Applications of Artificial Intelligence in Smart Grids: Present and Future Research Domains

Conference Paper · August 2021

DOI: 10.1109/SEGE52446.2021.9534914

3 authors:

Farhad Khosrojerdi
Université du Québec en Outaouais

Stephane Gagnon
Université du Québec en Outaouais

Raul Valverde
Concordia University Montreal

Applications of Artificial Intelligence in Smart Grids: Present and Future Research Domains

Farhad Khosrojerdi, Stéphane Gagnon
Département d'informatique et d'ingénierie
Université du Québec en Outaouais
Gatineau, Canada
khof01@uqo.ca, stephane.gagnon@uqo.ca

Raul Valverde
John Molson School of Business
Concordia University
Montréal, Canada
raul.valverde@concordia.ca

***Abstract*—In the last decade, Artificial Intelligence (AI) have been applied overwhelmingly in various research domains in the context of smart grid. It has been one of the main streams of advanced technological approaches that the research community offered for developing smart grids. However, the broad scope of the subject matter launch complexity for scholars to identify effective research approaches. In this paper, we present a literature review about utilizing AI in the key elements of smart grids including grid-connected vehicles, data-driven components, and the power system network. This will result in highlighting technical challenges of the integration of electric vehicles to the grid and the power network operation as well. Moreover, we discuss the four key research areas in the context of AI and its applications in intelligent power grids. The proposed research fields aid PhD candidates to consider these areas as the promising domains for investigation.**

***Keywords*—AI research, EV, power network operation, research opportunities, scholars, vehicle-to-grid**

I. INTRODUCTION

In the past decade, Artificial Intelligence (AI) techniques and methodologies have been used by researchers studying the smart grid [1]. The combination of AI and the smart grid offers a broad range of study fields. The concept of the smart grid and its characteristics allocates academics from distinct scientific disciplines to experiment the applications of AI in order to provide practical solutions to increase efficiency in the power system. The infrastructure of the smart grid is encompassed with several components allowing scholars to study and practice different approaches. The contributions earned in this manner can aid early-career researchers to establish a secure path for their future. The characteristics of the smart grid are known as: I) power system stability and reliability, II) the integration of distributed energy resources (DERs) including solar power, wind farms, vehicles-to-grid (V2Gs), and III) economic and financial benefits concerning power generations and demand-side management [2, 3]. Furthermore, AI-based methods can be utilized in the development of various subsections of smart grids including smart cities [4] and microgrids [5]. Complying with these features will result in producing a large amount of multi-type data which are originated from various sources [6]. AI methodologies offer data analysis for these types of information, that means the optimization and prediction of the real-time power transmitted through the network [7]. There exist numerous research prospects related to intelligent power grids applying AI approaches. Searching for articles in academic databases in this subject will result in countless articles representing unlike academic perspectives and backgrounds. Thus, PhD candidates and scholars encounter an impossible task of choosing appropriate domains and subjects for their research.

In this paper, we highlight the recent study interests and future directions of AI-based approaches in the context of smart grid. In addition, we address new players in the research domain including IoT, sensor technologies, and cellular data that can be deemed for experiments. To accomplish these goals, we review the applications of AI in key components of the smart grid. This review aids scholars and academic students to explore prospect knowledge areas that correlate the future power networks to the AI-based technologies.

In the remainder of this paper, we overview the characteristics of the smart grid and the applications of AI. Key elements of smart grids including data-related components, V2Gs, and power system networks are described in section III. We discuss research domains in the four subsections including data-driven analysis, electric vehicles (EVs), power system operation, and business aspects in section IV. In the final section, the conclusion is made.

II. SMART GRIDS AND AIS

A. *Characteristics of the Smart Grid*

The concept of a traditional electric power network, including power generation, power transmission, and power distributions, have been changed into a different platform due to the applications of advanced technologies. The infrastructure of smart grids make it difficult to provide a single definition introducing the smart grid. There are several definitions for the smart grid describing its characteristics based on the technologies used and interests of stakeholders [8]. Canadian Electricity Association defines it as [3], "*the smart grid is a suite of information based applications made possible by increased automation of the electricity grid, as well as the underlying automation itself; this suite of technologies integrates the behavior and actions of all connected supplies and loads through dispersed communication capabilities to deliver sustainable, economic and secure power supplies.*" Unlike a centralized traditional power grid, DERs play an important role in modern power networks. In this manner, a connected load to the smart grid can act as an energy producer in different hours a day. Furthermore, there is a two-way communication of data between this node and the power web. Additional to wireline communications (copper, fiber) of conventional power networks, smart grids deploy a wide application of wireless technologies involving cellular network over satellite systems [9], cloud data, and data centers related to power entities. In fact, data play a significant part in the infrastructure of intelligent power grids. Fig. 1 depicts the key components of the smart grid consisting of power generations, power transmission lines, power distributions, power consumptions, and data-linked concepts.

