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Big data driven smart energy management: From big data to big insights

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ABSTRACT

Large amounts of data are increasingly accumulated in the energy sector with the continuous application of sensors, wireless transmission, network communication, and cloud computing technologies. To fulfill the potential of energy big data and obtain insights to achieve smart energy management, we present a comprehensive study of big data driven smart energy management. We first discuss the sources and characteristics of energy big data. Also, a process model of big data driven smart energy management is proposed. Then taking smart grid as the research background, we provide a systematic review of big data analytics for smart energy management. It is discussed from four major aspects, namely power generation side management, microgrid and renewable energy management, asset management and collaborative operation, as well as demand side management (DSM). Afterwards, the industrial development of big data-driven smart energy management is analyzed and discussed. Finally, we point out the challenges of big data-driven smart energy management in IT infrastructure, data collection and governance, data integration and sharing, processing and analysis, security and privacy, and professionals.

Contents

1. Introduction

With the rapid development of sensor technology, wireless transmission technology, network communication technology, cloud computing, and smart mobile devices, large amounts of data has been accumulated in almost every aspects of our lives. Moreover, the volume of data is growing rapidly with increasingly complex structures and forms. A research report of International Data Corporation (IDC) [1] pointed out that 1.8ZB data were created and replicated in 2011 worldwide, and it is estimated that this figure will increase by 50 times by the year 2020. The big data era has arrived [2].

In the energy sector, large amounts of energy production and consumption data are being generated and the energy systems are

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being digitized, with the increasing penetration of emerging information technologies [3]. The innovations brought by big data are changing the landscape of traditional energy industry. Currently, the energy sector is facing various challenges [4], such as challenges in operational efficiency and cost control [5], system stability and reliability [6], renewable energy management [7], energy efficiency and environmental issues [8], as well as consumer engagement and service improvement [9]. To better deal with these challenges, energy big data analytics provide new opportunities by achieving smart energy management. Specifically, to achieve the goals of clean power generation, efficient power transmission, dynamic power distribution and rational electricity consumption, smart grid that incorporates distributed generation resources and innovative storage solutions have been proposed [10–14]. Smart grid introduced the concept of "information flow". It is designed to integrate information flow and energy flow, thus achieving data collection and energy transmission at the same time [4]. In smart grid, large amounts of and various types of data, such as device status data, electricity consumption data, and user interaction data, are being collected. Then, many data analysis techniques, including optimization [15–17], forecasting [18–20], classification and clustering [21–25], can be applied on the large amounts of smart grid big data. Thereby, power generation and operation can be optimized in real time, electricity demand can be predicted accurately, electricity consumption patterns can be discovered precisely, and dynamic pricing mechanisms can be developed effectively. Based on big data analytics, smart grid can detect and restore from failures rapidly, response electricity demand quickly, supply more reliable and economical energy, and enable customers to have more control over their energy use [26]. Big data analytics can provide effective and efficient decision support for all of the producers, operators, customers and regulators in smart grid.

Big data is changing the way of energy production and the pattern of energy consumption. Energy big data have brought opportunities and challenges at the same time for us. Some of the primary and urgent challenges include: (a) how to effectively collect, store and manage the energy big data; (b) how to efficiently analyze and mine the energy big data; (c) how to use the energy big data to support more effective and efficient decision makings; (d) how to get insights and obtain values from the energy big data; and (e) how to effectively prevent risks and protect privacy while utilizing the energy big data.

To realize the full potential and deal with the various challenges of energy big data, as well as get insights to achieve smart energy management, we present a systematic and comprehensive study of big data driven smart energy management in this paper. To the best of our knowledge, this is the first attempt to systematize both the extraordinary opportunities and the tough challenges of big data in energy sector. In the next Section, we discuss the sources and characteristics of energy big data, and propose a process model of big data driven smart energy management. Then in Section 3, taking smart grid as a research background, we present the research issues of big data driven smart energy management from four major aspects, namely the power generation side management, microgrid and renewable energy management, asset management and collaborative operation, and demand side management (DSM). The industrial development of big data driven smart energy management is also surveyed and discussed. Finally, Section 4 provides the summary and future challenges of big data driven smart energy management.

