Review Article

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The Paradigm Revolution in the Distribution Grid: The Cutting-Edge and Enabling Technologies

<https://doi.org/10.1515/comp-2020-0202>

Received Aug 09, 2019; accepted Jan 21, 2020

Abstract: Bi-directional information and energy flow, renewable energy sources, battery energy storage, electric vehicle, self-healing capability, and demand response programs, etc., revolutionized the traditional distribution network into the smart distribution network. Adoption of modern technologies like intelligent meters such as advanced metering infrastructure & Micro-phasor measurement units, data storage, and analysis techniques and incentive-based electricity trading mechanisms can bring this paradigm shift. This study presents an overview of popular technologies that facilitate this transformation, giving focus on some prime technologies such as real-time monitoring based on Micro-phasor measurement units, data storage and analytics, blockchain technology, multi-agent systems, and incentive-based energy trading mechanisms

Keywords: Big data, Energy market, Demand response, Micro-phasor measurement units, Internet of energy, Blockchain Technology, Cloud computing

Abbreviations

DER	Distributed Energy Resources
RES	Renewable Energy Sources
DR	Demand Response
EV	Electric Vehicle
ESS	Energy Storage System
PMU	Phasor Measurement Unit
Micro-PMU	Micro-Phasor Measurement Units
AMI	Advanced Metering Infrastructure
WAMS	Wide Area Monitoring System

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SCADA

Supervisory Control And Data Acquisition

RTP

Real Time Pricing

SDN

Smart Distribution Network

MAS

Multi Agent System

DG

Distributed Generator

SG

Smart Grid

BSS

Battery Storage System

DN

Distribution Network

DSM

Demand Side Management

PV

Photo Voltaic

CNN

Convolutional Neural Network

RNN

Recurrent Neural Network

Multi-SVM

Multi Class Support Vector Machine

PCA

Principal Component Analysis

1 Introduction

Today's grid is characterized by high penetration of Distributed Energy Resources (DER) and two-way energy and information flow. DER includes Renewable Energy Sources (RES) like wind and solar generator, Electric Vehicles (EV), Battery Storage System (BSS) and customer loads that can take part in Demand Response (DR) programs. The benefits of RES include zero marginal cost of power production, practically nil carbon emission and minimization of transmission power losses due to the generation of power near to the consumer centers.

The widespread assimilation of DER has many drawbacks. The output of DER is seasonal. The output of solar and wind generation is weather dependant and hence the dispatch of this generation to the load is more uncertain. Meantime, the exact prediction and control of the customer load pattern are also not feasible. The charging pattern of EV is also uncertain. The two-way flow of energy creates congestion and voltage stability problems if not controlled properly. The electrical energy output of DER should be known to the utility provider. Otherwise, the utility produces more power than necessary, and this contributes to high electricity prices.

The integration of DER and EVs causes a change in the supply-demand patterns at the distribution level of the grid. Maintenance of supply-demand equilibrium is a critical issue in a highly DER penetrated distribution grid. To manage the effects of these distributed supply and demand patterns, distribution grid operators and regulators are adopting modern technologies and methods. The traditional approach of energy management is to utilize large power plants for maintaining supply-demand equilibrium by increasing or decreasing their power production. One way to keep the supply-demand equilibrium in a grid with significant penetration of RES is to use Energy Storage System (ESS) for storing the surplus energy from RES. There are several challenges to the widespread implementation of ESS like high investment cost, lack of experience in implementation and further current utility regulations which were worked out for the conventional electricity system [1]. All these circumstances necessitated advanced control techniques for effectively managing DER.

DERs like wind, solar, Combined Heat & Power (CHP) plants and EV can supply power to the grid and thereby helps to meet the load demand. EV can function as a distributed energy resource and further has a role in the ancillary service market by providing various services like grid frequency regulation, voltage, and reactive power support, etc. Grid-connected equipment like home energy management system, smart thermostat, and customer smart appliances can provide flexibility services to the grid by scheduling or curtailing their demand in response to Demand Response (DR) programs and thereby enhancing grid reliability. The use of DERs and DR programs for maintaining energy balance is more favorable than the conventional scheme as the former can accomplish the balancing operation more promptly than the latter [2].

Owing to the ever-rising demand for electrical energy and high penetration of DER the distribution lines are obliged to carry power more than their rated carrying capacity and cause congestion problems. The development of additional infrastructure is not a practical option due to the high cost involved. Another solution is to enforce demand-side management and demand response programs, which is much recommended owing to its low implementation cost and reasonable response time required. The demand response is the readjustment of consumer's load through load curtailing, shifting to off-peak hours, etc. in return to utility signals like price, penalties, and incentives. Incentive-based Demand Response (IDR) [3, 4] forces customers to willingly cooperate in DR programs by offering some incentives in return to their flexibility services. Market-based methods like Real-Time Pricing (RTP), incentive-based DR program and prosumer

to prosumer trading, etc. can enhance the reliability and efficiency of the distribution system, can assist the network operator to maintain supply-demand equilibrium and helps to optimize the grid assets.

Proper monitoring is needed to ensure the safe and reliable operation of the distribution system. Conventional transmission grid monitoring through the SCADA and Energy Management System (EMS) gives only local awareness, which is not sufficient to prevent blackouts. Wide Area Monitoring System (WAMS) gives a snapshot of the entire transmission system through Phasor Measurement Units (PMU) located at important system buses. PMUs gives a time-synchronized measurement of voltage and current phasor of all nodes of the transmission system together with frequency and rate of change of frequency. Distribution phasor measurement units, otherwise known as Micro-Phasor Measurement Unit (Micro-PMU) and Advanced Metering Infrastructure (AMI), are the widely used monitoring system nowadays to monitor the DN. Micro-PMU monitors medium voltage distribution network and AMI monitors low voltage distribution network.

One of the fundamental issues in the distribution network management is the effective treatment of massive chunks of information accessible to the network operator. This data includes measurement data from AMI & Micro-PMU, forecasting data such as weather, load & generation forecast, and historical data. Decisions of the distribution network operator in emergency conditions depend on quick and explicit recognition of abnormalities from the data available to them. Since distribution network data falls under the category of big data, advanced storage and analytic techniques are desired for efficiently handling these data.

The most important responsibility of a distribution system is to assure safe and reliable supply to all of its consumers, which can only be attained through a fast self-healing process. The areas without supply can be fed by appropriate service reconfiguration or by creating islands with Distributed Generator (DG). It is imperative that throughout these operations, the system variables such as bus voltage and feeder current should be within the permissible limits, the radial topology of the distribution network should be maintained carefully and fast restoration of supply after the clearance of fault are the key issues which draw more attention to be taken care of. The complexity of the restoration process increases as the penetration level of DER in the system increases. Currently, DGs are disconnected from the system as soon as a fault is detected. However, this cannot be done for a system with high penetration of DGs because without DG supply-demand balance will not be met. DGs interconnection to a

feeder causes voltage increase because of the active power injection and may contribute to voltage violation. Therefore, it should also consider the voltage profile and capacity of the feeder while determining the reconfiguration of the distribution network in the presence of DGs [5]. Self-healing can be brought about by the assimilation of all the advanced technologies of smart grid-like data analysis techniques, advanced monitoring through Micro-PMU & AMI, cloud-based platform for data storage and processing, advanced communication technologies like the machine to machine communication and Internet of Things (IoT).

For the efficient operation of all these advanced programs like DR, DSM, self-healing, etc. and for efficiently utilizing DER for the benefit of both utility and DER owners, proper monitoring, the exact interpretation of measured data, accurate forecast of demand and generation and involvement of customers in the DR programs are needed. Active distribution management with smart monitoring devices, data analysis techniques, and incentives for the consumers and DER owners helps to accomplish the goals discussed above.

Apart from advanced metering technologies, modern communication technologies also play a vital role in realizing distribution automation in SDN. An overview of the communication requirements of SDN is presented in [6]. The authors also provided a detailed discussion about the modern communication technologies available for the

smart grid. Industrial wireless sensor network and Internet of Things based routing protocol for SDN communication is discussed extensively in [7–11], in the context of smart grid industry 4.0.

