Big Data in Power Generation

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Abstract. The coal-fired power plant regularly produces enormous amounts of data from its sensors, control and monitoring systems. The Volume of this data will be increasing due to widely available smart meters, Wi-Fi devices and rapidly developing IT systems. Big data technology gives the opportunity to use such types and volumes of data and could be an adequate solution in the areas, which have been untouched by information technology yet. This paper describes the possibility to use big data technology to improve internal processes on the example of a coal-fired power plant. Review of applying new technologies is made from an internal point of view, drawing from the professional experience of the authors. We are taking a closer look into the power generation process and trying to find areas to develop insights, hopefully enabling us to create more value for the industry.

Keywords: Big data · Power industry · Coal power plant · Predictive analytics

1 Introduction

Power plants are places of the coexistence of various types of IT and OT (operational technology) systems. A long lifetime of assets, non-hyper-competitive environment and regulation restrictions cause a substantial delay in the adoption of new technologies, for example, big data and cloud computing. Indisputably, especially in modern times data is an asset which can be utilized to create value and improve businesses. In this specific environment of centralized financial, ERP systems and distributed operation technology systems it is impossible to ignore outstanding opportunities for the application of big data analytic techniques. Desirable effects can be achieved by decreasing the cost of data storage as well as through still developing analytic tools. Many current activities, for example: making reports, spreadsheet calculations, intuitive decisions can be boosted, automatized or transformed to provide better performance and efficiency. There are also risks and problems we have to tackle as far as implementing this new technology is concerned in the IT environment of power plants.

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2 Big Data Characterization

2.1 Big Data Definition

Big data refers to these types of data sets which processing causes a lot of problems or is simply impossible when traditional relational databases are employed. There are many definitions describing big data, and one of them says shortly "Big data is where parallel computing tools are needed to handle data". Big data not only refers to the size of data as the other features are well explained in, for example, the concept of three V's, which are: *volume*, *variety*, *velocity*. The occurrence of more than one of these features could mean we are dealing with big data. There are also two complementary features, which have come out recently and possess massive commercial use. These are *veracity* and *value* [20]. 5V's (Fig. 1) may be described as follows:

Volume: The quantity of generated and stored data. Most people define big data in tera or petabytes [22]. Machine-generated data is produced in much larger quantities than traditional relational data. For instance, a single jet engine can generate 10 TB of data in 30 min [7]. The number of variables and the frequency of data generation make this volume so big. For example, a steam boiler has about 20000 variables and produces 4–5 GB samples every month.

Variety: The type and nature of data. Big data draws from text, images, audio, video; and it completes missing pieces through data fusion [8]. Variety of sources use many different data types to analyze reasons for a variety of processes [13]. Data is categorized as: structured (e.g. relation-based databases), semi-structured (e.g., XML, JSON, RSS feed) and unstructured (e-mails, videos) [22].

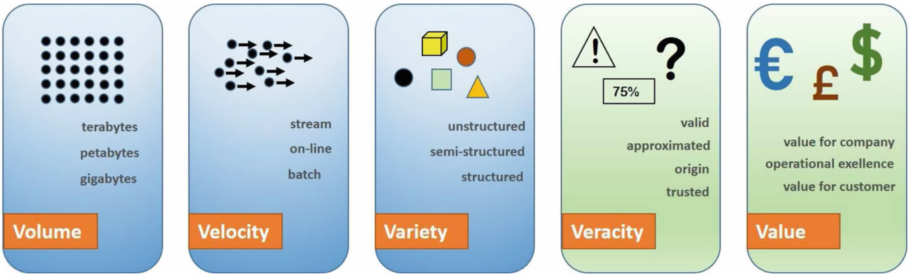

Fig. 1. The 5V model of Big data

Velocity: The frequency of data generation or the frequency of data delivery. For example, a continuous stream of data could be adjusted with a once-in-a-while event triggering data from a sensor. Although the majority of power system sensors are event-triggered, there are also sensors, for example, PMUs both at transmission and distribution level, which produce data streams at high rates [3].

Veracity: The quality of captured data. Means how much data is accurate (error free, raw or currently analyzed, integrated). Taking into consideration some information gathered from external sources, for instance, social media, we can observe that they cannot be fully trusted and its quality may be debatable.

Value: The worth derived from exploiting big data. Means internal value to the company. An important thing in DaaS (data as a service) and data monetization concepts [20].