2. Energy big data and smart energy management

2.1. Sources of energy big data

In a certain sense, smart energy system can be regarded as the convergence of the Internet and the various intelligent devices and sensors spread throughout the energy system [27]. In smart grid, the main source of data is the advanced metering infrastructure (AMI) [28,29], which is one of the underlying enabling technologies of smart grid. AMI deploys a large number of smart meters and other measuring terminals at the end-user side.

The smart meters usually collect customers' electricity consumption information every 15 mins, and the meter readings alone have created and accumulated massive amount of data. It is estimated the number of readings will surge from 24 million a year to 220 million per day for a large utility company when the AMI is adopted and implemented [30]. A large amount of meter reading data will be collected in a distribution network with 1 million metering devices, and the volume of the data can grow exponentially. If the size of each collection record is 5 Kb, the amount of records and the volume of data with different collection frequencies in a year are shown in Table 1.

Table 1 indicates that the large amounts of AMI data grow very quickly. When the data are collected every 15 mins by the 1 million metering devices, the total records will reach 35.04 billion and the volume of meter reading data will surge up to 2920 Tb.

Nevertheless, the big data in smart grid are not just the meter data. Many other intelligent devices like BAS, sensors and thermostats used throughout the whole process of power generation, transmission, distribution, substation and consumption are also collecting vast quantities of data. Ref. [32] summarizes four types of big data sources in utilities, namely AMI data (smart meters), distribution automation data (grid equipment), third-party data (off-grid data sets), and asset management data (firmware for all smart devices and associated operating systems).

The weather data, such as the angle of the sun, wind speeds and temperature, play an important role in supporting smart energy management. For example, the weather data can be used for renewable energy power generation forecasting, system fault identification, and user energy consumption forecasting, thus supporting the decision-makings of different participants in energy systems. It is believed that weather data, mobile data, thermal sensing data, Hadoop and energy database, clean energy data, electric vehicle data, transmission line sensor, real estate data, dynamic pricing, and energy consumption control through behavioral analysis are the ten ways that big data is remaking energy and utilities [33]. It is estimated that weather data will one day become the next generation infrastructure platform of energy-saving services and applications, like maps and location data that form the basic platform for a lot of services. Currently, industry has realized the significance of weather data. WeatherBug, founded in 1992, is a company that provides live weather data, information and services. In 2010, it has launched its smart grid products and solutions, by selling its weather services to the smart grid industry [34,35].

In addition, the Geographic Information System (GIS) data is also an integral part of energy big data. GIS is a traditional source

Table 1
The amount of data collected by 1 million metering devices in a year.

Collection frequency	1/day	1/hour	1/30 min	1/15 min
Records (billion)	0.37	8.75	17.52	35.04
Volume of data (Tb)	1.82	730	1460	2920

Source: Ref. [31]

of big data, which can provide important decision supports for energy systems [36,37]. GIS data describe the geographic features of a certain region, and it mainly include spatial and attribute data. GIS data have some specific characteristics compared with other kinds of data. First, GIS data not only include the general attribute data of geographic features, but also a lot of spatial data that describe the spatial distribution of geographic features. Second, GIS is a complex giant system that describes resources and environment using a variety of data. The amount of data is huge. Third, the GIS data are not updated in real-time. The GIS database usually has a long update cycle. The GIS big data can play many important roles in supporting smart energy management. For example, in smart grid environment, the GIS data layers can be used to correlate electrical networks to geographical locations.

Due to the fact that energy big data are collected from many different sources by different data acquisition devices, database integration becomes a crucial aspect in energy big data analytics. The data from different platforms and applications are usually heterogeneous, independent and mutually closed. Also, the data structure, format and quality vary widely. Many big data analysis tasks cannot be completed without data integration. Currently, many models and approaches of database integration have been proposed [38–40].

2.2. Characteristics of energy big data

Businesses and organizations can “extract value from very large volumes of a wide variety of data by enabling high-velocity capture, discovery, and/or analysis” [41]. Therefore, big data have the characteristics of “4V”, i.e., volume, velocity, variety and value [41–43]. For the energy big data, their “4V” characteristics are reflected in the following aspects.

Volume. The introduction of smart metering devices and sensors in smart energy systems, as well as the combination of other data sources, present many new opportunities as well as many tough challenges. The first challenge is the massive amount of data. Though the volume of energy big data may not equal to those generated by traditionally data-intense industries, the large amount of data also present a big challenge for energy sector. This challenge is not only reflected in the storage side, but more importantly in the analysis and processing of the energy big data [31].