Modern information, computing, and communication technologies together with engineered physical power distribution systems formed a cyber-physical power distribution system. The inter-dependency between the power distribution system and the cyber system makes the distribution system more vulnerable to attacks & threats, and requires the assistance of advanced technologies to ensure the reliability and security of the distribution system [12]. Figure 2 shows the architecture of a smart distribution network. The prominent technologies for SDN are given in Figure 3.

In this paper, various challenges of smart distribution grid implementation and their solution through different modern technologies are discussed through a vast literature survey.

The scope of this review is limited to the published content for the period from 2010 to 2019. There were 29855 research papers published in Science Direct on Smart Grid Technologies when the general search was carried out. Out of this total content, 22118 publications were research articles and 2609 were book chapters. Search on IEEE Xplore Digital Library brought 21298 publications on Smart Grid Technologies. There were 17285 conference materials, 3264 research articles, 79 books, etc. on IEEE Xplore. An ad-

Figure 1: Research flow diagram indicating the detailed review process

Figure 2: Architecture of a smart distribution network

Figure 3: Advanced technologies for SDN

vanced search on Smart Grid Technology that related to high-performance computing techniques, database management platforms, blockchain technology, cloud computing, Micro-PMU, etc. yielded many research articles. In the first stage, a total of 6774 articles were screened according to the title or abstract. However, 6265 articles were found either irrelevant or out of the scope of the study. Therefore, a total of 509 full-text articles were arranged subject-wise for the review in the second stage. Finally, 224 arti-

cles were reviewed and included in the present study. A research flow diagram indicating the detailed review process is given in Figure 1.

This article is organized as follows. The first section discusses the significant issues in the distribution grid and the need for advanced technologies to overcome these issues. The second section illustrates the major goals of SG. The various data storage and analysis techniques employed in SG are discussed in the next section. The fourth section discusses various open-source database management platforms available for handling smart grid data. Various blockchain-enabled SDN applications are summarized in the next section. Cloud, Fog and Edge computing applications are discussed thereafter. The ninth section discusses the applications of the Internet of Energy in the distribution grid. The tenth section discusses the MAS applications in the power system. The applications of Micro-synchrophasor measurements in SDN monitoring are reviewed in the following section. DR programs for the efficient management of SDN are discussed in the final section.

2 Objectives of SDN

The overall objective of SDN is to provide a cost effective, efficient and reliable power distribution system through the implementation of distribution automation operations

Figure 4: Major objectives of SDN

such as self healing, demand response, real time pricing, etc. Figure 4 shows some of the major objectives of a smart distribution network.

2.1 Customer participation

The supply-demand mismatch is a serious challenge to the reliability of the power system and can occur due to the line, load, or generator outage. The volatile and unpredictable nature of RES is further contributing to supply-demand mismatch. Conventional approaches solely rely on adjustments in the supply side for managing supply-demand equilibrium, whereas the contemporary and most powerful approach is to exploit demand-side resources for this purpose and is known as Demand Side Management (DSM). DSM programs are mainly classified into two types [13]: Energy efficiency improvement programs and the Demand Response (DR) Program. The required energy is minimized in energy efficiency improvement programs. Demand response can be defined as “the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time.” DR is a momentary alteration of electricity usage in response to the price signals or a contingency. Further, DR can be divided into two types such as incentive-based DR and price based DR [13].

2.2 Accommodation of all generation and storage options

The conventional energy resources are not adequate for satisfying the ever-increasing demand for electricity. Concerns about carbon emission, energy efficiency, and transmission losses result in adopting distributed energy resources like wind, solar combined heat and power plants, etc. for power production. To deal with the volatile and uncertain nature of RES energy output, they are incorporated with storage devices like battery storage devices and EV.

2.3 New products, services, and market

The bulk producers of electricity like hydro, coal, and gas power plants could serve as flexibility service providers by increasing or decreasing their power production for meeting demand-supply equilibrium. Besides these bulk power plants, consumer load could also act as flexibility service providers. EV can perform as a load, storage device, and flexible service provider. Prosumers are entities

that both produce and consume electricity. The development of new generation technology, intelligent monitoring systems, demand-side management, data analysis, data storage and communication infrastructure, etc. has redefined the concept of active distribution network. To gain most out of active distribution networks, efficient management of distributed generators, battery storage devices, establishing demand response programs, and managing prosumers are necessary. Managing all these are complex tasks. Market methods have turned out to be the best way to extract the full potential of prosumers and DER. An efficient pricing scheme should be able to incentivize DR resources to interact with the grid and helps to attain supply-demand balance.

2.4 Provision of power quality for the range of needs

The smart grid is characterized by a wide variety of loads that differ in their power quality demands. The grid should be intelligent enough to provide electric power to loads with their demanded grade of power quality.

2.5 Optimization of asset utilization and operating efficiency

Optimum utilization of existing infrastructure and maximizing operating efficiency are two important aspects of the smart grid. An efficient DR program can relieve the grid from expensive transmission expansion, and manage supply-demand equilibrium with the current grid infrastructure without the need for additional transmission lines or generators [14]. Grid operators can easily monitor and optimize grid assets and operating efficiency by using real-time information and modern computational technology.

2.6 Provision of resiliency to disturbances, attacks, and natural disasters

Today's power system has grown immensely, demand has increased, and there is a high penetration of DER in the distribution grid. All these factors make the power system easily prone to disturbances. A resilient grid is one that can tolerate fault and is able to provide power continually with a reasonable degree of power quality. The introduction of different generating options, storage technologies, fast and accurate fault diagnosis, outage management sys-

tem and self-healing technology will transform the grid into a resilient grid.

Fast diagnosis of the type and location of the fault is crucial for fast service restoration, which is necessary for attaining a safe and reliable power system. Proper information about the system topology and system knowledge such as the status of protective relays & circuit breakers are necessary for diagnosing faults more accurately. Furthermore, advanced data analytics techniques like ANNs, Petrinets, Bayesian network systems, etc. helps to make more precise and fast fault diagnosis [15].

The concept of self-healing, initially introduced by EPRI is the capability of the system to return to its pre-fault operating condition after the clearance of the fault. A self-healing grid should be able to automatically detect and isolate the faulty areas from the rest of the power system. After isolating the faulty area, it should provide supply to the unaffected areas within minimum time with minimum switching operations. After the clearance of fault, it should also regain the original state of the power system as soon as possible. All these operations should be carried out with minimum human intervention. Self-healing can be achieved by the integration of all the advanced technologies of the smart grid such as data analysis techniques, wide-area monitoring, and smart metering system, cloud-based platform for data storage and processing and advanced communication technologies like the machine to machine communication and Internet of things.

3 High-performance computing techniques for smart distribution grid

Big Data analytics is the field of data analysis, which handles data characterized by 3Vs: Volume, Velocity, and Variety. The data required for the efficient management of SG, like Smart metering data, PMU data, data generated from various types of forecasts like load forecast, weather forecasts, consumer behavior forecast, and generation forecasts, etc. makes big data storage and analytics techniques necessary for handling SDN data efficiently.

In order to optimally utilize the assets, the utility and customers should effectively plan their energy production and usage. The most challenging task of SDN is to make customers take part in demand response programs. To enhance the operational efficiency of SDN, efficient management of network data is essential, which could be done through advanced data storage and processing tech-

niques, like algorithms for extracting load patterns from large scale data sets, machine learning algorithms for forecasting and cloud computing for distributed and real-time processing.

3.1 Database systems for smart grid

Database systems are an integral part of the modern smart grid architecture which allows the storage, processing, and analysis of the massive SDN data in a systematic way. There are two perspectives of database systems; database management and data mining. The database management system is for storage, transaction processing, and querying. Data mining is for retrieving patterns and useful information from the huge data.