2.2 Big Data Architecture and Components

Lambda Architecture. Described by Nathan Marz and James Warren lambda architecture is an elegant explanation of how big data works. It shows a way to achieve a scalable system with all requirements of big data system including low latency, high volume and error tolerance (listed in Table 1). Lambda architecture as it is shown in Fig. 2, contains three components: batch, speed, and serving layer [15].

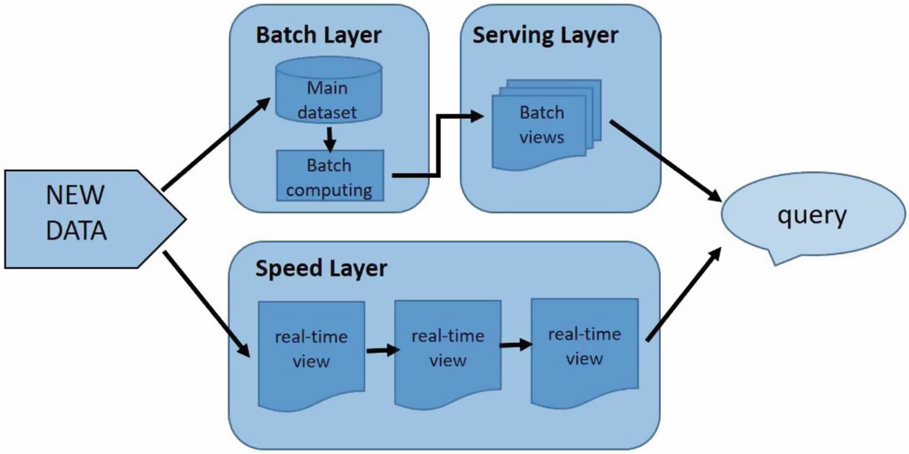

Fig. 2. Big data block schema

Batch Layer includes the main dataset called also "data lake". It is a repository of raw data in its native format. Data is stored in a distributed file system to provide greater scalability and capacity [14]. The repository recomputes all the data from the distributed file system to the batch views, which are accessible through fast queries. Recomputing is a slow process but the data is integral and accessible.

Table 1. Features of big data system

Low latency	Most applications require low delay regarding data access. It is not the most important thing concerning tasks similar to creating the annual report but in the case of real-time control or anomaly detection it is quite significant
Reliability and fault tolerance	Big data should be resistant to human errors and hardware breakdowns. High availability is provided by replication and distributed file system (e.g. Hadoop File System). Both failures and handmade errors can be fixed by renewed batch computing
Scalability	Ability to keep performance with fast grooving data storage and high load. Big data is vertically scalable by adding new clusters [18]
Extensibility	Big data is easy to develop. New functions and changes in the existing code do not need much effort in data migration and programming
Ad-hoc queries	Each and every query regarding the whole data set can be called at any time
Debug-ability	Big data allows to follow input and output (batch view) values

Speed Layer records incremental data from recent updates. It is a response to the requirement of velocity and it is a great complement to the batch layer. The speed layer stores data updates, taking place between consecutive recomputing processes, in the batch layer.

Serving Layer merges data from the Batch and the Speed layers and gives a real-time view of data.

2.3 Comparison with Traditional Data Analysis

In comparison with the standard data warehouse, there are some distinguished features characterizing big data.

From ETL to ELT. When we want to follow the traditional way of collecting and utilizing data, we must first design a database schema as well as collect and execute prepared operations. Taking that into consideration, we may observe a difference reflected in a simple fact that big data analysis is "closer" to data. It means that data is firstly collected in a simple form and then it is transformed and analyzed.

In-Database Analytics. Instead of copying data to other locations and processing it in a dedicated tool, it is possible now to do complex computing, machine learning operations or set operations within a database engine. This enables faster responses from databases, through which data could be fetched nearly in real time.

Distributed Computing. Data warehouses tend to be centralized systems. This kind of a system is vertically scaled, what means that to scale it up the system needs more RAM, a faster CPU or more CPUs. Distributed systems allow horizontal scaling by adding other machines. It makes big data solutions more cost-effective [17].

Unstructured Data. Decreasing the cost of data storage makes many types of unstructured data justified to store, even if its value remains unknown. By contrast, data warehouses operate only on relational databases and are designed for a specific purpose.

2.4 Electric Power Data

Following the big data definition, it is worth to check if we are really dealing with big data as defined by 5V's. Traditionally, operation technology systems work in distributed, firewalled environments to avoid noise and to provide adequate security.