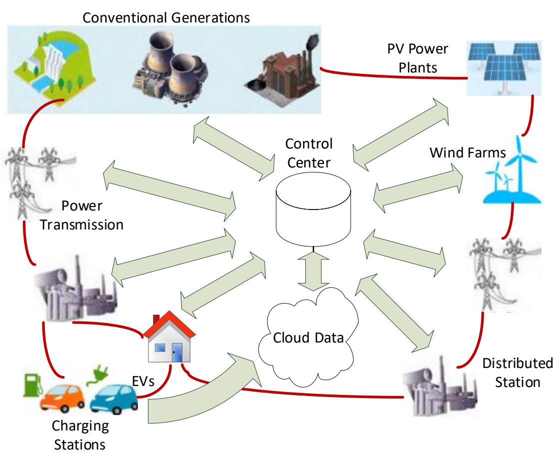

Fig. 1. The smart grid key components

Deploying information and communication technologies (ICTs) [10] allows the data to be transferred between the elements of the smart grid providing flexible, cos-efficient, but also reliable communications [9]. The two-way channel of communication allows stakeholders in utility companies to analyze the data and efficiently operate the grid.

B. *The Application of AI*

As a computer science approach, AI-based methods have been mostly applied in smart grids for energy and load predictions [10]. AI is categorized primarily based on their techniques, for instance expert systems (ESs), fuzzy logic (FL), artificial Neural Network (ANN), and generic algorithm (GA) [11]. However, machine learning, as a subdivision and a trend to achieve AI [6], is the algorithm that has been tied with it. In the smart grid, the information is transmitted between two nodes of the power network. Machine-learning methods prove useful in determining the performance of different levels of energy data aggregation [12]. Regardless of the common interests of using AI in smart grids [10], optimization methods and load prediction, there exist an enormous range of utilizing the methodology in different areas of power networks. Using AI techniques to render electric vehicles (EVs) is the focus of many literature reviews, for instance [13]. Herein, we present some examples applications of AI-based approaches instead of explaining AI classifications and techniques.

Bimal *et al.* describe a few applications of AI in modern smart grids and renewable energy systems including the automated design of modern wind generation system and its health monitoring, fault pattern identification and control of smart grid based on real-time simulator [11]. The use of intelligent devices has opened new possibilities for time series data analysis, for instance cloud-computing technologies [14]. Using machine-learning methods, the problem of forecasting demand in district heating and cooling systems at the individual consumer level is possible [15]. Using the average hourly voltage and load data from smart meters and distribution topology data from a GIS system with a linear programming (LP) optimization algorithm, more accurate topology information can be obtained towards detecting and locating electricity theft [16]. Similarly, the smart meter data can detect and correct topology errors in existing GIS records of the distribution system [17]. Likewise, consumption anomalies are detected using a supervised learning and statistical-based anomaly detection method [18]. In another article, an AI-based algorithm is applied to correct errors in the GIS representation of distribution network topology [19]. Leveraging voltage data from customer smart meters enables improving the efficiency of field operations leading to lower costs of field visits and improved customer experience [20]. Using a cloud computing approach, analysis of an EV owner's social media information and sensor data enables analysis of the accuracy of electricity demand prediction at the household level towards improving optimizing smart grid management [21]. The functionality of the smart grid allows us to detect utility damages caused by storms by a variety of technological sensors, geospatial databases, and on-line social media [22]. Data management based on a knowledge cube that is an intelligent and adaptive database supports the capture and tracking of dynamics data and is useful for analyzing the big variety of data in the smart grid [23]. Big Data and cloud computing technologies enabled obtaining real-time insights on phasor data from Phasor Measurement Units (PMU) introduced to improve the reliability and efficiency of power grids. The PMUs directly measure phase angles in real-time [24].

