316 (2017)
126. Eskandarpour, R., Khodaei, A., Arab, A.: Improving power grid resilience through predictive outage estimation. In: *2017 North American Power Symp. (NAPS)*, pp. 1–5. IEEE, Piscataway, NJ (2017)
127. Guikema, S. D., Quiring, S. M., Han, S.-R.: Prestorm estimation of hurricane damage to electric power distribution systems *Risk Anal.: An Int. J.* 30(12), 1744–1752 (2010)
128. Glavic, M., Fonteneau, R., Ernst, D.: Reinforcement learning for electric power system decision and control: Past considerations and perspectives. *IFAC-PapersOnLine* 50(1), 6918–6927 (2017)
129. Huang, Q., et al.: Adaptive power system emergency control using deep reinforcement learning. *IEEE Trans. Smart Grid* 11(2), 1171–1182 (2020)
130. Maharjan, L., et al.: Machine learning based energy management system for grid disaster mitigation. *IET Smart Grid* 2(2), 172–182 (2019)
131. Brewer, D. : The economics costs of forecasting errors in the PJM interconnection due to the COVID-19 quarantine. In: *Energy Forum* (2020)
132. Benatia, D. : Reaching new lows? The pandemic's consequences for electricity markets. USAEE Working Paper No. 20–454 (2020) <https://ideas.repec.org/p/crs/wpaper/2020-12.html>.
133. Ruan, G., et al.: Quantitative assessment of u.s. bulk power systems and market operations during the COVID-19 pandemic. *Appl. Energy* 286, 116354 (2021)
134. Buechler, E., et al.: Power and the pandemic: exploring global changes in electricity demand during covid-19. *arXiv:2008.06988*, (2020)
135. Alasali, F., et al.: Impact of the COVID-19 pandemic on electricity demand and load forecasting. *Sustainability* 13(3), 1435 (2021)
136. Chen, Y., Yang, W., Zhang, B.: Using mobility for electrical load forecasting during the COVID-19 pandemic. *arXiv:2006.08826*, (2020)
137. Zografopoulos, I., et al.: Cyber-physical energy systems security: Threat modeling, risk assessment, resources, metrics, and case studies. *arXiv:2101.10198*, (2021)
138. Yao, R., et al.: Unsupervised anomaly detection using variational auto-encoder based feature extraction. In: *2019 IEEE Int. Conf. Prognostics Health Manage. (ICPHM)*, pp. 1–7. IEEE, Piscataway, NJ (2019)
139. Biswas, S., Meyur, R., Centeno, V. A.: Devlearn: A deep visual learning framework for determining the location of temporary faults in power systems. In: *2020 IEEE Int. Conf. Commun., Control, Comput. Technol. Smart Grids (SmartGridComm)*, pp. 1–6. IEEE, Piscataway, NJ (2020)
140. Zheng, R., Gu, J.: Anomaly detection for power system forecasting under data corruption based on variational auto-encoder. In: *Eighth Renewable Power Generation Conf. (RPG 2019)*, pp. 1–6. IET, London (2019)
141. Takiddin, A., et al.: Variational auto-encoder-based detection of electricity stealth cyber-attacks in ami networks. In: *2020 28th European Signal Process. Conf. (EUSIPCO)*, pp. 1590–1594. IEEE, Piscataway, NJ (2021)
142. Yang, Y., et al.: Network intrusion detection based on supervised adversarial variational auto-encoder with regularization. *IEEE Access* 8, 42 169–42 184 (2020)
143. An, J., Cho, S.: Variational autoencoder based anomaly detection using reconstruction probability. *Special Lecture IE* 2(1), 1–18 (2015)
144. Sun, J., et al.: Learning sparse representation with variational auto-encoder for anomaly detection. *IEEE Access* 6, 33 353–33 361 (2018)
145. Osada, G., Omote, K., Nishide, T.: Network intrusion detection based on semi-supervised variational auto-encoder. In: *S. N. Foley, D. Gollmann, E. Sneekenes, (eds.) Comput. Secur. – ESORICS 2017*, pp. 344–361. Springer, Cham (2017)

146. Goodfellow, I. J., et al.: Generative adversarial networks. arXiv:1406.2661, (2014)
147. Liu, J., et al.: A small-sample wind turbine fault detection method with synthetic fault data using generative adversarial nets. *IEEE Trans. Ind. Inform.* 15(7), 3877–3888 (2019)
148. Adiban, M., Safari, A., Salvi, G.: Step-gan: a step-by-step training for multi generator gans with application to cyber security in power systems. arXiv:2009.05184, (2020)
149. Zhang, Y., Wang, J., Chen, B.: Detecting false data injection attacks in smart grids: A semi-supervised deep learning approach. *IEEE Trans. Smart Grid* 12(1), 623–634 (2021)
