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Summary

The power system operators, as well as asset and outage management personnel are now experiencing significantly enlarged amount of data obtained through field measurements, historical maintenance records, and external sources such as variety of weather data. In this paper we surveyed our work focused on the role of machine learning (ML) and artificial intelligence (AI) methods applied to a) managing and controlling future power system by automatically analysing transmission line faults using synchrophasor data, b) predicting the risk of forced outages in the distribution system using historical outage records and weather data at different spatiotemporal horizons, and c) examining how the outage risk predictions may be used to determine availability of the distributed energy resources (DERs) for participation in the wholesale market ancillary service products (ASP) aimed at aggregators bidding for ASP aiming at preventing overall system outages.

We start our survey with first discussing development of data models for automated faults analysis using synchrophasor data and indicate how the ML model training and testing may be done using both field-recorded and model-simulated data. We illustrate such approaches using recent studies where we had access to utility synchrophasor data, and we point out to the variety of data issues that must be carefully examined when such applications are developed.

Next, we focus on introducing the concept of State of Risk (SoR) prediction, and associated optimization techniques aimed at minimizing or eliminating the distribution system outage impacts through appropriate risk management and mitigation measures. We present experiences from recent utility demonstration projects where we used the historical outage data combined with variety of weather data to develop SoR maps for predicting risk of outages. We also suggest a set of mitigation measures aimed at helping the utility customers to deal with outage impacts ahead of the time.

As a final example, we elaborate on the issue of aggregation of DERs with a purpose of meeting Ancillary Service Product (ASP) requirements designed to help market operators maintain power system reliability and integrity during imbalances between supply and demand. We illustrate how the SoR outage prediction may be used to improve the bidding strategy for the aggregators.

In the conclusions, we highlight how ML/AI methods may be utilized to enhance reliability and resilience of power system operation at the transmission and distribution level, as well at the level of the end customer.

Keywords

Power System-Outage-Machine Learning-Artificial Intelligence-Risk-Resilience

1. Introduction

ML/AI have been used in power systems to deal with the big data problem for the last decade [1]. During this time many applications have been developed and some have been demonstrated using utility data [2]. One of the key findings was that ML/AI may be effective if variety of historical data is available and properly labelled and stored for future issues. Particularly, the weather data turned out to be very useful when predicting power system outages and planning for resilient electric grid operation [3,4].

Our focus in this paper is on three applications where ML/AI may be used to create automated assessment of power system operation, which in turn may be used to enhance power system resilience against disturbances and imbalances between power supply and demand.

First, the discussion is focused on the use of ML/AI in detecting and classifying power system faults, and other disturbances that may lead to system-wide power system outages. We examine the use of synchrophasor data for building the data models for automated analysis of streaming synchrophasor data captured by phasor measurement units (PMUs) sparsely located in the field. Based on our recent experiences from projects that use field-recorded data, we reported many possible approaches to developing ML/AI models to help operators deal with making decisions under an overwhelming volume of synchrophasor data that may be used to analyse the events online [5-11]. We also summarized our experiences in recent CIGRE papers [12-13]. In this paper we addressed some key issues when developing ML/AI models, namely the data quality, feature selection, and data model training.

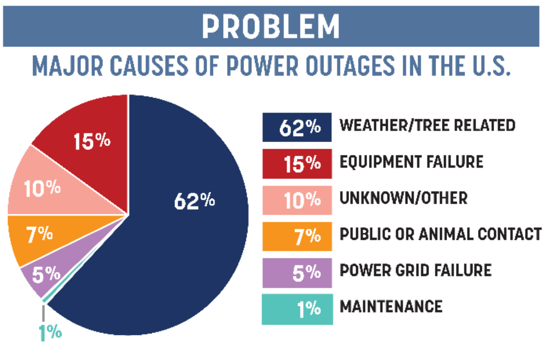

Figure 1. Major Causes of power outages in the USA

The next application we present is related to prediction of outages in the distribution networks. As may be seen from Figure 1, the outages are mostly caused by weather, vegetation intrusion and equipment failure due to wear and tear.