III. Key Elements of a Smart Grid

A. *Data-Related Sectors*

In transitioning an existing power grid into a smart grid, it is essential to integrate data from separated domains in real-time and provide seamless analytics without increasing the security risk. In this matter, there is a need for a computer center for gathering and analyzing real time data. Supervisory control and data acquisition (SCADA) computer systems are used for gathering and analyzing real time data [25]. AI and analytics-driven approaches efficiently convert massive SCADA datasets into valuable data to be used for data analytics [26]. Establishing a reasonable relationship between technical characteristics of distinctive sources in the smart grid [27] and being able to share this information where is needed to increase efficiency in the operation of the power grid. Improving power quality in the smart grid is achieved using the analyzed data. Processing various data and correcting atypical values [28], the performance improvements of the smart city architecture [29], automated fault and disturbance analysis [30] are a few examples of performance development associated with using applications of data-driven analytics. A data analytics-based system that enables cross-domain monitoring by obtaining raw and analyzing data from existing systems and seamlessly integrating this data helps smart grid integrated operating system [31]. A cloud-based software platform for data-driven analytics with scalable machine-learning models trained to predict demand for addressing supply-demand mismatch is useful toward achieving smart grids [32]. The application of model-driven software design (MDSD) for visualizing, specifying, analyzing, and documenting the distributed object-oriented data can assist in managing and optimizing the smart grid data [33].

B. V2Gs

Almost more than 60% of the world's oil productions are consumed by vehicles on roads [34]. Gas driven internal combustion engines are low efficiency systems that emit several harmful gases and establish an unsustainable and inefficient transportation system. In a study [35], it is reported that vehicles are responsible for 30% of the world total energy consumptions and 27% of total greenhouse gas emissions. In fact, the growing awareness of global warming [36], incentives and tariffs [37, 38], and fast growing automakers' interests [39] require a special attention to the V2Gs penetration. All types of battery driven vehicles in terms of hybrid electric vehicles (HEVs) or battery electric vehicles (BEVs) capable of trading power with the grid either at residential houses or commercial power stations are recognized as V2Gs [40]. The integration of V2Gs into the smart grid can be explored concerning power distribution network and the voltage and frequency of the power grid.

The impact of grid-connected vehicles on smart power grid operation and management would be more crucial when the penetration is significant [34]. The level of this type of load strongly depends on household demographics such as the income, the educational attainment and household ownership [41]. As a matter of fact, these household demographics define the level of V2Gs intermittency and unreliability that influence power grid management [42]. The excessive usage of the modern power electronics equipment jeopardizes the overall system performances [43]. Nonlinear nature of electronic devices, which is the characteristic of grid-connected vehicles with uncontrolled and unidirectional charging system, is the reason for: I) increased harmonic emissions and electromagnetic interference in low voltage (LV) networks, II) upgrading feeders and distribution transformers [44], and III) the transient heat transferred to the underground cables in a power distribution level [45, 46]. The harmonic problem imposes other challenges such as improper operation of protection and switchgear equipment and interference with power line carrier signals and other grid communications, as well as additional requirements for filtering, reactive power compensation and regulation of voltage profiles, imbalances and flicker [43]. Moreover, the uncontrolled battery charging/discharging affects the transformers to be overloaded and as a result their life expectancy can be reduced [44]. The excessive current and voltage rates of residential power lines set up a new maximum power imposed to the local transmission lines as well [47].

Enormous and uncontrolled V2Gs penetration fluctuates power system frequency because of an imbalance supply and demand [48]. In order to match the supplied power to the system load, it is necessary to wait until the generators recognize the change in system loading which results in a frequency deviation. Then, the generator's response will temporarily meet the load deviation resulting in a steady-state frequency error [38]. In addition, overloaded transformers and overheated underground cables cause voltage unstability and power losses [49, 50].

C. Power System Networks

Improving efficiencies in different sectors of the aging infrastructure of a power grid is the most important contribution of implementing smart grids. Using advanced technologies including AI have changed the way power grids are operated. In terms of electrical equipment, smart power grids are known as systems using advanced technologies for automation, employing DERs, and considering demand-side management [2]. They establish a reasonable relationship between technical characteristics of distinctive sources in a smart grid [27]. The information can be shared where needed to increase efficiency in the power grid operation. Improving power quality is achieved using the analyzed data. . data-driven approaches can be employed to compile the produced data. Processing various data and correcting atypical values [28], the performance improvements of the smart city architecture [29], automated fault and disturbance analysis [30] are a few examples of their applications. Therefore, applications of AI-based approaches for data analytics contain a broad range of estimations and predictions for power generation, load and energy consumption, power quality, monitoring and controlling the system, detection, and protection [4, 51, 52].