3.2 Database Management System (DBMS)

Massive data generated from AMI, PMU, etc. and forecasting data about weather, load, and generation are stored and arranged in DBMS. DBMS can be of two types; Relational databases that store data as tables (Oracle, Microsoft SQL Server, IBM DB2, Informix, MySQL) and Post relational database systems like NoSQL. Parallel and distributed file systems such as Apache Hadoop and Google map-reduce are best suited for power grid applications due to their distributed and geographically scattered nature. Another approach is to store databases in the cloud. Examples of cloud-based platforms are Amazon Web Services (AWS), IBM Netezza and Microsoft Azure, etc.

3.3 Data integration

One of the main issues with the smart grid big data is the integration of data generated from various sources with different formats into a common format database. Data integration techniques include data warehousing, XML, and ontology-based techniques. In [16], a metadata mining concept was introduced for integrating heterogeneous smart grid data from various sources. [17] presents a method known as the Summary Schema Model (SSM) for integrating heterogeneous data from multiple sources to minimize query response time.

3.4 Dimensionality reduction

The big data of SDN deals with real-time data which are generated from intelligent smart grid devices (PMU

Table 1: Dimensionality reduction techniques

Dimensionality reduction technique	Application
Gaussian approximation based on dynamic-nonlinear learning technique [20].	Smart meter readings compression
Compressive sampling [21]	For bandwidth saving between AMI and the data collector
Wavelet domain singular value decomposition (WDSVD) [22]	Compressing measurement signals for SG monitoring
Singular Value Decomposition (SVD)	State estimation
Principal Component Analysis (PCA) algorithm [23]	State estimation
t-distributed stochastic neighbor embedding method [24]	Feature extraction
Pearson Correlation Coefficient based Extra tree classifier [24]	Feature selection to remove irrelevant data
Support Vector Machine (SVM) classifier [24]	Electricity price forecasting
Sparse auto encoder [25]	Over voltage identification based on feature extraction
Multi level Discrete Wavelet Transform (DWT) [26]	Dimensionality reduction of daily load curve
Fuzzy Based Feature Selection (FBFS) [27]	Feature selection
Swinging Door Trending (SDT) [28]	PMU data compression
Principal Component Analysis (PCA) [29–31]	Dimensionality reduction of PMU data
Event oriented auto-adjustable sliding window method [32]	Event detection

and AMI), historical data and forecasting data (weather, consumer and generation power patterns). The sizes of these heterogeneous data are measured in terabytes and petabytes, which causes congestion and requires an increased bandwidth for the communication paths. This congestion leads to a delay in data transmission, which would adversely affect the reliability and security of SDN. This type of huge heterogeneous data could be managed properly by employing dimensionality reduction techniques.

Dimensionality reduction is the process of downsizing the data by reducing the number of variables under consideration. It can be of two types; feature selection and feature extraction. Feature selection is the process of selecting the most prominent features from the original data sets. Feature extraction is the process of developing a new set of features by the transformation of the original set of features. The feature extraction process is irreversible as some features are lost during this process. Dimensionality reduction helps to efficiently store and retrieve data and also improves the signal to noise ratio of the data.

Tensor is a representation of data sets as multidimensional arrays. A tensor-based database management system for storing and dimensionality reduction of SDN big data is presented in [18]. In [19], knowledge cube has been created with SDN data. Different knowledge cubes are combined by an association component to form an adaptive knowledge management system for the SDN. Various feature extraction and selection techniques are listed in Table 1.

3.5 Data mining

Data mining is an interdisciplinary branch of computer science involving the extraction of useful information from a large database and processes it as an easily understandable form for further use. Today's grid is said to be smart if we can extract valuable information from the large data generated from all SDN data sources. A mathematical model is created using this extracted information. Using real-time data and the mathematical model of the system, the current state of the system is estimated, and this helps to determine the possible actions to be performed to solve potential problems. The time-critical power system applications like fault detection, service restoration, self-healing, and energy management need quick and efficient analysis of real-time and historical data. Various data mining techniques should be adopted to dig the customer load pattern, event detection, price forecasting, etc. from the raw data available from monitoring devices like AMI, SCADA, and PMU and various forecasting data.

The outage management system is the core of self-healing architecture. Plenty of data like smart metering data, synchrophasor data, SCADA data, historical data, and forecasting data, etc. are available to the distribution system operator. After analyzing these data if some fault or abnormal event is detected, the outage management system primarily gives an alarm signal to the operator to make them aware of the abnormality in the system. In addition to that, by employing advanced data analytics techniques, it correlates this data with the various events and implements appropriate control actions like system reconfiguration, islanding, etc. The control actions are decided based on the operating states of the power system. A self-healing scheme based on operating state classification is proposed

Table 2: Data mining techniques

Technique	Application	Data source
SVM [38]	Event detection	AMI
Random matrix theory [39]	Anomaly detection and location	AMI
Spectral clustering [28]	Phase identification of smart meters /customers	AMI
Online Sequence Extreme Learning Machine (OS-ELM) [40]	Intrusion detection which is used to detect the attack in AMI	AMI
Wavelet transform [26]	Load curve clustering algorithm	AMI
Multi-instance clustering algorithm [41]	Consumer Segmentation	AMI
Euclidean distance-based anomaly detection schemes [42]	Covert cyber deception assault-detection	AMI
Ensemble Classifier Bootstrap Aggregation [43]	Intrusion detection	AMI
Data Mining of Code Repositories (DAMICORE) [44]	Islanding detection of synchronous distributed generators	Micro-PMU
OPTICS [45]	Segment data and finds the outliers in the segmented data	Micro-PMU
CNN [46], RNN [46]	Power system transient disturbance classification	Micro-PMU
Multi-SVM [47]	Data driven event classification	Micro-PMU
Multi-SVM and PCA [48]	Disruptive event classification	Micro-PMU
Auto-encoder together with softmax classifier [48]	Disruptive event classification	Micro-PMU
kernel Principle Component Analysis (kPCA) [49]	Abnormal event detection	Micro-PMU

Table 3: Forecasting techniques

Forecast	Machine learning technique
Electricity price forecasting	Spatial interpolation technique [50] Ensemble Extreme Learning Machine (EELM) [51] Weighted voting mechanism [52] Hilbertian ARMAX Model [53] Dynamic Trees [54] Neural networks with an improved iterative training algorithm [55] Combining wavelet, SARIMA and GJR-GARCH models [56] PSO based artificial neural network [57] Convolutional neural network and Long short-term memory network [58] Hybrid nonlinear regression and support vector machine [59] Support vector machine classifier [24]
Wind power generation forecasting	Self-organizing Inductive Modeling [60] k-nearest neighbors technique [61] Evolutionary Neural Networks [62] Auto-regressive Integrated Moving Average (ARIMA) [61]
Electricity Demand forecasting	Kernel-based multi-task learning techniques [63] ARIMA models [51] Support Vector Regression (SVR) [64] Fuzzy prediction interval modelling [65]
Solar power generation forecasting	Neural Networks (NN) [66] Weighted gaussian process regression [67]
EV charging demand forecasting	Traffic flow model and M/M/s queuing theory [68] ARIMA [69–71] Support Vector Machines [72]
Forecasting Carbon Dioxide Emissions	Evolutionary Neural Networks [62]

for distribution networks with DGs in [33]. The operating states of the system are determined based on the performance index, which is used as an indicator of system stability, reliability, and security. The operating state classification is done by hierarchical classification method.

The occurrence of power quality events like voltage sag, swell, interruptions, harmonics, etc. results in unex-

pected operation of several power electronic devices and may lead to blackouts. A pattern recognition based PQE monitoring algorithm is developed in [34] to address this issue. The authors employed extreme learning machine for pattern recognition.