We formulate the concept of the state of risk (SoR) prediction that is based on weather data and historical outage data. We combine such data using ML/AI methods and create SoR maps that represent the risk of outage occurrences due to inclement weather and environmental conditions such as vicinity of trees. In an earlier example, we illustrated how such SoR maps may be used to optimize the vegetation management tasks aimed at reducing the number of outages caused by trees growing into the distribution feeders [14]. We also examined how wind modelling may be used to estimate such intrusion caused by high winds blowing the tree branches into the feeders [15]. In this paper we share our experiences aimed at selecting the weather data, developing spatiotemporal SoR maps, and deciding on the mitigation strategies that may be used by the utilities and customers.

Our final application is related to preserving power system operation under grid stressful conditions by utilizing DERs through aggregation and participation in the ASPs [16]. In the past, we focused on a particular ASP related to the flexiramp service that may be offered by DER aggregators [17]. Recently, we focused on how the aggregators may develop their biding strategy using SoR outage predictions under inclement weather conditions [18]. In this paper we elaborate on why the aggregator faces uncertainty in its bids for ASP, how such uncertainties may be mitigated by making estimates of DER energy resources under outage conditions, and how such mitigation measures may be incorporated in the aggregator ASP bidding strategies.

We conclude the paper by pointing out the benefits and challenges when using ML/AI approaches to enhance the grid reliance under inclement weather conditions causing grid outages and instabilities.

2. Data Models for Automated Analysis of Faults Using Synchrophasors

The use of synchrophasor data from PMUs for power system protection has become increasingly important in recent years. Machine learning algorithms have shown great promise for improving power system protection and fault analysis using PMU data. The development of an effective machine learning algorithm for detection and classification of faults starts at data preprocessing. The quality of input PMU data can highly impact the performance of any machine learning model that works with the data. It has been a common experience that PMU data can be influenced by factors such as PMU measurement errors, data communication dropouts, and missing or corrupted data, which are the issues that must be addressed before moving on to the next step, feature extraction. Feature extraction is a crucial step since the extracted features are used to describe the underlying patterns in the data and highlight the relevant information for the model to learn from.

With the extracted features, several models can be designed to perform the analysis of any set of events captured by PMUs. Multiple factors may be varied to train the machine learning models chosen to perform the study, including the type of machine learning algorithm, the way the data is split into training and testing subsets, hyperparameter tunning etc. For example, depending on the data distribution and the type of events targeted by the study, a temporal split may be more useful than a random split of training and testing data. It is also crucial to address any imbalances in the data. The unbalanced dataset, where enough instances of each class of events are lacking, can lead to poor performance when a machine learning algorithm is tested on field data.

2.1. Data Quality

The wide deployment of PMUs across the power system has made it possible to perform fault analysis, among other studies, using field-recorded data, as opposed to using only simulated data. Our experience with fault analysis using synchrophasor data revealed that the main issues that field-recorded PMU data suffers from is missing data, outliers, data duplicates, and inconsistent values [9]. The labels that accompany these recordings are the most valuable source for training a supervised learning model since they contain information about fault start and end times, fault type, and other descriptions such as the cause of the fault. In our experience, they might exhibit a slightly shifted fault time or, occasionally, the wrong fault type. The most dependable approach to mitigate this problem was for a domain expert to visually inspect and apply any necessary corrections to these labels. This solution is not a practical one for all the labels created for all recorded PMU data given how much effort and time it requires. However, in the case of developing and training specific fault detection algorithms, it is the most effective way to ensure that these machine learning models would be trained and tested on credible data [12,13].

Missing data proved to be most challenging for many PMUs in several datasets. Figure 2 shows the percentage of missing data among these PMUs for different PMU measurements [12]. In some cases, especially when the percentage of missing data exceeded 60%, it proved beneficial to exclude specific PMUs from a dataset. Otherwise, data quality issues have been mitigated using data preprocessing techniques as well as machine learning models that are specifically designed to deal with noisy data. Using a multi-modal data approach to integrate data from various sources such as weather data, maintenance records, and fault records can significantly enhance the overall quality of data [5]. Additionally signal processing techniques such as the Butterworth filter to remove high frequency noise [6] or Empirical Mode Decomposition (EMD) to