IV. Research Domains: A Discussion

Considering the previous sections, we propose the four subsequent portions as the major promising research domains in the context of smart grid. In addition to the followings, a scholar may envisage new perspectives concerning research in the smart grid. For instance, new forms of energy systems such as Energy Internet integrating energy, information, and business [53] can be classified into the future power networks. The most recent and future research areas can be classified into data-driven analysis, EVs, power network operation, and business aspects.

A. Data-Driven Analysis

Smart grids depend on the reliability, correctness, and security of the data that is circulated in the power system. Many research endeavours study different aspects of the data containing source, type, structure, proprietorship, and collected online or historically gathered. The significance of data quality is an important subject that requires more studies because of its role in the power system operation and management [54]. Data-driven approaches are broadly applied in data centers for energy pattern profile of specific use-cases, regional consumption mapping, retrofit strategies and guideline making [7]. In an article, the authors propose an ICT framework to assist local control centers in forecasting the energy and price of delivered power [55]. The identity-based signcryption (IBSC) security scheme presented in the study introduces a security-linked subject matter. In another study, the objective of fast processing of a sequence of time series utility data is accomplished by offering online data mining and analytics system (DMAS) [56]. Analyzing EVs data through social media, sensing data, and big data analysis to extract information is the research endeavours examined in [21]. Visualizing data concerning power consumption of ICT devices in real time can be considered as noteworthy field of research [57]. The main reason is the use of Semantic Web technologies to deal with various types of data originated from dispersed sources.

B. EVs

The integration of EVs and associated technical challenges, data analysis of the large-scale deployment, and developing smart scheduling have been recognized as the main areas of research for years [58]. Different charging technologies and existing standards are supplementary to the existing topics. In an article [59], the authors review several EV charging patents. Computation offloading techniques for improving performance for autonomous vehicle are reviewed in [60]. The presented tools, scenarios, subjects, strategies, and objectives in fact represent various directions for the future research studies. Driving prediction techniques and drivers' behaviors dealing with energy management strategies are comprehensively analyzed in [61]. The research approaches can be perceived in the same direction of the latter subject matters.

Additional to the well-known research opportunities new fields of research have been revealed due to the involvement of cloud-computing and different characteristics of data including social networks, cellular data, and satellite systems. Cross-sectional research interests among several components of the smart grid further create new realms for investigation. For example, Sankaran *et al.* address Range Anxiety and factors influencing EV Range, and EV Purchase Pain Points in Indian market [62]. The behavior and motivations of EV users and strategies for the simulating regional adoption [63] are examples of studies about socio-demographics and neighborhood characteristics providing novel research areas.

C. Power System Operation

Energy sustainability, standardization, and cybersecurity of power grids in addition to testing and verification of technical problems embody latest perspectives for research endeavors. There is a need for next-generation analytical tools to confront transit and dynamically unbalanced future power grids [27]. Using AI capabilities within utilities assists the system operators to apply big data analytics, IoT technologies, and smart monitoring for optimization and energy consumption [5]. The use of novel AI-based approaches can continuously be applied for analyzing smart electricity meters [64]. Sensors and data analytics provide tremendous exploration potential, for instance, to detect physical characteristics of power network equipment including vibration, ice built, hot spots, aging deterioration of assets, metal fatigue [65]. In an article [66], Caicedo *et al.* propose a prediction model for energy consumption using sensor data in lighting system. These cases depict research prospects in utilizing a variety of sensors in different components of the smart grid.

D. Business Aspects

The most important challenge in the smart grid is how to take advantage of the users' participation to reduce the cost of power [67]. From a business point of view, applications of AI methods affect organizational and operational factors associated with them. According to [68], AI-driven business analytics projects require extensive investment in complementary assets to enable business value creation. The demand-side management domain including field studies such as policymaking, regulatory interests [69], energy data management systems [70], electricity market [71], and business aspects of trading power [72] is and will persist the major scales for study.

V. Conclusion

The purpose of the paper is to identify research prospects for scholars interested in the applications of AI in the smart grid. We define the four components of data-driven analytics, EVs, power system operation, and business aspects as the most promising fields in the recent and future research opportunities. The amount of data produced by new key players in the infrastructure of the smart grid, PhD candidates and early-career scholars can deploy a variety of AI-based approaches in technologies used in today's power grids including autonomous vehicles, IoT, sensors, cellular data, etc. These research prospects draw a preliminary platform that can be used to inform researchers to find their path in the research domain. Providing a systematic literature review about the subject is considered as a future work of this paper. Furthermore, EVs and technologies used in the sector can be investigated elaborately in the next version.