Fault location identification from the measured data is a critical application of data analytics techniques. The

Table 4: Visualization techniques

Visualization technique	Description
GridCloud [78]	An open-source platform for real-time data acquisition, sharing, and monitoring
FNET/GridEye [75]	Visualization of system stress
3D visualization using AVS Express7.3 [79]	Visualize real-time power system information and relationship utilizing SCADA data
Tableau [80, 81]	SG data visualization
Microsoft Power BI [82]	Smart meter data visualization
Animation loops [83]	Combine periodic snapshots of the grid into time-lapse videos defined across geographic areas
Sparklines [83]	Summarize trends in time-varying PMU data as word-sized line plots
Google Earth [64, 84]	SG data visualization
Cartography and spatial analysis techniques [85]	Visualize, yield and performance map of grid-connected PV systems
GIS [77]	To display real-time operational data

voltage and current signals generated at the fault point travels in both directions and is reflected & refracted at the line ends and at the fault point. These transients have high energy contents and are known as traveling waves. The sinlet mother wavelet function was used to extract the energy attribute of fault transients using wavelet transform and feature extraction technique in [35, 36]. The location and nature of the fault can be extracted from these energy attributes.

The fault estimation algorithm on radial distribution networks works based on the calculation of fault impedance up to the fault point. This method fails to locate the accurate fault location due to the estimation of multiple points with the same distance measure. This drawback is addressed in [37], using a cloud-based data mining approach. All the smart grid data including the measurements from intelligent meters are stored in the cloud-based platform, and a data mining tool named DAMICORE (a python based clustering and classification tool) is employed to extract the necessary information to locate the accurate location of the fault. Various data mining techniques discussed in the literature are listed in Table 2. Various methods employed for forecasting are listed in Table 3.

3.6 Data visualization

Identification of weaknesses and prediction of potential problems are the main implications of Contingency Analysis (CA). As power system protection is very time-critical, CA results should be presented in an easily understandable way which helps the system operators to perceive the security status of the system quickly and intuitively. Advanced visualization techniques are needed to efficiently present the overall security status and the level and location of contingencies.

An overview of visualization techniques for smart metering data is presented in [73]. A panoramic visualization scheme for SDN is presented in [74], which can visualize risk warning, fault self-healing, etc. FNET/GridEye is a low-cost GPS synchronized frequency measurement network. FNET/GridEye servers at the University of Tennessee and Virginia Tech can visualize the system stress as animations of frequency and angle perturbations [75]. Correlating PMU data with PMU location and system topology system stress is visualized as variations in frequency and phase angle in [76] with the help of FNET/GridEye. In [77] implementation of an online monitoring system with Geographical Information System (GIS) in which all the grid assets are displayed in a map with the real-time operational data. Some of the visualization techniques discussed in the literature are listed in Table 4.

4 Database management platforms for smart grid

Various open-source frameworks are available for storing and analyzing smart grid big data. Popular among those frameworks are Hadoop, Cassandra, Hbase, SPARK, Hive, Eukalyptus, etc. Various database platforms for advanced computing for SDN are listed in Table 5.

4.1 Hadoop

Hadoop is an open-source software developed by Apache for big data storage and analysis. Hadoop framework is established in such a way to avoid failures and to ensure reliability to customers. Instead of storing and processing huge data sets centrally using high capacity servers,

Table 5: Database management platforms for SDN

Database platform	Application
Apache spark	Knowledge discovery [64] Automatic demand response and real time pricing [94] Energy forecasting models in a distributed environment [96] Data processing for load scheduling [97]
HDFS-based HBase database	Storage system for SDN management [97] Storage system for electrical consumption forecasting [98] Load balancing of intermittent energy sources [99]
Open stack	An architecture to monitor and predict the energy usage in smart grid [100, 101]
Amazon EC2.	Energy forecasting [102]
Amazon's AWS	'GridCloud' for power grid simulation and 'GridControl' for state estimation [103]
NetLogo.	Energy management for smart homes [104]
Hadoop Big Data Lake	To perform parallel batch and real-time operations on distributed data [80]
FlumeLake.	Data aggregation and transmission [80]
Cassandra.	Data storage and analysis platform [39]
Eucalyptus.	Information management platform known as smart frame [93]

Hadoop is using Hadoop Distributed File System (HDFS) for storing, and map-reduce for processing the data sets by using a set of local computers. Hbase is the database system of Hadoop. Distributed file systems are beneficial for the smart grid because of its geographically dispersed structure. At present Facebook, Google, etc. are using Hadoop for storing and processing their data sets. In [86], the authors used a cloud-based platform for SDN visual analytics, specifically for smart meter data by employing Hadoop for storing and managing SDN data and Tableau software for visual analytics. The paper [87], addresses real-time event detection using Open PDC. They employed Hadoop clusters for analyzing patterns in historical data using instance-based learning. The authors of [88] developed a smart meter data analytics platform based on the Hadoop cluster, which can perform data storage, query, and data visualization function on large data sets. Hadoop Big Data Lake [80] is a data management platform comprising one or more Hadoop clusters. They can store various types of smart grid data including smart meter data, images, and videos and can perform parallel batch and real-time operations on distributed data.

4.2 Cassandra

Apache Cassandra is an open-source disseminated database system. It stores and maintains a large number of data on low-cost servers. This platform could cater to real-time data and read-intensive databases for massive data sources. At first, Cassandra was dedicated for Facebook. In place of the master and named nodes, it has peer-to-peer symmetric nodes to avoid single-point failures.

Apache Cassandra automatically diverts data through all the nodes in the database cluster. However, the administrator has the authority to define data for replication and the creation of a number of copies. Cassandra is also employing cloud infrastructure for storing and analyzing data. In [39] Cassandra is employed for storing information about temperature, user load pattern, and generation profile.

4.3 HBase

HBase [89] is a highly reliable, high performance, column-oriented, scalable distributed database system whose data is stored in HDFS as a file. In [90], HBase is employed to store the heterogeneous measurement data from low voltage measurement systems and fault recorders together with a cloud computing platform. In [91], an Hbase based database management system is proposed in which the data storage is organized according to the data access patterns of respective applications.

4.4 Hive

Hive is an open-source data warehouse software developed by Apache foundation which is built on top of Hadoop for data query and analysis. In [92] Hive is used for compression and analysis of substation monitoring data.

4.5 Eucalyptus

Eucalyptus is an open-source framework for building Amazon Web Services (AWS). AWS is owned by amazon.com, and it provides on-request support of cloud computing to individuals and companies on a paid basis. In [93] an information management framework called the smart frame is proposed for SDN, in which the entire SDN is divided into several zones and a cloud computing center is responsible for the storage and primary processing of data originated from that zone. It is responsible for the efficient management of all smart devices in those zones. Finally, the entire data of SDN is stored in a central cloud center. The cloud computing platform is realized by Eucalyptus. In the smart frame, there are four clusters, one for storing the SDN data, another one for providing customer service, the third one for managing and controlling SDN, and the last one for managing the distribution of electricity. They also proposed a centralized cloud layer for coordinating information flow throughout SDN.

4.6 SPARK

Spark is a tool applied for batch processing of data. This has a real-time processing capability with Spark Streaming. Spark employs tools such as Spark SQL, Spark Streaming, machine learning library, and GraphX for processing of large-scale data. This makes Spark an appropriate platform for smart grid data management. In [94], a data storage and analytics framework using Apache SPARK has been presented for applications like automatic DR and real-time pricing. An intrusion detection framework based on Apache SPARK has been developed in [95].

5 Blockchain technology

Blockchain is a distributed database through which we can implement direct transactions between two parties without a central authority. It is a collection of technologies like a ledger, cryptography, and consensus technology [105]. Blockchain technology is termed as the 'Fifth Evolution' of computing. All the transactions between the peers are documented in ledgers, which is like a logbook. All the peers have a copy of the ledger. The transactions stored in ledgers are made secure by applying cryptographic tools. Through a consensus mechanism, it is ensured that the transactions stored in ledgers can be modified if and only if all the participants or peers agree with it. This makes the blockchain system transparent and mediator-less.

The electricity market adopted blockchain as a method to improve transactions. The definition and a brief history of Blockchain technology are presented in [106]. The main Blockchain-based applications are comprised of Ethereum (the first decentralized computing platform), cryptocurrencies such as Bitcoin and Ether. The main areas where blockchain technology can be applied to the electrical power system are the electricity trading market, for establishing an energy certificate and for providing a decentralized energy platform.