Velocity. This characteristic refers to the speed requirement for collecting, processing and using the energy big data. In smart energy systems, the speed of data collection and processing are very fast ranging from 5- or 15 mins interval to sub-second interval. There are many streaming data and relatively large volume data movement. For the many real-time tasks in smart energy systems, such as equipment reliability monitoring, outage prevention or security monitoring, the analytical algorithms that need many hours or more time to run are not competent.

Variety. Variety means the increasing complex of data types. In smart energy systems, the data are not only traditional structured relational data, but also many semi-structured data like the weather data and Web services data, as well as unstructured data like customer behavior data and the audio and video data. The energy big data is a mix of structured, semi-structured and unstructured data [26]. With the increasing utilization of social media and call center dialogs in energy sector to support decision makings, the energy big data will become more varied.

Value. Energy big data itself is meaningless unless valuable knowledge that supports effective and efficient decision makings throughout the energy management process can be discovered. We can get insights from the energy big data to promote consumer engagement and efficiency improvement, to enhance system reliability, to understand energy consumption patterns, and to develop competitive marketing strategies. Also, the value of energy big data is sparse, which means that the knowledge mined and the value obtained from large amounts of data may be limited. Therefore, in the era of big data, we should pay more attention to the overall data rather than the sample data [44].

Besides the “4V” characteristics of energy big data, Ref. [45] also presented the “3E” (energy, exchange and empathy) characteristics of energy big data. Energy (data-as-an-energy) means that energy savings can be achieved by big data analytics. Exchange (data-as-an-exchange) refers to that the big data in energy system need to exchange and integrate with the big data from other sources to better realize its value. Empathy (data-as-an-empathy) means that better energy services can be provided, users' needs can be better satisfied, and consumer satisfaction can be improved based on energy big data analytics.

The “4V” and “3E” characteristics of energy big data are shown in Fig. 1.

2.3. Data-driven smart energy management

To achieve the smart energy management objectives based on big data analytics, we propose a process model of big data driven smart energy management, as shown in Fig. 2.

Fig. 2 indicates that it consists of seven major steps for big data driven smart energy management tasks. In the process model, data collection, transmission, storage, cleaning, preprocessing, integration and feature selection are important preparation phases for big data mining. Then, data mining and knowledge discovery is the key step and the core content of big data driven smart energy

Fig. 1. “4V” and “3E” characteristics of energy big data.

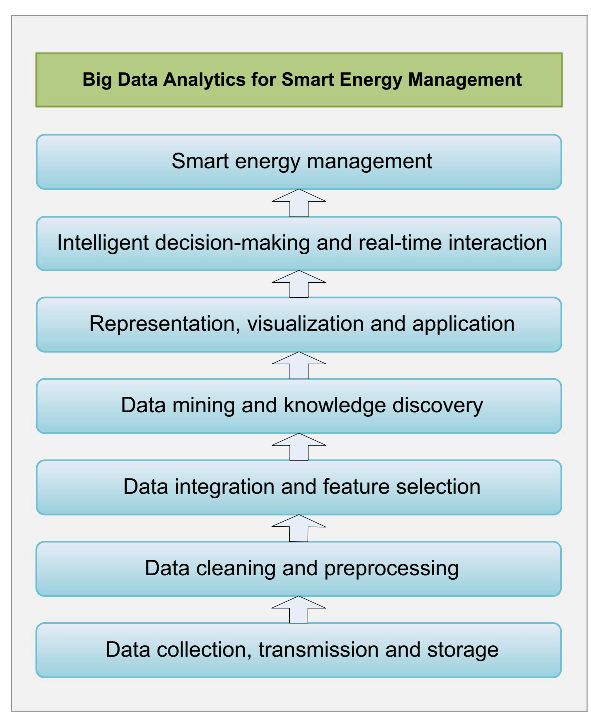

Fig. 2. A process model of big data driven smart energy management.