The number of samples and control signals fulfill the criteria of velocity. Examples of some data charts from PGIM (Power Generation Information Manager) visualized in Grafana system are shown in Figs. 4, 5 and 6. However, designing big data in a way it could deal with island-like OT systems is a challenge. The growing number of devices with m2m (machine to machine) or Wi-Fi interfaces, could provide some additional information for analysis. Both volume and variety are characteristics of OPC servers (Open Platform Communications), which store historical data including process data, triggered events, and alarms.

The majority of data is either not logged, or it is overwritten very quickly. For example, in most protection relays and related sensors, the data collected is discarded shortly after internal use. If a pre-programmed event is not detected, then no data is automatically stored [3]. Accordingly, while many of the recently deployed or emerging power data measurement systems lie in the description of Big Data, the way that they are currently managed does not exactly match the spirit and purpose of Big Data. Once such hidden data is collected, managed, and analyzed, they will constitute the real Big Data in power systems [3].

There are also many external sources of data related to the energy sector, which can complete our big data set. For example, also shown in Fig. 3: weather conditions, GPS data, traffic information, social-media can support the real-time market or load management.

There is a large potential to use Big Data techniques in the analysis of power system data. Various data sources with smart analytics lead to intelligence while performing operational processes and tactical management.

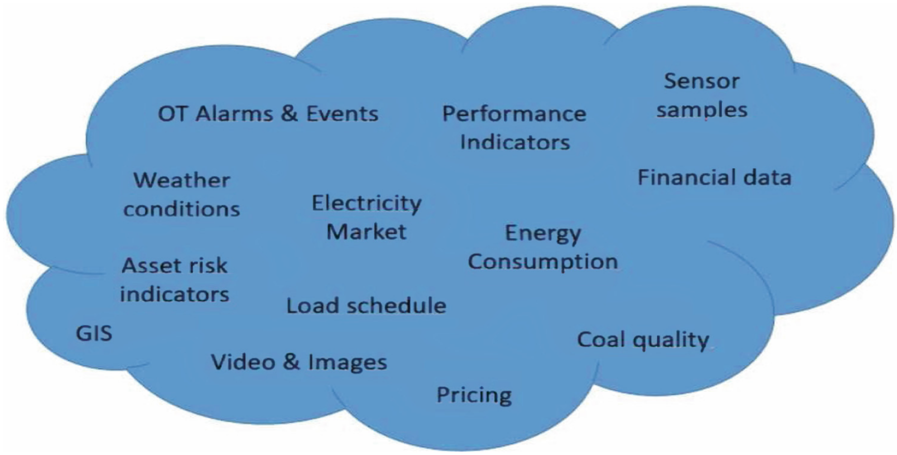

Fig. 3. Data types that could be used in Big Data analytic

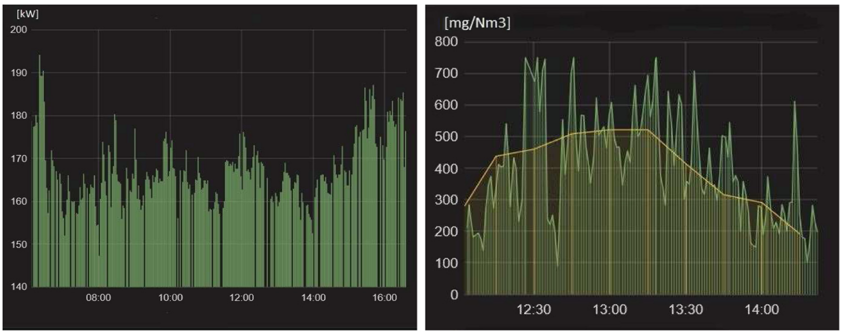

Fig. 4. Sample of process data: fan power and instant CO emission

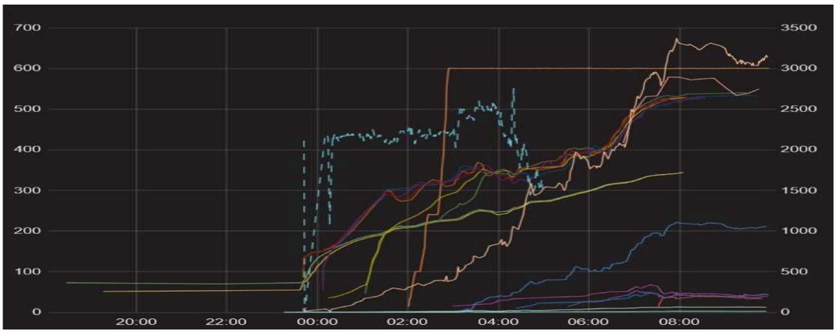

Fig. 5. Example graph of a power plant startup

Fig. 6. Turbine active power

3 Big Data Analytics Approach

Big data analytics means using advanced analytic techniques operating on big data [22]. Hardware solutions and platforms like Hadoop [1] and Spark [2] allow for massive data collection and storage. These can well feed analytic tools to enhance its results [22]. The tools cover techniques, like data mining, machine learning (classification, regression, clustering), artificial intelligence (cognitive simulation, expert systems, perception, pattern recognition) statistical analysis, natural language processing, and advanced data visualization [3,12,23,24]. Data analytic tools can analyze huge amounts of data at speed impossible for humans without technology. However, any analytic method is useless, if no action is taken [5] (Table 2).

Table 2. Example way from data to wisdom [5]

From			To
Data	-3	Celsius	Information
Information	$-3\,^\circ$C	At $3\,^\circ$C it's cold out	Knowledge
Knowledge	$-3\,^\circ$C	Need to dress warmly	Wisdom

Data analytics is categorized in some areas, depending on the purpose, scope, and techniques used:

Descriptive Analytics - interpretation of historical data. Helps to compare and understand data from the past, for example, annual reports comparison, assessment of generation unit capital project, key performance indicators as mean time between failures or month by month upkeep costs sets. It answers the question: "What happened?"