5.1 Blockchain based trading

Blockchain technology helps to establish a Peer to Peer (P2P) trading platform within the smart grid. The utilization of the Blockchain would help to remove third-party mediation, and allow for electricity trading to be exercised in a P2P manner. This guarantees the trust, economic transaction because of the simplified trading manner, and assurance of user privacy within the smart grid. In [107], a platform to develop an energy trading based on smart contracts and blockchain technology is discussed. In [108], a blockchain-based application for realizing microgrid energy settlement is discussed. In 2014, a methodology for electricity trading and implementing a demand response program in a power grid with renewable energy through virtual currency known as NRGcoin was proposed in [109]. The participants of the electricity market trade renewable energy through the exchange of NRGcoin, in return to energy export. Brooklyn Micro-grid project established a communal micro-grid for blockchain model energy transactions in 2016 [110]. In Brooklyn, Micro-grid customers can select their energy resources locally. PONTON, an IT service provider, has developed a blockchain-based application for energy trading and management in a smart grid named Enerchain. Over 40 energy trading organizations became a part of Enerchain PoC in 2017-2018. The target was to develop a distributed trading platform for power and gas in Europe [111]. TennetT, a transmission system operator in Europe, launched a blockchain-based energy trading project which is at present in the first test phase [112]. A secure EV charging scheme is developed with the help of Blockchain technology for IoE enabled smart community in [113]. According to the official website of KWHCoin [114], "KWHCoin is a blockchain-based community, ecosystem, and cryptocurrency backed by units of clean, renewable energy. Physical units of kWh energy are leveraged from multiple sources, including smart meters, sensor readings, and green button data. This measurable output is tokenized on the blockchain to create KWH to-

Table 6: Existing energy trading platforms based on Blockchain technology

Blockchain based energy trading platform	Description
Appolochain [123]	Energy trading platform based on smart contracts
powerledger [124]	Australian blockchain-based cryptocurrency and energy trading platform
Power-port [125]	EV metering and settlement
Techmahindra [116]	Microgrid-as-a-Service' (MaaS)
Brooklynmicrogrid [126]	Community-powered microgrid
EXERGY [127]	Blockchain-based transactive energy platform for peer-to-peer energy trading
Energyweb [128]	Open-source platform for energy sector's regulatory, operational, and market needs
Emotorwerks [129]	peer-to-peer EV charging
Oxygeninitiative [130]	peer-to-peer EV charging
Gridplus [131]	Platform offering consumers access to wholesale energy markets using Ethereum blockchain
SolarCoin [115]	Rewards for solar energy producers with blockchain-based digital tokens
M-PAYG [132]	Prepaid solar energy systems through small-scale mobile repayments
coinify [133]	Crypto currency for solar energy transactions
KWHCoin [114]	Blockchain-based cryptocurrency backed by units of clean renewable energy
impactppa [134]	Delivering access to clean renewable energy from a mobile device
The enchain Project [135]	Blockchain-based energy trading platform developed by ponton
sunexchange [136]	Bitcoin-based Solar Energy Finance Platform
solshare [137]	peer-to-peer solar energy trading platforms based on distributed ledger technology
conjoule [138]	peer-to-peer energy platform based on Blockchain technology
NRGcoin [109]	Digital currency for renewable energy trading

kens". SolarCoin [115] is a reward for solar energy producers. The SolarCoin Foundation rewards solar energy producers with blockchain-based digital tokens at the rate of one SolarCoin (SLR) per Megawatt-Hour (MWh) of solar energy produced. Techmahindra [116] is implementing a project named Microgrid-as-a-Service' (MaaS) in Canada and India in which each entity in the market can produce their own power and can share the electricity with others. Various blockchain-based platforms for smart grid energy trading are listed in Table 6.

5.2 Decentralized computing platform

Blockchain helps to establish sophisticated and complex applications to make the grid safe and reliable by adding computational functionality. The authority has established renewable energy certificates to keep an eye on the renewable energy produced, but keeping track of this is very cumbersome. Blockchain technology helps to establish green energy certificates [117] and can establish a highly secured distributed electricity trading infrastructure [118]. Blockchain can help to prevent failures in the power system. The different nodes of the power system are connected to each other and to the blockchain. They notify the blockchain about any failure or a possibility of failure in the system with the possibilities of correction and reconfiguration. Blockchain also contains all the information about past events [119]. In [120], a blockchain-based con-

troller for microgrid energy management is proposed. The goal of the controller is the efficient utilization of produced energy within the microgrid without relying on external energy sources. The proposed controller named ETHome is implemented with the help of Ethereum software, which is a python based open-source software for blockchain implementation. The Share & Charge Foundation, a nonprofit organization, provides a blockchain-based framework for EV charging, which is built on Ethereum software for realizing a seamless, smart, and secure charging process [121]. Grid stabilization using a home energy storage system employing blockchain technology is discussed in [112]. A prosumer centric electricity market based on blockchain is discussed in [122].

6 Cloud computing

Cloud computing provides on-demand access to computing resources and storage to smart grid applications. In [139], the authors proposed a cloud-based platform for the efficient management of SDN. All forecasting services like user demand forecasts, weather forecast, and generation forecasts are carried out through Wavelet Neural Networks (WNN) and Graphic Processing Unit (GPU) parallel architecture is used for optimization. WNN is also employed for managing the battery energy system storage. In [86], cloud-based infrastructure is employed for a dynamic de-

mand response program. The authors also developed a mobile app and web page for looking at both historical and real-time energy consumption data. They also proposed the use of a reliable depository for sharing and storing customer data and results. Machine learning is employed for predicting user demand and electricity prices from historical data. Cloud computing-based real-time substation monitoring was proposed in [140]. A Distributed State Estimation (DSE) process, which exploits the Cloud-based Internet of Things (IoT) model is discussed in [141]. The estimation process is adaptive in the use of updated precision for the measurement devices. In case dynamics are detected, the measurement data are sent to the DSE at higher rates, and the estimation process runs consequently, updating the accuracy values to be considered in the estimation.

7 Fog computing

Due to its centralized architecture and communication dependence, cloud computing is not efficient for applications that have a geographically distributed architecture, are fast-moving, and demand low latency. Another drawback of cloud computing is its internet dependency and the need for high bandwidth. Customer privacy and security are the main challenges of cloud computing when dealing with smart metering applications [142].

Fog computing, originally introduced by Cisco [143], possesses another layer in between cloud computing and network edge. As the computing resources are sent nearer to user nodes, which are geographically distributed, latency problems can be avoided. Fog computing is a computing paradigm in which computational capacity and intelligence are exercised nearer to the edge devices where data is generated or collected so that the validation and verification of data can be done locally nearer to the data origin itself. This intermediate-level for computing and data analysis is placed nearer to the user ends in a fog node or IoT gateway in the Local Area Network (LAN). In fog computing, multiple devices are aggregated into a small cluster, and data from each cluster is sent to LAN. This data is stored in LAN, and the initial processing and decisions are done locally, and thereafter, the pre-processed data is sent to the cloud for further processing.

A cloud-fog computing platform for efficiently utilizing resources in a smart grid is proposed in [144]. Fog computing is used for smart metering applications and is implemented in the Hadoop platform with the help of Hive language. Non-Intrusive Load Monitoring (NILM) is

one of the popular techniques for demand-side management. However, it is a threat to consumer's privacy as by monitoring this data, one can easily identify the life routines of consumers. In [145], fog computing-based secure NILM is proposed. In [27], a fog based load forecasting method is presented, which consists of two phases; data pre-processing and load prediction phase. Data pre-processing stage consists of detecting and eliminating outliers from the received data and feature selection process. Load prediction is made in the second phase.

8 Edge computing

Edge computing is very similar to fog computing. Both store and process the data in a platform very near to the edge devices, but the difference lies in the actual place of data processing. Fog computing processes data in Fog nodes situated in LAN whereas Edge computing processes data in the edge devices itself. There is no need for data transmission from end devices to LAN for processing. However, for processes that require more equipped algorithms, the data has to be transferred to the cloud for processing [146]. Jiangsu Electric Power Company has implemented an IoT and Edge computing-based direct load control platform named 'Grid Sense' [147] with the help of Non-Intrusive Load Monitoring (NILM) technique.