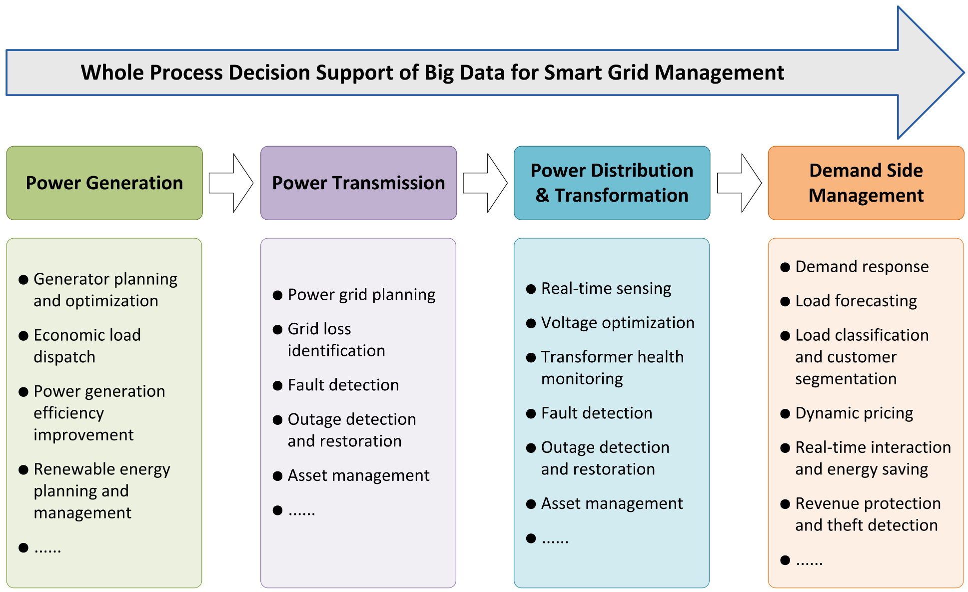

Fig. 3. Whole process decision support of big data for smart grid management.

management. Afterwards, the knowledge extracted from energy big data should be represented, visualized and applied, thus supporting the decision making and control throughout the energy system. Finally, the various smart energy management objectives, including energy efficiency, consumer engagement, real-time monitoring, demand response, intelligent control, and dynamic pricing, can be achieved.

Big data analytics play an important role in the whole process of smart grid management, including power generation, power transmission, and power distribution and transformation, as well as demand side management.

For smart grid, the whole process decision support of big data is shown in Fig. 3.

The application of these energy big data means significantly improved efficiency and new business opportunities. Based on the big data analytics and services, energy is now being saved in ways that were not possible in the past. It is reported that installing smart meters could generate between $40 and $70 in annual savings for each customer [30]. Through the various advanced data collection, processing, analysis and visualization tools and techniques, we can discover new trends and patterns, optimize existing business processes to drive productivity and operational efficiency, discover hidden values, and get additional insights from the energy big data. GTM Research has estimated that the value of the global utility data analytics market at a cumulative $20 billion between 2013 and 2020, growing from $1.1 billion in 2013 to $3.8 billion globally in the year 2020 [46].

3. Research status and industrial development of big data driven smart energy management

3.1. Research status of big data driven smart energy management

In smart grid environment, the studies of big data analytics based decision support and intelligent control are mainly in the following four aspects, namely, power generation side management, microgrid and renewable energy management, asset management and collaborative operations, and DSM.

Based on big data analytics, power generation and planning can be optimized. Power generation planning [47–49] and economic load dispatch (ELD) [50–52] are two of the most important decision making processes in power generation. Taking advantage of the widely collected energy big data and advanced big data analytics techniques, the energy production efficiency can be significantly improved and the production costs can be greatly reduced.

Renewable energy is an important part of modern energy systems. Microgrid [53] is a promising distributed power generation model which integrates the renewable energy power generation. In smart grid, wind power and solar power are two major renewable energy power generation methods. However, their outputs are significantly affected by weather conditions. Big data analytics play an important role in renewable energy and microgrid management. For example, renewable energy power generation forecasting will be more accurate and efficient based on the massive weather data analysis. The integration of energy production and consumption data, GIS data, and the weather data (e.g., temperature, atmospheric pressure, humidity, cloud cover, wind speed, and wind direction) can support the sites selection of renewable power generation devices, thus to improve power output and energy efficiency.