Diagnostic Analytics - a way to determine factors and causes of a particular event. Can be used for example in fraud detection or to understand failures from historical data. It answers the question: "Why did it happen?"

Predictive Analytics - this type of analytics uses statistics and modeling to determine future performance. It can help to predict financial trends, create reliability models or foresee asset management issues [5]. It is able to advise which feed pump should be running to give the best operational efficiency. It answers the question: "What can happen?"

Prescriptive Analytics - simulates possible paths and gives the best option according to predicted results. Can calculate the potential economic profits from steam-boiler renovation. It answers the question: "What should we do?"

Cognitive Analytics - uses advanced machine learning, cloud computing or artificial intelligence to give a real-time decision making aid. For example, can control in real time combustion process to achieve less nitrogen dioxide emissions.

4 Potential Benefits of Using Big Data in Power Generation

Big data and digitization process coming along with machine-generated and enterprise data can unlock new business opportunities. Not all of the areas are visible now, but many cases indicate some potentials to improve operational excellence and performance, as well as to reduce costs.

4.1 Fault Detection and Condition Monitoring

Early fault detection allows to improve system availability and to avoid additional downtime costs and regulatory fines. Data from control systems, diagnostic reports and videos can be analyzed in real time giving information on the current equipment condition; and therefore, potential failure occurrence. For example, based on data from SCADA (Supervisory Control And Data Acquisition) systems, it is possible to detect wind turbine failure by monitoring gearbox oil temperature, power output, and rotational speed [19]. Similarly, if used on other assets it could significantly reduce the operational and maintenance cost. Anomaly detection can also catch events not visible for control systems. For example, if a measurement tool has a predefined min-max range, the control system will not alarm us even though the reading is anomalous (as shown in Fig. 7).

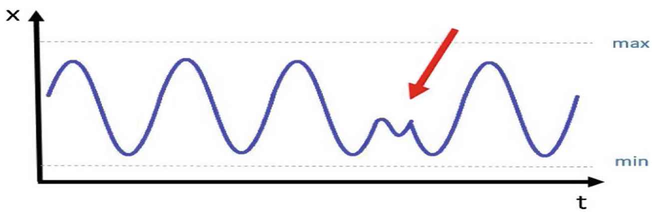

Fig. 7. Anomaly example

4.2 Operations-Planning Convergence

By integrating data from various sources and processes the possibility to convergence has been enhanced. The term operations-planning convergence refers to the ability of a utility enterprise to realize the future conditions of the power system with high probability and high accuracy. This is difficult to achieve without systematic data management and unified models [10]. Operational planning refers to preparation for weather, load, and generation conditions changes in the next minutes, hours, and days. There are various reasons for this convergence gap (e.g., diverse models, diverse data sources and data formats) and inefficient data management tools, which all can be overcome with the unified methods and systematic data management [3]. To simulate system behavior we can use analytic tools, e.g., predictive analysis, machine learning, stochastic analysis, etc. It is an interesting concept to create a digital copy of assets or the whole power plant.