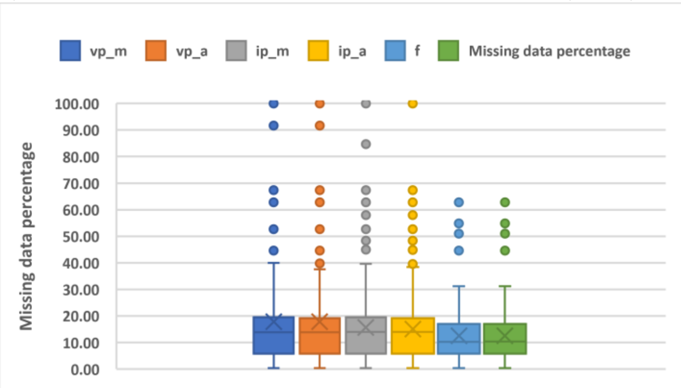

Figure 2. Percentage of missing data of one PMU dataset

decompose the data into simpler and more manageable components [5] have been used successfully in the data preprocessing stage. To handle the size of large PMU datasets computationally effective approaches were proposed in [19,20].

2.2. Feature Extraction

Feature extraction is another step of the algorithm development process that may either be done in a systematic way that relies on the understanding and experience of domain experts or it may be done as part of the algorithm's learning process. Fast feature extraction technique based on frequency thresholds was used in [19] to identify frequency events. The feature named "Rectangular Area" computed from PMU reported voltages and frequencies was shown to be a powerful predictor of different events [20]. A more complex approach of hierarchical convolutional neural network (HCNN) was utilized in [6]. Several convolutional layers helped in extracting non-linear latent features at multiple levels of abstraction. The hierarchical approach leads to features extracted at different levels of granularity, from raw PMU measurements to event-level features. The HCNN approach helped in identifying relevant features and improving the performance of the models. Similarly, combining the use of a convolutional neural network (CNN) and a sliding window approach to extract short-time Fourier transforms of the data helped in identifying relevant features and reducing the noise in the data in [8]. Physics-based feature engineering has also been pursued by our team in several studies. For the study of low-frequency oscillation events in the power system, for example, features were extracted based on the Prony method of modal decomposition of the signals [10]. The decision to extract these features was based on knowing the relevance of Prony analysis to the aspects of low-frequency oscillation in the power system such as oscillation frequency, amplitude, and damping ratio. For identifying different classes of line faults, features were engineered from the three-phase voltage signals recorded by PMUs. To capture the patterns of voltage drops of these classes, the features consisted of a normalized sum of the difference between the maximum and minimum voltage values within a sliding time window [11].

2.3. Data Model Training

An important decision to make regarding data model training is how to split the data into training and testing datasets. Splitting data randomly, for example, might lead to overlapping in the training and testing data when an event's signature exists over several time windows. This problem was encountered while training low-frequency oscillation detection models [10]. Splitting the data purely based on a temporal split can risk not training a model on a specific type of event that only exists within a specific time range in the data. A convolutional neural network architecture that considers the temporal relationships between phasor measurements was the approach successfully employed in [8], where the training process included data augmentation and the selection of hyperparameters.

Oftentimes, even with the presence of good-quality PMU data, properly labeled and varied training data is not sufficient to start training machine learning models. Data labels are generally imbalanced to reflect the events that are more common in the system, which leads to a scarcity regarding other events that appear less frequently. The challenge of scarce labeled data was addressed in [7]. A transfer learning technique was used, in which pre-trained deep neural networks were utilized to learn relevant features from the data. The transfer learning approach helped in leveraging the features learned from a large dataset in one power system and applying it to a smaller dataset to improve the performance of the models in another. Another solution for scarce labels is the use of a synthetic network to create simulated PMU data that can be integrated with field-recorded data [11]. Simulated data seems to be unrealistically stable and constant in the time surrounding a fault, which makes it not dependable as the only source of training data. Nevertheless, the integration of simulated data with field-recorded data in [11] to balance the number of instances of each fault class has remarkably improved the performance of the machine learning classifiers.

3. Outage Risk Prediction Using Weather and Historical Outage Data

Outages in power systems pose significant safety hazards and economic burdens on society. Utility companies are increasingly concerned about frequent outages in the distribution network and the need to improve the quality of electrical supply to customers while enhancing the grid's resilience. The environmental conditions such as strong winds, lightnings, rain/snowstorms etc. contribute to a majority of the forced outages in the power systems.