Power industry is a typical asset-intensive industry. Both the power generation companies and the power grid enterprises often face many asset management problems, such as resource sharing, asset retirement monitoring, operation and maintenance management, procurement monitoring, and inventory management. The efficiency of asset management and collaborative operation can be improved based on energy big data analytics. The data of production, operation, marketing and management can be integrated, and data sharing can be achieved throughout power generation, transmission, transformation, distribution, and consumption. By coordinating the management of electricity production, operation, maintenance, and sales, the allocation of resources can be optimized and the production efficiency and resource utilization rate can be improved. The power grid reliability and stability can also be improved by means of big data analytics. The massive sensor data collected from power system infrastructure, combined with advanced big data analysis and visualization techniques can change the traditional ways of power system operation and maintenance. Thus, the efficient operation, real-time monitoring and fault diagnosis, and intelligent scheduling management of power system can be achieved. The risk and unnecessary expenses of manual operation can be reduced, and the reliability of power

Table 2
Some research on big data driven smart grid management.

	Tasks	Data sources	Methods	Refs.
Power generation side management	Power generation planning	Carbon emission data, generating units data	Constraint programming, fuzzy possibilistic model	[47–49]
		Technology cost and performance data	Constraint programming and compromised modeling	[62–64]
		Generating cost data, budget and capacity constraints data etc.	Portfolio-theory, dynamic programming	[65, 66]
	Economic load dispatch (ELD)	Load demand, generator parameters, transmission loss	Biogeography-based optimization (BBO) algorithm	[17, 50]
		Load demand, operating zones data, transmission loss	Particle swarm optimization (PSO) based methods	[51, 52, 67–69]
		Load demand, operating zones data, ramp-rate limits data	Differential evolution based methods	[70–72]
		Load demand, generator parameters	Harmony search based methods	[73–76]
Microgrid and renewable energy management	Microgrid optimal load distribution	Load demand, distributed generator parameters	Single-objective and multi-objective optimization	[16,77–79]
	Investment planning	Cost data, distributed generator capacity data	Cost–benefit analysis	[80,81]
	Wind power forecasting	Past power measurements, wind speed and direction	Self-organized map, quantile regression, artificial neural network, time series models, support vector machine (SVM)	[82–87]
	Solar power forecasting	Past power measurements, meteorological forecasts of solar irradiance, relative humidity and temperature	Time series models, autoregressive (AR) models, artificial neural network	[88–92]
	Hybrid wind-solar power generation	Wind and solar power generation, load demand, energy storage data	Time series analysis, system control, operational management	[93–96]
Asset management and collaborative operations	Asset management	Condition monitoring data, operating observations, network data, component reliability data	Condition assessment techniques, the Health Index, reliability-centered method, service-oriented architecture	[97–101]
	Operation and control	Substation data, operation conditions data	Automated analysis, credibility theory, random fuzzy model	[102,103]
	Fault diagnosis	Diagnostic signatures, control signal, local current and voltage signals	Qualitative physics based approach, multi-agent system, wavelet based methods, artificial neural network, SVM	[104–106]
	System reliability Improvement	Load data, failure data, equipment information	Sequential Monte Carlo simulation, fault tree analysis, risk importance measures	[107–109]
Demand side management (DSM)	Load forecasting	Historical load data, temperature, wind speed, cloud cover	Neural Networks Approach	[18,110,111]
			Support vector regression	[20,112]
			PSO based methods	[113,114]
			Ant colony optimization	[115,116]
			Hybrid approaches	[117–119]
	Load classification and consumers segmentation	Load profiles, electricity consumption data	Fuzzy c-means (FCM) clustering	[21,120,121]
			K-means clustering	[122,123]
			Hierarchical clustering	[124,125]
			Self-organized Mapping (SOM)	[126]
	Dynamic pricing (variable pricing or real-time pricing)	Load demand, power supply, user behavior data	Simulations, least-squares SVM, economic modeling	[58–60]
	User response to dynamic pricing	Load demand, time-of-use rates, critical-peak pricing (CPP) tariffs	Survey, empirical studies, linear programming, price prediction	[127–129]
	Non-technical loss (NTL) detection	Historical load data, customer load profiles, electricity consumption behavior information	SVM based method, harmony search, Bayesian networks, decision trees	[130–133]

Table 3
Some companies that provide big data-driven smart energy management products and services.