9 Internet of Energy [IoE]

IoE is a technology that integrates the Internet of Things (IoT), machine learning, and data analytics into the distributed generation system. Smart sensors are the key bones of IoE, similar to IoT. The objective of IoE is to increase energy efficiency and to decrease the energy wastage. In an IoE implemented network, the distributed energy sources like solar, wind and battery storage systems, and the user appliances or loads, are connected to the internet. The consumption schedule of the loads is automatically adjusted by the generation profile of distributed energy resources, which is done by IoT technology. The other goals of IoE include assets performance management, operations optimization, and business optimization (maximizing customers' profit) [148]. A road map of the internet of energy applied to the smart grid is given in [149].

9.1 IoE based energy trading

The energy management process in an IoE based system is more complex than that in the traditional system due to the involvement of intermittent RES, huge demand and consumption, large amount of streaming data and the uncertainty involved in the EV charging process. Hyperledger-Fabric, which is one of the blockchain frameworks, is employed for energy trading in an IoE based smart grid in [150]. The day-ahead energy scheduling algorithm for an IoE based smart grid is proposed in [151]. A fog-based transactive energy management scheme is proposed in [152], which consists of three layers. The first layer is a home gateway, which is composed of smart sensors and collects all the energy information related to local energy production and consumer consumption. The second layer comprises a fog node for doing local energy management operations, which also acts as the retail electricity market. The third layer is the cloud platform for doing advanced operations. An overview of the IoE based energy management scheme for smart buildings is given in [153].

9.2 IoE based DR program

There are two types of DR programs, centralized and decentralized schemes. In a centralized DR program, data from distributed generators, battery storage devices, and end-user devices are transmitted to a centralized processing center like a cloud and all the data processing is done centrally in the cloud. This creates latency problems and loss of energy in a network containing a large number of customers and DERs. The above-said limitations of centralized DR can be overcome by a decentralized DR program. In a decentralized DR program, the energy data is stored and processed locally or in fog nodes without being transmitted to a central cloud platform. In an IoE enabled smart grid, since most of the DERs and user devices are equipped with smart sensors, distributed DR programs can be efficiently implemented [154]. A fog computing based DR program is subjected to security threats like distributed denial of service attacks and collusion attacks. A fog computing based secure DR program for an IoE enabled smart grid is proposed in [154] which employs consensus technology. A fog-cloud based demand response scheme for IoE based smart grid is proposed in [155]. In [156], a smart socket for receiving the price signals from the electricity market is proposed. The price signals obtained through the smart socket are employed for optimizing energy consumption in an IoE enabled smart grid.

Cloud computing is essential to handle the huge amount of data generated from IoE devices. A fog layer is added between the cloud and the IoE layer to improve the response time and energy efficiency. A cloud-fog based IoE system demand-side management in the smart grid is proposed in [155]. LoRaWAN technology is employed for establishing a communication medium for this IoE based system. Energy management through peak load shifting for an IoE enabled power grid is proposed in [157]. An energy management scheme for IoE enabled smart home is proposed in [158].

9.3 IoE based DER management

A charging scheme for EV and BSS for an IoE enabled end-user is proposed in [159]. IoE based electric mobility is proposed in [160], which is meant for developing a communication technology for facilitating the operation of EV. The technologies that promote the transformation of the wind energy conversion system into a cyber-physical system for enabling IoE technology are discussed in [161]. Energy management schemes for EV in an IoE enabled grid with distributed energy sources are discussed in detail in [162].

10 Multi Agent System (MAS)

MAS is a computer-based system that consists of multiple interacting intelligent software agents that can do complex actions and decision making, which may not be possible by a single agent or a single processing center. The operation of MAS is based on distributed artificial intelligence. JIAC and JADE are two common platforms that can be utilized for developing MAS based applications. The advantages of JADE and JIAC are their flexibility, ease of use, and support for mobile agents. There are several MAS platforms exclusively developed for power system applications like MASGrIP, MASCEM, mosaic, DEMAPOS, VOLTRON, Symphony, AMAS Atena etc. The various MAS platforms with their field of application are listed in Table 7.

10.1 MAS applications in voltage and reactive power control

Keeping bus voltage and reactive power within specified limits is most important for reliable operation of the power

Table 7: MAS platforms for SDN applications

MAS platform	Application
MASGriP [181]	A Multi-Agent Smart Grid Simulation Platform
MASCEM [182]	A multi-agent simulator system, for electricity markets
mosaic [183]	Platform for the Evaluation of agent-based smart grid control
'DEcentralized Market-Based POver Control System' (DEMAPOS) [184]	Market-based decentralized control of generators and consumers.
JACK [185]	Distribution grid congestion management with EV
Adaptive Multi-Agent System (AMAS) Atena [186]	State estimation of distribution network
VOLLTRON [187]	Python-based platform for intelligent sensors and controllers
Symphony [188]	Platform for distributed smart grid experiments
JADE [189]	Location awareness in multi-agent control of DER
Multiagent Control Using Simulink with Jade Extension (MACSim)X [190]	Distributed energy management and DSM of a solar microgrid
MATLAB and JADE [191]	Distributed agent-based framework for detecting and isolating faults
Java Intelligent Agent Componentware (JIAC) [192, 193]	Multi-stage smart grid optimisation with a multi-agent system
JIAC [194]	Multi-stage optimization for EV charging

system. Usually, this is achieved by the use of capacitor banks and voltage regulators. In a distribution system with high penetration of DER, DER can also be used to keep voltage and reactive power within limits. MAS can be used for coordinating DER, voltage regulator, and capacitor banks for keeping voltage and reactive power within acceptable limits. A backup control scheme can also be employed for voltage control through network reconfiguration [163].

10.2 MAS application in feeder congestion management

The high penetration of DER allows distributed generation and local consumption of produced power nearer to the source itself. Although it is advantageous to the grid in-terms of lesser power loss, low carbon emission, etc. it creates serious problems in the power system like the voltage, congestion, and overload problems. MAS is employed for feeder congestion management in [163], by distribution system reconfiguration.

10.3 MAS application in monitoring power control

MAS based energy management scheme for the inverter-based DER integrated system is proposed in [164]. The use of fuzzy systems in MAS based monitoring and control of the power system is discussed in [165]. The objective of the fuzzy system for the MAS based grid was two-fold. One was to compress the huge amount of smart grid data for reducing the storage space needed. The second objective is to

provide a similarity search through this compressed data, to enable the agents to take fast and efficient control decisions. A MAS-based protection and control scheme for a distribution system with DER is proposed in [166]. In [167], a MAS based energy management scheme for microgrids by forming a coalition of several autonomous microgrids is proposed. MAS is developed in JADE platform [168].

10.4 MAS application in electricity power market

Multi Agent-based modeling of the microgrid electricity market mechanism is discussed in [169]. An energy management scheme for multi microgrid containing DER and DR program is proposed in [170]. A game-theoretic framework for market operation based on MAS technology is proposed in [171]. The authors implemented three levels of market operations; a day ahead, an hour ahead and a real-time market. Agent modeling was done in DiGSILENT PowerFactory. An organization-based MAS system for the electricity market is implemented in [172]. A MAS-based architecture for the electricity market ResMAS is proposed in [173].

10.5 MAS applications in self-healing

There are two different approaches for self-healing control, namely centralized control and distributed control [174]. Distributed control is the most efficient, fast and suitable method due to the geographically distributed architecture of the smart grid. For the proper coordination of different intelligent devices distributed throughout the power net-

work, proper communication and control actions are required. This can be applied well with the help of MAS technology.