Recent advancements in ML algorithms offer a promising solution to the problem. By using ML models, one can predict the risk of outages and take preventive measures to enhance grid resiliency, lower economic losses, and increase customer satisfaction. The combination of Big Data, machine learning, and geographic information system (GIS) software enables the analysis of historical outage data to construct an ML model that predicts risk levels for individual parts of the system on desired time horizon. This approach enables utility companies to take proactive measures to mitigate outage risks by developing dynamic tree trimming schedules, issuing customer notifications, initiating backup generator start-ups, and executing targeted restoration plans for specific parts of the system [21].

3.1. Data Selection and Processing

The solution utilizes the information about weather conditions in the proximity of the fault appearances from the past. We begin with cleansing the historical outages dataset and determining where and when the faults occurred in the system. The outage dataset usually spans 4-7 years. We then turn to the providers of historical weather datasets, such as National Oceanic and Atmospheric Administration (NOAA) [22], to obtain the weather data for the selected time in the region where the network is located. The weather data may include several parameters, such as wind speed and direction, temperature, humidity, air pressure, cloud cover, precipitation etc. When using multiple sources of data, one needs to pay close attention to proper data alignment in both temporal and spatial dimensions. Weather data is not the only source of useful information for the solution. The satellite and aerial imagery, vegetation indices, radar data, lightning detection networks data, the history of previous trimming schedules etc. may provide valuable addition to the weather data and enhance model performance [23,24]. Once data is collected and stored, it must be preprocessed, cleaned, and transformed into the suitable form. Bad and missing data handling are implemented at this stage.

A critical dataset used for the application is the historical outage dataset, which reflects the location and time of past outages in the system. Such dataset is usually proprietary and is maintained by a utility company. The outage information needs to be processed as well, to select only environmentally related outage instances. Outages that were a result of a human error during maintenance events are discarded.

The next step is the spatiotemporal correlation of faults and weather. Projecting all available data into the same coordinate system and using single time zone is advised. In such manner we have gathered data that reflects the environmental conditions, for each given fault in the system. Additionally, we need a comparable number of instances, where the faults did not occur. These examples are usually selected randomly from the same period of operation. The resulting dataset serves as a foundation for the training of the ML algorithm. The algorithm learns to discern between non-hazardous conditions when the grid operates normally and high-risk conditions when the faults occur.

As the nature of the faults is probabilistic, the output of the model is outage State of Risk (SoR). It reflects the estimated probability of an outage occurrence in the given period for a given part of the power grid [25].

3.2. Developing spatiotemporal SoR maps

Prediction of the SoR levels paves the way for risk-aware grid operation. One of such applications is SoR maps that are designed to convey the information of the grid vulnerabilities under given weather conditions. The SoR map is created by projecting the ML model's predicted outage SoR levels onto the GIS map superimposed on the power grid.

SoR maps can mainly be used in the control room by the utilities for day-to-day operations. The examples of SoR maps for low-risk and high-risk conditions are presented in Figure 3. Since the SoR is always a number between zero and unity, one can predefine the color scheme where each risk interval would correspond to a different color.

Different spatiotemporal resolutions can be utilized for SoR maps. Spatially, one can narrow down to a single feeder or have an average SoR reflected for a part of the network that may consist of several substations. Temporally, ML model can be trained to output predictions every hour based on short-term weather forecast or a model can be focused on estimating risk for a next several days. The ever-present trade-off between model performance and spatiotemporal resolutions is influencing the selection of the optimal level for temporal and spatial horizons.

SoR maps enhance situational awareness of personnel and enable their quick assessments of current conditions. The areas with risk over a preset threshold may be further emphasized to draw operator's attention. In addition to improving situational awareness, SoR maps can also be utilized to inform decision-making and risk management strategies. By visualizing areas with higher risk, personnel can prioritize their efforts and resources towards mitigating those risks and reducing the likelihood and impact of adverse events. Another application of SoR maps is to facilitate identification of trends and patterns in risk levels over time, which can be used to create long-term risk management plans and strategies. By analyzing the data from SoR maps, utilities can gain insights into the underlying causes of risk and develop effective measures to address them.