Company	Founded	Brief introduction	Big data-driven products or services	Refs.
3TIER	1999	An integrated suite of renewable energy assessment, forecasting, and asset optimization services delivered to customers.	Solutions: Renewable energy project feasibility, energy marketing, and asset management.	[135]
EnerNOC	2001	A provider of energy intelligence software and services for customers, electric power grid operators and utilities.	Products: DemandSMART™, EfficiencySMART™, SupplySMART™, EnerNOC Demand Resource™, EnerNOC Demand Manager™, EnerNOC's Network Operations Center (NOC). Services: Demand response and demand management, energy consumption and energy project management, energy supply and utility bill management.	[136]
Silver Spring Networks	2002	It delivers the open, standards-based networking platform, software and services for utilities and cities to support multiple smart grid and smart city applications and services on a single, unified network.	Products: Smart Energy Platform™ (including metering devices, distribution automation devices, in-home devices, network infrastructure, and software solutions). Services: Business system integration, customer support, hosting choices, installation support, mesh design, monitoring and maintenance, and training.	[137]
Tendril	2004	A utility-to-home-energy-management company that provides the infrastructure, analytics, and understanding required to deliver personalized energy services.	Product: Data-driven Energy Service Management (ESM) platform. Services: Energy efficiency, demand management, customer engagement.	[138]
EcoFactor	2006	A company that delivers predictive cloud-based home energy management platforms, automated energy savings, comfort and control through energy efficiency, demand response and HVAC performance monitoring services.	Products: Cloud-based energy platform and open thermostat APIs. Services: Proactive energy efficiency, optimized demand response, and HVAC performance monitoring.	[139]
Efergy	2006	A global manufacturer of energy monitors and energy saving products.	Products: Wireless energy monitors. Services: Energy consumption monitoring, energy usage information, carbon footprint, energy saving.	[140]
EnergyHub	2007	A provider of cloud-hosted software platform, web and mobile apps, and smart devices for managing energy use in homes and small businesses.	Product: Mercury smart thermostat platform. Services: Real-time energy usage information, remote monitoring and control energy management, notifications, peak power reduction, energy saving, energy efficiency, and customer engagement.	[141]
Opower	2007	A provider of cloud-based software platform to enable utilities to achieve energy efficiency, customer engagement and demand response, and present insights and suggestions to consumers to motivate reductions in household energy consumption and enable savings for the individual.	Product: Cloud-based software platform Opower 5-Flex. Services: Energy efficiency, customer engagement, demand response, thermostat management.	[142]
C3 Energy	2009	A SaaS analytics company that leverage big data, grid analytics, social networking, and cloud computing to improve energy efficiency, customer engagement, and smart grid operations.	Products: C3 Energy Smart Grid Analytics™, C3 Energy Grid Analytics™, and C3 Energy Customer Analytics™. Services: Revenue protection, outage analysis, prediction & restoration, AMI operations, reliability & safety, voltage optimization, customer segmentation & targeting, demand response, substation automation, volt/VAR optimization, energy efficiency, customer engagement, etc.	[143]
FirstFuel	2009	An energy analytics company that helps utilities and government agencies deliver scalable energy efficiency across their commercial building portfolios.	Product: Remote Building Analytics (RBA) platform. Services: Energy efficiency, meter data analytics, improving commercial building efficiency, energy management information systems.	[144]
Grid Navigator	2009	A provider of intelligent energy management systems (EMS) for commercial & industrial applications.	Products: BACnetXchange server, GridRadar, smart thermostat, lighting widget. Services: Energy management system, lighting system, and solar metering solution.	[145]
Simple Energy	2010	A SaaS company that motivates people to save energy.	Products: Engagement Platform (Energy Insights, Energy Community, Energy Rewards), Marketplace (a utility branded e-commerce platform).	[146]
Nest	2010	A home automation company that designs and manufactures sensor-driven, Wi-Fi-enabled, self-learning, programmable thermostats and smoke detectors.	Products: Nest Thermostat and Nest Protect. Services: Auto-schedule, personalized services, remote control, automatic updates, sensing and learning, multiple devices communications, smoke and carbon monoxide detection.	[147]
AutoGrid	2011	It is dedicated to organize the energy big data and make it useful and actionable for electricity generators and providers, grid operators and customers, by its scalable software system.	Products: Energy Data Platform (EDP), Demand Response Optimization and Management System (DROMS). Services: Real-time load forecasting and event monitoring, demand management, modeling of grid physics, measurement, verification, analytics and reporting.	[148]
Bidgely	2011	A technology company providing innovative energy monitoring & management solutions.	Solutions: Customer engagement, energy efficiency, demand management, and utility insights.	[149]
Big Data Energy Services	2012	A cloud-based service provider and consultancy providing data services for demand response, data analytics, meter data and transaction management.	Solutions: Big data analytics, data transformation & management, demand response, settlement & forecasting.	[150]