Digital Twins is a digital power plant model allowing to simulate and visualize its performance and behavior in varied scenarios. Digital model would make it possible to determine how the real plant would respond to different conditions, supplies or even weather events [11].

4.3 Asset Management

Asset management is a systematic process of developing, operating, maintaining, upgrading, and disposing of assets cost-effectively. Big Data analytics may drive forward asset management maturity model to be integrated and automated.

Predictive Maintenance. Owing to equipment monitoring and fault detection it is possible to make a transition from preventive to predictive maintenance methods. Health-based maintenance of equipment provides better scheduled fixing plans minimizing planned and unplanned downtimes. It means:

– reducing unnecessary repairs of equipment in good condition,
– minimizing the probability of downtime by real-time health monitoring.

Predictive maintenance needs comprehensive information about the asset. Big data technology could fulfill this requirement in an inexpensive way of collecting data from existing systems.

Enhanced Planning. Complete assets data including current condition, repair costs, and risks, could be used for asset managers to diversify maintenance methods (including reactive or preventive maintenance where it is justified) [25]. Maintenance methods are described in more detail in Table 3. Implementing the right maintenance strategy can optimize costs and availability indicators. Critical equipment needs more predictive and preventive approach, while non-critical, cheap to repair devices sometimes could run to failure.

Table 3. Comparison of maintenance methods.

	Reactive	Preventive	Predictive
Description	"Fix on fail". Repair is done already when equipment is broken	"Time-based" maintenance. Equipment is serviced in regular time intervals based on the vendor's recommendations, MTBF (Mean time between failures) or other statistics	"Fix as required". Condition based maintenance. Service is done before failure is expected
Advantages	No service and inspection cost	Keeps equipment in high condition. Doesn't cause production halts	Less service costs. Better fault detection
Disadvantages	Less production availability. High overhead costs. Lost production costs	Requires planning. Vulnerable to random failures	High cost of monitoring and skills needed

Integrated Data. Another economical aspect refers to comparing asset performance before and after maintenance. Such analysis allows evaluating the profitability of service activities. Moreover, big data could also feed service crews with complete and accurate equipment information. The more adequate the information is, the faster the service task may be completed.

Procurement and Materials. Gaining knowledge about the current condition from big data could help in optimizing the procurement process, reducing its time and cost. It has also a positive influence on the inventory size and better supply planning.

4.4 Performance Optimization

Datasets coming from information technology systems and control systems used in the real-time analysis would constitute great feedback for operators controlling the production process. Understanding the power system as a black box, where parameters like steam pressure, steam temperature, and coal flow are inputs, and efficiency or generated power is an output, dramatically simplifies modeling process. Using data mining or machine learning techniques makes it possible to find the right way to optimize efficiency or emissions [6,16].

Another example is to control additive chemicals applied to coal. Owing to advanced analysis, it is possible to adjust the number of additives to current load or other parameters. Such operation provides emissions compliance and prevents overfeeding chemicals [21].

Renewable power generation units and fluctuating market dictate new flexibility requirements to coal-based power plants. It means not only working in highly efficient constant conditions, but also quickly adjusting the load to the current demand. It needs start-up characteristics improvement by reducing starting and stopping time and optimization of load gradient.

4.5 Data Analysis and Visualization

Big data tools and techniques enable visualization and exploration of large volumes of data. It includes also enhancing the reporting ability of existing business intelligence systems and discovering new things for the enterprise. Unlike standard dashboards or charts, big data needs more advanced tools to present multidimensional, high-volume data. Visualization involves graphical representation of data structures and techniques making data more transparent, like aggregation and hierarchization. Data analysis is supported by advanced techniques and tools, like predictive analytics, data mining (IBM SPSS Modeler, KNIME, WEKA), statistical analysis (Matlab, RStudio, Python), complex SQL, data visualization (MS Power BI, Qlikview, Tableau), artificial intelligence (Keras, Tensorflow), or natural language processing (Natural Language Toolkit, Apache OpenNLP). Some spreadsheet-based reports could be substituted and automated, also the decision-making process could evolve from intuitive to data-based.