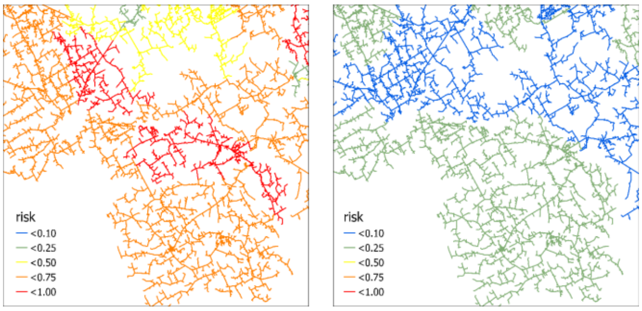

Figure 3. High and Low risk conditions on SoR maps

Overall, the novel approach of SoR maps creation is a valuable tool for enhancing resiliency and reducing risk. By providing clear and actionable information about risk levels, these maps can help prevent outages, protect personnel and assets, and improve overall operational efficiency and effectiveness.

3.3. Outage Mitigation Strategies

The SoR levels serve as a basis for consequent outage mitigation strategies. Mitigation measures range in volume, scale, time, impact and enacting entity. The ways that a utility may address the high-risk conditions are different from mitigation actions that a customer would employ. Depending on time horizon that is used to obtain SoR levels in the grid, operator or a customer can implement various mitigation actions.

For the short time horizon, it is important to communicate the possible risks to the customers. Industrial, residential and commercial types of customers can deploy various mitigation measures, depending on the resources they possess and how critical electrical supply is for their operations/activities. These may include back-up generation start-up, food and water storage, corrections to business hours, alternative transportation routes etc. Given a prior notice to customers, one turns an unexpected outage into planned outage, reducing the detrimental random impact.

For long time horizon, stakeholders may use strategies that take longer to deploy. Utilities can use adaptive tree trimming schedules to target the areas with substantial risk. Risk levels can be considered when planning for grid expansion or modernization. Equipment maintenance can also be prioritized in the area with persistently high SoR levels. On the customer side, SoRs can be utilized to make decisions about investments into back-up power sources, energy storage or internal grid redesign for better resiliency. Businesses can also revise their list of suppliers and have agreements in place for outage conditions: delivery of non-essential goods and materials can get postponed during high-risk conditions, but for the essentials a plan of delivery, handover and reception, and storage may be developed. DER Aggregators may benefit from predicted SoR levels and adapt their strategies accordingly [18, 26].

4. Aggregator Bidding Strategy for ASP Products Using Outage Risk Prediction

A unique opportunity for DER profitability while improving the grid reliability and resilience is ancillary service products (ASPs) procurement in the wholesale electricity market (WEM) [27, 28]. DERs require a third-party entity named the aggregator to aggregate their resources and offer ASPs in the WEM on their behalf [29, 30]. The DER aggregator may benefit from the outage risk predictions to avoid over-procurement of ASPs in the day-ahead market (DAM) and prevent penalties for not delivering the committed amounts in real-time. The type of DER we are interested in, since it can be widely implemented, is distributed prosumer (DP). A DP has the power generation, consumption, and storage capabilities and is referred to residential or commercial building with rooftop photovoltaic generation (PV), controllable electric load and storage capacity such as fixed battery energy storage system (BESS) and/or electric vehicle (EV) chargers [31, 32]. The controllability of DP resources brings about the flexibility that can be harnessed for ASP procurement. The schematic of the DP/aggregator participation in the WEM is presented in Figure 4.

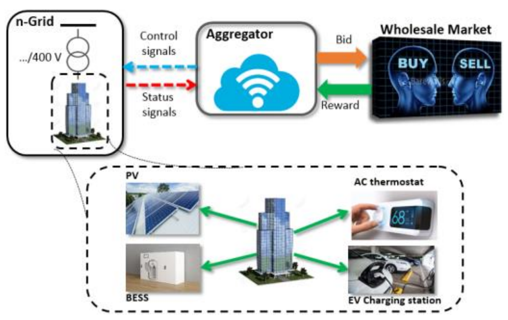

Figure 4. Aggregator/DP participation in the WEM.

4.1. Uncertainties in the Aggreator Bid for ASP

The DER aggregator must submit its energy and ASP bids for the next day to the DAM. Hence, it needs to cope with different uncertain DER resources and make accurate forecasts. These uncertainties include PV generation, DP load, ambient temperature, EV arrival, departure times and initial state of charge (SoC) and market prices [33]. Another source of uncertainty stems from the risk of outages in the distribution grid, which can be assessed by the ML models presented in previous section. The distribution grid is the physical means of trading energy and delivering ASPs committed by DPs. Outages in the distribution grid may lead to the disconnection of DPs from the grid. During an outage, DPs use the energy stored in their storage resources to supply their load. Thus, when connected back to the grid, they may be drained of energy and not able to deliver the committed ASPs [25]. By providing the aggregator with the DP outage SoR predictions, it can make a more conservative bidding strategy such that it does not over-commit to ASP provision and avoid penalties for not delivering ASPs in real-time [34].