Note: The companies are sorted according to their founded years.

grid system can be improved. In addition, based on the energy consumption data and the correlation analysis between network failures and power outages, the fault locations can be precisely identified, and real-time fault diagnosis and recovery can be achieved. Also, through the real-time monitoring, collection and analysis of energy consumption data, peak load shifting can be carried out to reduce the risks of power failure and grid collapse. The weather data is also important in enhancing system reliability and stability. The particular weather patterns discovered can be used to predict future outages and identify the problem positions or areas, thus leading to faster failure warnings and recovery [30].

DSM is one of the most extensive application areas of big data analytics, ranging from consumer segmentation to dynamic pricing [54]. A lot of valuable knowledge can be discovered from the massive electricity consumption data collected in near real time by intelligent metering devices. This knowledge can support many demand side decision makings and marketing strategies development. Load forecasting [55] is an important research content in smart grid, which means the forecasting of future load demand based on historical load data, weather data, and social factors, etc. For different purposes, load forecasting can be divided into short term, medium term and long term load forecasting. Currently, many load forecasting models and methods have been proposed [18,20,56]. Load classification [21,57] is the process to partition different load profiles into groups using the various clustering methods. The energy consumption patterns of different users can be identified by load classification, which can support the development of competitive marketing strategies and the offering of personalized energy services. It can also help different consumers develop their energy saving plans at the same time. Dynamic pricing [58–60], also referred to variable pricing or real-time pricing, can guide the user's energy consumption behaviors and improve the reliability of power system by different pricing strategies. Knowing how customers respond to dynamic pricing programs is also a field where analytics can play an important role [61]. It is also possible to use massive metering data and big data analytics to analyze energy diversion, identify grid loss, and prevent theft.

Table 2 shows a summary of the data sources, common methods and some references of different big data driven smart grid management tasks.

In addition, risks and privacy are key issues throughout the whole process of big data driven smart energy management. To fully achieve the economic and social benefits of energy big data, individuals' privacy must be effectively protected and the potential risks of using data must be reasonably avoided. Therefore, both technological and non-technological measures are important to re-conciliate the benefits and security & privacy risks of energy big data. In terms of technological means, for example, energy companies that used individuals' data should disclose the logic underlying their decision-making processes to the extent possible without compromising their trade secrets or intellectual property rights. The classification of big data resources (e.g., private big data, public big data and hybrid big data) is also an important technological measure [134]. As for non-technological measures, legal supervision, ethics education, and the enhancement of self-protection awareness are all necessary.

3.2. Industrial development of big data driven smart energy management

With the further research on big data driven smart energy management, the related industries are also developing rapidly. In recent years, the IT giants like IBM, SAS, Oracle, Teradata, EMC and SAP, and grid giants including General Electric, Siemens/eMeter, ABB/Ventyx, Schneider Electric/Telvent, Toshiba/Landis+Gyr and more, are beginning to provide energy big data and smart energy management related products and services for both utility companies and consumers [61]. In addition, many startups that focus on the big data-driven smart energy management products and services also have a rapid growth in the past few years.

Industrial development and scientific research are mutually reinforcing. Practical applications that promote economic and social development are the ultimate goal of scientific research. Also, tracking the industrial development process and trends contributes to relevant scientific research. Therefore, in this section, we present an overview of the industrial development related to big data driven smart energy management.

Table 3 summarizes the founded years, brief introduction, and some big data-driven products and services of some startup companies that focus on big data driven smart energy management.

The industry of big data-driven smart energy management has been developing rapidly in recent years, and many related startups continue to emerge. Therefore, Table 3 just listed some selected representatives. Nevertheless, most of the startup companies that provide big data-driven smart energy management products and services were founded around the year 2009, when the concepts of "big data" was just proposed. This further demonstrates that the research and industrial development of big data-driven smart energy management were mutually reinforcing. The rapid development of related industries also reveals the insufficiencies of current energy systems and people's increasing demand for the achievement of smart energy management, as well as the potential that big data analytics can play in promoting smart energy management.

As for the products provided by these startups, we find that cloud computing, big data analytics and sensing technologies based intelligent hardware devices, software, platforms and systems are the most common. Their services and solutions are mainly focused on real-time monitoring and forecasting, demand response and demand side management, customer engagement, energy efficiency optimization, energy consumption notifications and reports, and targeted marketing. Most of these services are the key objectives of big data-driven smart energy management.