Service restoration, which is an integral step of self-healing, is the process of restoring power supply to the optimum number of loads in minimal time with the minimal number of switching operations. Currently, the restoration process has been carried out centrally by the Distribution Automation System (DAS). The drawback of this centralized process is the huge data it has to analyze for making the decision. Therefore it takes about 5 minutes to complete the restoration process. MAS can do this process in less time.

The application of a remote self-healing scheme for the complete distribution network can result in nuisance tripping, constraints violations, and power quality risk if the coordinated dynamics of the load and the existing protecting equipment are wrong. In [175], a multi-agent immune algorithm composed of the rule layer, process layer, and the physical layer is proposed for self-healing of the distribution system.

A multi-agent system consisting of zone and feeder agents is proposed for self-healing operation in [176]. The power system was divided into several zones based on the location of protective devices. Each zone was under the control of a zone agent. The protective devices in each zone constantly monitor that particular zone and give alarm signals to the zone agents if any abnormality is detected. Zone agents detect and identify the exact location of the fault and inform feeder agents about it. Feeder agent is responsible for making control actions such as isolating the faulty areas and deciding on proper restorative action by constantly analyzing system constraints like voltage limits, line current limits and radial nature of the distribution network [177–179].

10.6 MAS applications in distribution grid management

There are mainly two types of distribution grid management, centralized control and multi-agent system based control. In centralized control architecture, all the activities of the distribution grid are managed and optimized centrally. But in multi-agent-based control, there will be several intelligent computer agents who can manage a portion of the grid containing an aggregation of customers and prosumers, and who can communicate and share information among the agents. In [180], it is demonstrated that with the aggregation of small distributed energy resources like DGs and battery energy storage devices,

the grid can replace the conventional bulk power supply which relies on centralized power plants.

11 Phasor Measurement Units for distribution grid

Historically, as the distribution grid is built in a radial structure and supposed to carry one-way power flow, while only peak loads, fault currents, etc. are monitored continuously. The high penetration of Distributed Energy Resources (DER), Demand Response (DR) programs and new types of loads like Electric Vehicles (EV), etc. causes strain on the distribution grid and may cause congestion and power quality issues. This may lead to equipment failure and eventually to blackouts. All these factors necessitate continuous monitoring of operating states which can be attained by monitoring voltage and current phasors.

11.1 Need for a high precision monitoring system in a distribution grid

The distribution grid usually operates at medium and low voltage levels and hence carry high currents. This makes the conductor area and resistance high. Due to the less spacing between the conductors in overhead distribution lines, the reactance is very high. All these made the R/X ratio of distribution lines a high value compared to the transmission line. The angle difference between two points in the line determines the power flow between those two points. The power angle is the measure of power transfer capability of the system and hence an indicator of the stability of the system. The power angle in the distribution line is very small compared to that of the transmission line. Hence, to accurately measure the power angle in the distribution system, a very accurate and precise monitoring system is needed [195]. Therefore, phasor measurement units in the distribution system should be capable of measuring phasors at very small time steps. The typical reporting rate needed by the distribution PMU, otherwise known as micro-PMU, is 512 samples/second [196]. Due to the high penetration of DER in DN, there will be multiple energy resources in each feeder that cause severe impacts on DN behavior. This can only be observed with the help of a high precision monitoring system.

11.2 Applications of Micro synchrophasor

11.2.1 Automatic network reconfiguration

The authors in [197] proposed a wavelet-based event detection and location algorithm to detect DN events using real-time data from Micro synchrophasors. They also developed a method to reconfigure the network if needed based on the event automatically.

11.2.2 Phase labeling of connected loads

Identifying the connected phase of loads is crucial in DN as it is necessary for phase balancing and renewable energy integration purposes. The authors of [198] propose a phase labeling approach for DN loads employing the measurement data from Micro-PMUs.

11.2.3 Monitoring and protection of distribution system equipment

It is practically impossible to correctly monitor and control the DN resources like DR, RES, and EV. At a very high penetration level, efficient management of these resources is a challenging job and often causes a severe strain on DN. Nowadays, the distribution network equipment is prone to failure because of aging and congestion [199]. All these necessitate advanced monitoring for DN equipment. Accurate event detection and classification results in accurate preventive maintenance scheduling of the critical assets. These can be done based on the warning signs of the pending electrical failures. Preventive maintenance is a beneficial task in terms of time, equipment replacement cost, maintenance crew utilization, avoiding unexpected outages, and consequently extending the life of the critical assets. Real-time data analytics can help to detect multiple failures, along with offering online monitoring of feeder operations. Therefore, it can provide utilities with useful information about faulty equipment in particular parts of the network. In [48], a preventive maintenance scheme employing Micro-PMU measurements is described. The authors also discussed the identification and classification of two types of device malfunctioning: on-load tap changer, and capacitor bank switching.

11.2.4 Intrusion detection

An event detection algorithm using micro synchrophasor data is presented in [200]. The authors proposed an automatic anomaly detection algorithm for a fast-changing distribution grid using Micro-PMU data. The authors of [201] analyzed the impact of the lightning strike on RES using Micro-PMU data. From the Micro-PMU measurements, we will also gain knowledge about any cyber-attacks which will disturb the physical layer of the grid. In [202], an intrusion detection system for the distribution grid is presented by utilizing the measurements from Micro-PMUs.

11.2.5 Model synthesis of DN

Accurate models of the DN are essential for studying distribution system events. DN modeling is a tedious process as the component parameters have to be determined by experiments. However, the model will change due to aging and parameter change. Therefore the DN model should be updated regularly, which is not practical in a conventional way. As the Micro-PMU measurement reflects the actual operating condition of the DN, it is possible to do real-time model synthesis by using Micro-PMU data.

The authors of [203] proposed a steady-state model synthesis of DN using Micro-PMU data. They also proposed the data analytics techniques to pre-process the Micro-PMU data to remove bad data and noises to make them suitable for model synthesis application. The authors of [204] proposed a Micro-PMU system working together with a cloud platform for identifying areas where the network parameters need to be updated. They discussed and compared the transformer impedance calculation and the impedance calculated from micro PMU data. In [205], the authors proposed a cloud-based model synthesis platform for detecting bad data employing Micro-PMU measurements. With the help of the Global Positioning System (GPS) and cloud platform, the Micro-PMU can determine its location and the component to which it is connected. In [206], a topology detection method based on the measurement of voltage angle difference is discussed.

11.2.6 Renewable generation monitoring

Due to the high penetration of RES, it is crucial to monitor the power outputs of RES to maintain the supply-demand equilibrium. The authors of [207] proposed a real-time estimation of solar generation from Micro-PMU measurements together with a proxy irradiance measurement.

11.2.7 State estimation

The authors of [208] proposed a three-phase state estimator for an unbalanced active distribution system. They also developed a network separation algorithm for decentralized state estimation using Micro-PMU. In [209], the authors proposed a linear state estimation algorithm that considers pseudo measurements along with Micro-PMU measurements. They used Taylor's approximation to linearize the pseudo measurements to include it in the linear state estimation. In [210], the authors proposed a state estimation algorithm to update the system states after the occurrence of an event in the DN using very few Micro-PMU measurements installed one at the substation and another one at the feeder lateral end.

12 Demand Response (DR) programs

The development of new generation technology, intelligent monitoring systems, demand-side management, data analysis, data storage and communication infrastructure, etc. has redefined the concept of an active distribution network. To gain most out of active distribution networks, efficient management of distributed generators, battery storage devices, establishing DR programs, and managing prosumers are necessary. Managing all this is a complex task. Market-based methods are found to be the best way to extract the full potential of prosumers and DER.

Conventionally, electricity is charged based on simple tariff, flat rate tariff, block rate tariff, two-part tariff, maximum demand tariff, and power factor tariff, etc. These conventional tariffs are not adequate for efficient pricing of electricity under smart grid regime, especially with a large scale integration of renewable energy sources and distributed storage systems.