4.2. Incorporating the SoR Prediction in the Aggregator Biding Strategy

The coordination among the aggregator, DPs, distribution utility, and ISO is depicted in Figure 5. The distribution utility provides the DP customer energy management system (CEMS) with the outage SoR predictions [25]. The CEMS has the ability to (i) receive the SoR data from the utility, (ii) receive the control signals from the aggregator, (iii) send the SoR + resource status data to the aggregator, (iv) and manage the DP resources in normal operation and during outages. The aggregator receives the outage SoR predictions from DPs. To tackle the uncertain nature of the bidding strategy problem, the aggregator needs to run stochastic optimization problem. It needs to define representative scenarios based on the historical data of the uncertain parameters and take advantage of stochastic optimization methods such as two-stage scenario-based, robust, and chance-constrained optimizations to solve such a problem [17]. Incorporating the outage SoR data into the bidding strategy problem enables the aggregator to make informed decisions in terms of the amount of ASP and energy to offer in the day-ahead and real-time markets [35]. The aggregator objective function is to maximize the profitability from energy trading and ASP procurement, which is subject to the technical constraints of DP resources, comfort of building occupants, uncertainty in parameters, and outage SoR predictions. The output of the optimization is the desired hourly ASP and energy amounts for the 24 hours of the next day that the aggregator submits to the DAM.

4.3. Managing DER Resources During Outages

During outages, the DPs must be able to supply their critical loads while minimizing their energy resources' distortion from the optimal operating point so that when they are connected back to the grid, they are able to deliver the committed ASP amounts. The DP resource management during outage is presented in Figure 6 [25]. First, the uncritical deferrable loads are postponed, and the thermal load is set to its minimum (comfortable temperature range is set by occupants). Next, if the remaining load is greater than the PV generation, the stored energy in the BESS and plugged EVs is used for power generation; otherwise, the extra PV power is stored in the EVs and BESS.

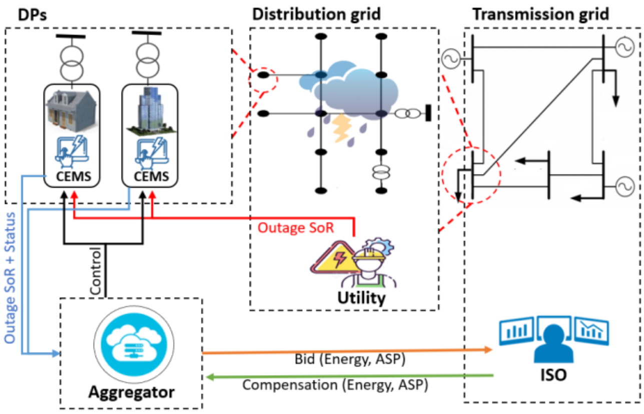

Figure 5. Coordination among utility, DP, aggregator and ISO.

Algorithm: DP resource management in outages

drop thermal load to minimum
postpone deferrable loads to after connection
if load lower than PV output:
  store in the connected EVs
  if more PV energy left:
    store in BESS
    if more energy left:
      set temperature to normal
else (load greater than PV output):
  discharge BESS
  if more energy required:
    discharge connected EVs
  remaining load is load loss

Figure 6. Resource management for disconnected DPs.

Conclusions

Using the three examples we illustrated several points about the use of ML/AI in dealing with faults and outages:

- In the transmission grid, synchrophasor data may be used to detect and classify faults and other disturbances online, which can help system operators make quick decisions how to mitigate the impacts in real time.
- In the distribution system, historical outage and weather data may be used to predict SoR of outage occurrence leading to preventive mitigation measure to reduce the impacts., which improves the resilience of the distribution grid
- In the customer owned DP system, a CEMS may be implemented to assess the internal energy resources and possible impacts of the grid outages, and inform aggregator what level of support to expect from the DP when procuring ASPs in WEM
- The use of ML and AI is inevitable in power system applications as the amount of data available to improve operator actions increases, overpowering the cognitive ability of decision-makers to react in real-time unless the data models provide automated support

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