4.6 Demand Response

Electrical energy cannot be stored, so production is adjusted to temporary energy consumption. Demand prediction includes also forecasting energy consumption and power generation from renewable sources (wind turbines, solar plants). Gathering data from smart meters, social media, analyzing consumption patterns enables us to predict the expected energy consumption [9]. Moreover, we can forecast weather impact on predicted power generation from renewable sources (wind, solar). Complete information gives chances to use existing power supplies in an optimized way and aids in load planning (containing also energy collecting and power-to-heat strategies). Accurate energy forecasting allows to avoid imbalance costs and gives the possibility to gain more from the real-time market.

5 Challenges in Big Data Adoption

5.1 Siloed Data

Effective big data analytics needs comprehensive data access. One of the challenges is to face silo mentality, meaning the situation in which some departments do not wish to share their data with others. There are many factors fueling silo mentality such as poor communication or internal competition. Departments have different goals, priorities, and responsibilities, so they often do not collaborate with each other to achieve common business goals. A more important problem is to save data confidentiality in compliance with legal and security regulations. Sensitive data like customers personal data, financial or trading data still need to be restricted from unwanted access.

5.2 Cybersecurity

Power plants and energy utilities represent critical infrastructure where data and IT systems would be principally protected. More significance of IT and data makes it more vulnerable to cyberattacks. Known threats like data stealing, system disabling can cause huge financial losses. Moreover, cyberattacks more often could be aimed for energy utilities. An example could be an attack on the Ukrainian power grid in 2015 [26] when hackers using malware software and taking control on SCADA systems were able to cause outages in 30 substations. Considering data as a valuable asset needs to provide relevant activities and protection to assure its confidentiality, integrity, and backup.

5.3 Skills

Adapting big data in organization forces requires acquiring new skills covering both infrastructure architecture and data analytics. Data architects, data scientists or data engineers are some of the new professions created by big data. Besides, to leverage big data impact organizations need many business users with analytical skills. To attract good employees, companies will need to develop a distinct culture, career paths, and recruiting strategy for data and analytics talents. However, there are many talented engineers with analytical skills in the electricity industry, so many of analysts could be trained, not hired.

5.4 Leadership and Organization

Transforming the decision-making process in organizations into one based on data and analytics, besides technical skills, requires applying leadership, organizational structures and communication to make the expected revenue. Due to survey results most significant challenges are ensuring senior management involvement in data analysis activities and designing an appropriate organizational structure to support analytics activities [4]. Organizational structures should provide good communication between the analytics team and departments. Greater impact on both cost and revenue was achieved with hybrid structure meaning central analytics organization that coordinates with employees who are embedded in individual business units [4]. An important thing is supporting and involving analytics by CEOs to align activities close to their vision and strategy.

5.5 Architecture and Technology

There are many commercial and open sources of software, architecture, tools offering big data analytics. Chosen solution should fit in the organization needs and provide integration with existing systems, training and support. It is a big challenge to gather data from sensors and devices working in real-time systems, which was not intended for analysis in system building process because of high cost or lack of analytic tools in past times.

6 Conclusion

This article presents the characteristics of big data issues in the context of the power generation industry. Technology progress gives the opportunity to handle and analyze new streams of data, it also enhances current business intelligence based on data warehousing and gives the possibility to explore values from data in a new way. Big data analytics can be capitalized in many specific internal processes in power generation industry improving operating efficiency. It also helps to make better and faster decisions, using modeling and prediction to optimize maintenance and reliability. It is inevitable for big data to face some challenges; for example, to gain expected revenue organizations must create structures, acquire skills and change culture and mentality.

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References

1. Apache Hadoop homepage. https://hadoop.apache.org. Accessed 27 Oct 2018
2. Apache Spark homepage. https://spark.apache.org/. Accessed 27 Oct 2018
3. Akhavan-Hejazi, H., Mohsenian-Rad, H.: Power systems big data analytics: an assessment of paradigm shift barriers and prospects. Energy Rep. **4**, 91–100 (2018). https://doi.org/10.1016/j.egyr.2017.11.002. http://www.sciencedirect.com/science/article/pii/S2352484717300616