Big data is still in its infancy, and most of the related big data-driven smart energy management technologies are not mature. With the deepening of scientific research and industrial development, people's understanding and awareness of smart energy management will also changing. Currently, we are still faced with some severe challenges to fulfill the potential of energy big data and fully achieve smart energy management objectives.

4. Summary and future prospects

Energy big data not only include the massive smart meter reading data, but also the huge amount of data from other sources, such as the weather data, the GIS data and the asset management data. The energy big data has the "4V" (i.e., volume, velocity, variety and value) and "3E" (i.e., energy, exchange and empathy) characteristics. According to the proposed process model of big data driven smart energy management, big data analytics play important roles in the whole process of smart grid management, ranging from power generation to demand side management.

In recent years, both the related scientific research and industries of big data driven smart energy management have developed rapidly. However, to fully realize the potential of energy big data and achieve the objectives of smart energy management, there are still some severe challenges that need to be addressed.

(1) Information technology (IT) infrastructure. The explosive growth of energy big data and the speed requirement for

collecting, processing and using of energy data have brought a serious of challenge for traditional IT infrastructure [151]. The IT infrastructure needs to be improved in network transmission capacity, data storage capacity, data processing capability, data exchange capability, data visualization capability and data interaction capability to better support big data driven smart energy management.

(2) Data collection and governance. Though the volume of energy big data is large and the energy big data contain a lot of valuable knowledge, their value is sparse and the data quality is not so high in most cases. The timeliness, integrity, accuracy and consistency of energy big data need to be improved [45]. The big data driven smart energy management requires complete data governance strategies, as well as organization and control procedures. High quality, standardization and format uniform are the prerequisites of many energy big data-intensive applications.

(3) Data integration and sharing. Currently, there are still many barriers on the integration and sharing of energy big data from various sources. Different data definition, storage, and management standards and models are often adopted among different energy companies or organizations, and there are also some redundant data collection and storage [45]. On the other hand, a lack of accessible data hampers researchers that are working on big data and smart energy management. In recent years, there have been some initiatives on energy big data integration and sharing. Green Button data (www.greenbuttondata.org), launched in 2012, is an industry-led effort that responds to a White House call-to-action [152]: provide electricity customers with easy access to their energy usage data in a consumer-friendly and computer-friendly format via a "Green Button" on electric utilities' website. In addition, WikiEnergy (www.wiki-energy.org), founded in March 2014 by a consortium of university and NGO researchers, is a suite of online research tools that includes the world's largest research database of customer energy and water use, and the data are free available for university and NGO researchers conducting scientific and public interest research and curriculum development [153,154].

(4) Data processing and analysis. Traditional data analysis techniques in data mining, machine learning, statistical analysis, data management and data visualization may encounter some difficulties in dealing with the energy big data. Effective and efficient big data processing and analysis techniques are the premise and important support of the many smart energy management tasks. The modeling and simulation in big data driven smart energy management always involve huge amount of data and a lot of parameters in many complex operational processes at different granularities of spatial and temporal. With different modeling elements and parameter settings at multiple scales, multiple models established and simulation results obtained should also be properly interpreted to support the various decision makings.

(5) Security and privacy. The energy system is vulnerable to be attacked, and a lot of privacy information is involved in energy big data. Therefore, security and privacy is one of the most serious challenges in big data driven smart energy management [155–157]. The security mechanism of the IT infrastructure of smart energy systems need to be further improved. Also, protecting the privacy of sensitive customer data is a key issue in energy big data analytics [26]. In smart energy management, consumers should have the right to own their data, and their personal data such as household electricity usage should be protected and only used as the consumer allows [30]. Industry self-regulation, technical means, and strengthened legislation should all combine to enhance the security and privacy of data-intensive smart energy systems.

(6) Professionals of big data analytics and smart energy management. Big data driven smart energy management is a multidisciplinary field. All of the energy experts, data scientists, IT professionals, engineering specialists and management experts are essential for big data driven smart energy management. Big data analytics and smart energy management are relatively new fields, and professionals in these areas are still lacking. Courses and programs in management science, data science, energy science, computer science and social science should be developed to train comprehensive talents that qualified for the various jobs of big data driven smart energy management.

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