150. Ying, H., et al.: Power message generation in smart grid via generative adversarial network. In: 2019 IEEE third Inf. Technol., Netw., Electron. Automat. Control Conf. (ITNEC), pp. 790–793. IEEE, Piscataway, NJ (2019)
151. Baranovic, N., et al.: Experiences from intelligent alarm processing and decision support tools in smart grid transmission control centers. In *Cigre Session vol. 46*, pp. 21–26. CIGRE, Paris (2016)
152. Pandey, S., Patari, N., Srivastava, A. K.: Cognitive flexibility of power grid operator and decision making in extreme events. In: 2019 IEEE Power Energy Soc. Gen. Meeting (PESGM), pp. 1–5. IEEE, Piscataway, NJ (2019)
153. Elizondo, D., et al.: Hidden failures in protection systems and their impact on wide-area disturbances. In: 2001 IEEE Power Eng. Soc. Winter Meeting. Conf. Proc., vol. 2, pp. 710–714. IEEE, Piscataway, NJ (2001)
154. Gao, X., Thorp, J. S., Hou, D.: Case studies: Designing protection systems that minimize potential hidden failures. In: 2013 66th Annual Conf. for Protective Relay Engineers, pp. 384–393. IEEE, Piscataway, NJ (2013)
155. Yang, F., et al.: Effects of protection system hidden failures on bulk power system reliability. In: 2006 38th North American Power Symp., pp. 517–523. IEEE, Piscataway, NJ (2006)
156. Jiao, Z., Gong, H., Wang, Y.: A D-S evidence theorybased relay protection system hidden failures detection method in smart grid. *IEEE Trans. Smart Grid* 9(3), 2118–2126 (2018)
157. Liao, W., et al.: Cascading failure attacks in the power system: A stochastic game perspective. *IEEE Internet of Things J.* 4(6), 2247–2259 (2017)
158. Jung, J., et al.: Adaptation in load shedding under vulnerable operating conditions. *IEEE Trans. Power Syst.* 17(4), 1199–1205 (2002)
159. Salfner, F., Malek, M.: Using hidden semi-markov models for effective online failure prediction. In: 2007 26th IEEE Int. Symp. Reliable Distributed Syst. (SRDS 2007), pp. 161–174. IEEE, Piscataway, NJ (2007)
160. Anshuman, A., et al.: Rt-rms: A real-time resiliency management system for operational decision support. In: 2020 North American Power Symp. (NAPS), pp. 1–6. IEEE, Piscataway, NJ (2020)
161. <https://www.knowi.com/coronavirus-dashboards/covid-19-api/>. Accessed 7 July 2020
162. Wang, L. L., et al.: COVID-19: The COVID-19 open research dataset. arXiv:2004.10706, (2020)
163. Wang, Y., et al.: Research on resilience of power systems under natural disasters: A review. *IEEE Trans. Power Syst.* 31(2), 1604–1613 (2016)
164. Noorazar, H.: Recent advances in opinion propagation dynamics: A 2020 survey. *European Phys. J. Plus* 135, 521 (2020)
165. Noorazar, H., et al.: From classical to modern opinion dynamics. *Int. J. Modern Phys. C* 31(7), 2050101 (2020)
166. Shang, Y.: Consensus and clustering of expressed and private opinions in dynamical networks against attacks. *IEEE Syst. J.* 14(2), 2078–2084 (2019)
167. Rubio, J. E., et al.: Enhancing security and dependability of industrial networks with opinion dynamics. In: *European Symposium on Research in Computer Security*, pp. 263–280. Springer, Cham (2019)
168. Alcaraz, C.: Cloud-assisted dynamic resilience for cyber-physical control systems. *IEEE Wirel. Commun.* 25(1), 76–82 (2018)
169. Chazal, F., Michel, B.: An introduction to topological data analysis: fundamental and practical aspects for data scientists. arXiv:1710.04019, (2017)
170. Kamruzzaman, M., Kalyanaraman, A., Krishnamoorthy, B.: Detecting divergent subpopulations in phenomics data using interesting flares. In: *Proc. 2018 ACM Int. Conf. on Bioinformatics, Computational Biology, Health Information*, pp. 155–164. ACM Press, New York (2018)
171. Chen, Y., Tan, Y., Deka, D.: Is machine learning in power systems vulnerable?. In: 2018 IEEE Int. Conf. Commun., Control, Comput. Technol. Smart Grids (SmartGridComm), pp. 1–6. IEEE, Piscataway, NJ (2018)
172. Franke, U., Brynielsson, J.: Cyber situational awareness—a systematic review of the literature. *Comput. Security* 46, 18–31 (2014)
173. Zheng, J., Dagnino, A.: An initial study of predictive machine learning analytics on large volumes of historical data for power system applications. In: 2014 IEEE Int. Conf. Big Data (Big Data), pp. 952–959. IEEE, Piscataway, NJ (2014)

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