4. Brad Brown, J.G.: The need to lead in data and analytics (2016). https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/the-need-to-lead-in-data-and-analytics. Accessed 22 Oct 2018
5. Canadian Electricity Association: Data to wisdom. Big data and analytics in the Canadian electricity industry (2017). https://electricity.ca/library/data-to-wisdom/. Accessed 20 Oct 2018
6. Chongwatpol, J., Phurithititanapong, T.: Applying analytics in the energy industry: a case study of heat rate and opacity prediction in a coal-fired power plant. Energy **75**, 463–473 (2014)
7. Dijcks, J.P.: Big data for the enterprise (2014). https://www.oracle.com/assets/wp-bigdatawithoracle-1453236.pdf. Accessed 20 Sept 2018
8. Hilbert, M.: Big data for development: a review of promises and challenges. Dev. Policy Rev. **34**(1), 135–174 (2016)
9. Huang, Z., Luo, H., Skoda, D., Zhu, T., Gu, Y.: E-Sketch: gathering large-scale energy consumption data based on consumption patterns. In: 2014 IEEE International Conference on Big Data (Big Data), pp. 656–665. IEEE (2014)
10. Kezunovic, M., Xie, L., Grijalva, S.: The role of big data in improving power system operation and protection, pp. 1–9, August 2013. https://doi.org/10.1109/IREP.2013.6629368
11. Lawson, S.: Cloud-based 'digital twins' could make power plants more efficient (2015). https://www.networkworld.com/article/2987521/cloud-based-digital-twins-could-make-power-plants-more-efficient.html. Accessed 15 Dec 2018
12. Leskovec, J., Rajaraman, A., Ullman, J.D.: Mining of Massive Datasets. Cambridge University Press, Cambridge (2014)
13. Małysiak-Mrozek, B., Lipińska, A., Mrozek, D.: Fuzzy join for flexible combining big data lakes in cyber-physical systems. IEEE Access **6**, 69545–69558 (2018). https://doi.org/10.1109/ACCESS.2018.2879829
14. Małysiak-Mrozek, B., Stabla, M., Mrozek, D.: Soft and declarative fishing of information in big data lake. IEEE Trans. Fuzzy Syst. **26**(5), 2732–2747 (2018). https://doi.org/10.1109/TFUZZ.2018.2812157
15. Marz, N., Warren, J.: Big Data: Principles and Best Practices of Scalable Realtime Data Systems, 1st edn. Manning Publications, Shelter Island (2018)
16. Mohamed, O., Al-Duri, B., Wang, J.: Predictive control strategy for a supercritical power plant and study of influences of coal mills control on its dynamic responses. In: 2012 UKACC International Conference on Control (CONTROL), pp. 918–923. IEEE (2012)
17. Mrozek, D., Daniłowicz, P., Małysiak-Mrozek, B.: HDInsight4PSi: boosting performance of 3D protein structure similarity searching with HDInsight clusters in Microsoft Azure cloud. Inf. Sci. **349–350**, 77–101 (2016)
18. Mrozek, D.: Scalable Big Data Analytics for Protein Bioinformatics. CB, vol. 28. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-98839-9
19. Qiu, Y., Chen, L., Feng, Y., Xu, Y.: An approach of quantifying gear fatigue life for wind turbine gearboxes using supervisory control and data acquisition data. Energies **10**(8), 1084 (2017)
20. Quitzau, A.: Transforming energy and utilities through big data and analytics (2014). https://www.slideshare.net/AndersQuitzauIbm/big-data-analyticsin-energy-utilities. Accessed 22 Oct 2018
21. Risse, M.: Using data analytics to improve operations and maintenance (2018). https://www.powermag.com/using-data-analytics-to-improve-operations-and-maintenance. Accessed 15 Sept 2018

22. Russom, P., et al.: Big data analytics. TDWI best practices report. Fourth Quart. **19**(4), 1–34 (2011)
23. Slavakis, K., Giannakis, G.B., Mateos, G.: Modeling and optimization for big data analytics: (statistical) learning tools for our era of data deluge. IEEE Signal Process. Mag. **31**(5), 18–31 (2014)
24. Tyagi, H., Kumar, R.: Optimization of a power plant by using data mining and its techniques. Int. J. Adv. Sci. Eng. Technol. **2**, 83–87 (2014)
25. Vesely, E.: Unsupervised machine learning: the path to industry 4.0 for the coal industry (2018). https://www.powermag.com/unsupervised-machine-learning-the-path-to-industry-4-0-for-the-coal-industry. Accessed 6 Oct 2018
26. Zetter, K.: The Ukrainian power grid was hacked again (2017). https://motherboard.vice.com/en_us/article/bmvkn4/ukrainian-power-station-hacking-december-2016-report. Accessed 20 Sept 2018