Demand Response is a key concept in SG, which can reduce consumer payments and electricity generation costs. There are two methods for achieving DR: Price based DR and incentive-based DR. Price based DR programs force the customers to adjust the usage of their flexible loads concerning the price of electricity. The second kind of DR programs are incentive-based schemes. They provide proper incentives to the customers in addition to the electricity rate for their contribution towards ancillary services. Another way to give demand response signals to the end customers and DER owners is through Distribution Locational Marginal Pricing (DLMP) which is an extension of transmission LMP to the distribution grid.

12.1 Price based DR

The utility can force the customers to participate in the load control program voluntarily through smart pricing. Some of the examples of smart pricing are Critical Peak Pricing (CPP), Time of Use Pricing (ToUP), and Real-Time Pricing (RTP).

12.1.1 Critical Peak Pricing (CPP)

Critical Peak Pricing (CPP) is combined with direct load control for demand-side management in [211]. The authors of [212] did a study on the demand impact of CPP on customer characteristics. A CPP scheme for conserving electricity and for inducing trip generation is proposed in [213]. They observed that CPP has a negative impact on elderly people due to their difficulties with mobility. CPP is combined with a day-ahead real-time price to design a home energy management controller in [214].

12.1.2 Time of Use Pricing (ToUP)

In Time of Use Pricing (ToUP), the electricity price depends upon the amount used and the time of usage. The price in the peak load time is very high, whereas low load times are charged less. With the ToUP, consumers can lower their electricity bills only if they know about the times of lower rates. Smart metering assists customers in attaining this goal. The current ToUP assumes a fixed time-period classification for a long time. However, because of the uncertain nature of renewable energy and demand, peak and valley periods of the day change every day. Based on the day-ahead load and renewable energy forecasts, the time-period partition updates daily into the peak, valley, and intermediate periods [215]. A market-based DR program through a game-theoretic framework is proposed in [216]. The authors developed a dynamic pricing model composed of both Real-Time Pricing (RTP) and ToUP.

12.1.3 Real Time Pricing (RTP)

In RTP the electricity price is different at different times of the day. The main disadvantage of RTP is the difficulty and confusion felt by the consumer for responding manually to the varying prices at each hour [217]. The applications of power modeling for real-time pricing based DR programs are given in [218]. Real-time energy management platform for customer "i-Energy" is proposed in [219]

which combines both RTP schemes and incentive-based DR programs.

12.2 Incentive based DR program

Incentive-based DR program includes direct load control, interruptible/curtailable service, demand bidding/buyback, emergency demand response program, capacity market program, and ancillary service markets.

12.2.1 Direct load control

Reliable and economical operation of the power system became a challenging job in the present RES integrated power system due to the uncertain and volatile nature of renewable energy. An efficient pricing scheme should be able to incentivize DR resources to interact with the grid and help to attain supply-demand balance.

One way to perform demand-side management is to accomplish direct load control through which the utility or an aggregator has direct control over the customer's load. Due to the privacy issue, direct load control may not be an effective option for load control in the distribution system.

In [220] and [221] a contract based direct load control program is proposed which is implemented through a genetic algorithm.

12.2.2 Interruptible/ curtailable service

This is a pricing scheme for demand-side management in which the utility offers a reduced tariff for customers in a short period, and the customer should in return agree to reduce their energy consumption or allow the utility to interrupt electricity supply during a higher demand period temporarily. Usually, this will be done for providing an uninterruptible supply for critical loads [222]. The customers are informed about the curtailment through advanced metering infrastructure and are required to respond within 30 to 60 minutes. Those who are not ready to do the curtailment are penalized. The loads which have a continuous duty period (silicon chip production) are not suitable for curtailment service.

In [222], an incentive-based DR program is implemented for interruptible/ curtailable loads which will benefit both the load characteristics and the customers.

12.2.3 Emergency Demand Response (EDR)

An EDR based load shedding scheme is presented in [223]. An EDR program is employed for mitigating voltage instability problems, the degree of which can be measured from the rotational speed of induction motor. According to the degree of voltage instability, various demand response sources, together with load shedding, are employed for attaining stability. The time, amount, and the place of load shedding is determined based on the degree of load shedding. A method to determine the most appropriate buses and time for establishing a DR program is presented in [224], based on their power transfer distribution factor and available transfer capacity.

12.2.4 Capacity market program

The capacity market is a means to ensure the reliability of supply by incentivizing suppliers to make them agree to be on-line and to make more investments in generation. In other words, it is a competitive way of obtaining future capacity. It is like an insurance policy against black-outs. A capacity market is created by aggregating suppliers who are willing to give capacity reserves by providing incentives proportional to the investments in generation capacity. Customers after getting a demand forecast, purchase capacity credits by making a bilateral contract with the supplier. The capacity credits are proportional to the sum of the peak load forecast plus the reserve capacity. The supplier who violates this contract is penalized. The performance of a capacity market in a system with a high share of RES has been discussed in [225]. To stabilize the market price under a huge share of RES, a forward capacity market is proposed in [226]. As the DR program and EES technologies have become more advanced, they have made it possible to obtain almost the same performance as the capacity market but at a lower cost of electricity [227]. A review of capacity market programs for a power system with high penetration of renewable energy is given in [228]. The integration of energy storage capacity to the capacity market auction is challenging due to its complex capacity characteristics and the lack of definite measures to incorporate it into the capacity market. The authors of [229] consider these challenges and developed a capacity auction model that considers the capacity of contributions from energy storage devices. In [230], a day ahead DR is employed to provide spinning reserve provision.

12.2.5 Ancillary service market

DER can be used to provide ancillary services like reactive power and voltage support to the grid [231]. The ancillary service market is meant to maintain a pool of generating resources that will be intended to give ancillary services or in other words, back up generation offers to the grid during emergency conditions like sudden generation outages, unexpected high demand, etc. There are mainly two types of ancillary services depending upon the speed with which they should be dispatched: Reserve and Regulation. The generating sources which can be synchronized with the grid and come up to the desired level of output within 30 to 60 minutes are considered under the category of the reserve, whereas those resources which can do the same within a few seconds come under the category of regulation.

A bidding strategy for Vehicle-to-Grid ancillary service is presented in [232] to get maximum benefits to both customer and utility. An agent-based distributed control framework for trading power and ancillary services is proposed in [233]. A PV based household energy management and ancillary service provision method is proposed in [234] in such a way as to provide maximum benefit to PV owners despite the intermittent nature of PV output.

12.2.6 Distribution Locational Marginal Pricing (DLMP)

DLMP is the cost of delivering the next Mega Watt of energy to the distribution nodes. DLMP varies from node to node based on congestion and losses. It acts as an effective price signal to reduce congestion and losses.

A two-stage optimization method for controlling residential consumers and small scale RES is implemented through DLMP in [235]. In [236] real-time price signals are generated by DLMP for real-time power balancing of the microgrid. A multi-agent-based framework for congestion management is proposed in [237] with the help of DLMP signals.

13 Prospective observations and critical findings

The significant findings of this research work are presented below:

- Precise data can be generated on grid condition and stability using Micro-PMU measurements.

- Self-healing, the most important characteristics of the smart grid can be realized by the deployment of blockchain technology.
- The best practice to use smart grids is to deploy smart contracts on the blockchain to maintain supply-demand balance and enable peer-to-peer trade rather than creating a centralized marketplace.
- MAS system is an asset to the smart grid that enables them to do prompt actions in a cooperative manner and re-configure on its own. Subsequently, SGs can promote the participation of consumers in the grid and consumers can produce energy through different distributed energy resources.
- Cloud computing is highly suitable for smart grid operations because of its intensive computing nature and a dependable storage medium. Cloud computing is more economical, flexible and scalable than traditional models.
- Efficacy of smart grid systems can be improved using intelligent devices along with edge computing technology to process the data at the edge of the IoT network.

14 Conclusion

Advanced data analysis and machine learning techniques are crucial for the efficient management of a modern distribution grid. Contemporary technologies like cloud, fog and edge computing, Internet of Energy (IoE) and blockchain technology have redefined the concept of distribution system management. This paper discussed some prominent technologies that transformed the traditional DN into the smart DN. Still, there are many untapped areas in smart grid communication which can be described as the backbone of successful grid operation.

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