References

[1] N. Bassiliades and G. Chalkiadakis, "Artificial Intelligence Techniques for the Smart Grid," *Advances in Building Energy Research*, vol. 12, no. 1, pp. 1-2, 2017.

[2] K. Sharma and L. M. Saini, "Performance analysis of smart metering for smart grid: An overview," *Renewable and Sustainable Energy Reviews*, vol. 49, pp. 720-735, 2015.

[3] M. E. El-hawary, "The smart grid-state-of-the-art and future trends," *Electric Power Components and Systems*, vol. 42, no. 3-4, pp. 239-250, 2014.

[4] K. T. Chui, M. D. Lytras, and A. Visvizi, "Energy Sustainability in Smart Cities: Artificial Intelligence, Smart Monitoring, and Optimization of Energy Consumption," *Energies*, vol. 11, no. 11, 2018.

[5] S. Khan, D. Paul, P. Momtahan, and M. Aloqaily, "Artificial Intelligence Framework for Smart City Microgrids: State of the art, Challenges and Opportunities," presented at the 2018 Third International Conference on Fog and Mobile Edge Computing (FMEC), Barcelona, Spain, 2018.

[6] J. Jiao, "Application and prospect of artificial intelligence in smart grid," presented at the 4th Int.

Workshop on renewable Energy and Development, 2020.

[7] Y. Wei *et al.*, "A review of data-driven approaches for prediction and classification of building energy consumption," *Renewable and Sustainable Energy Reviews,* vol. 82, pp. 1027-1047, 2018.

[8] G. Dileep, "A survey on smart grid technologies and applications," *Renewable Energy,* vol. 146, pp. 2589-2625, 2020.

[9] C. Wietfeld, A. A. Cardenas, H. H. Chen, P. Popovski, and V. W. S. Wong, "Smart Grids," *IEEE Wireless Communications*, pp. 8-9, 2017.

[10] Z. Wang and R. S. Srinivasan, "A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models," *Renewable and Sustainable Energy Reviews*, vol. 75, pp. 796-808, 2017.

[11] B. K. Bose, "Artificial Intelligence Techniques in Smart Grid and Renewable Energy Systems—Some Example Applications," *Proceedings of the IEEE,* vol. 105, no. 11, pp. 2262-2273, 2017.

[12] D. Ili´c, S. Karnouskos, and M. Wilhelm, "A Comparative Analysis of Smart Metering Data Aggregation Performance," *IEEE,* pp. 434-439, 2013.

[13] E. S. Rigas, S. D. Ramchurn, and N. Bassiliades, "Managing Electric Vehicles in the Smart Grid Using Artificial Intelligence: A Survey," *IEEE Transactions on Intelligent Transportation Systems,* vol. 16, no. 4, pp. 1619-1635, 2015.

[14] S. Prasad and S. Avinash, "Smart Meter Data Analytics Using OPENTSDB and HADOOP," presented at the IEEE ISGT Asia, 2013.

[15] S. Rongali, A. R. Choudhury, V. Chandan, and V. Arya, "A Context Vector Regression based Approach for Demand Forecasting in District Heating Networks," presented at the Innovative Smart Grid Technologies-Asia (ISGT ASIA), 2015.

[16] A. J. Berrisford, "A tale of two transformers: An algorithm for estimating distribution secondary electric parameters using smart meter data," presented at the Electrical and Computer Engineering (CCECE), 2013 26th Annual IEEE Canadian Conference, 2013.

[17] W. Luan, J. Peng, M. Maras, and J. Lo, "Distribution Network Topology Error Correction Using Smart Meter Data Analytics.," *IEEE,* p. 5, 2013.

[18] X. Liu, N. Iftikhar, P. S. Nielsen, and A. Heller, "Online Anomaly Energy Consumption Detection Using Lambda Architecture," presented at the International Conference on Big Data Analytics and Knowledge Discovery 2016.

[19] W. Luan, J. Peng, M. Maras, J. Lo, and B. Harapnuk, "Smart meter data analytics for distribution network connectivity verification," *IEEE Transactions on Smart Grid,* vol. 6, no. 4, pp. 1964–1971, 2015.

[20] R. Kota, V. Arya, and D. Bowden, "Inferring non-outage events using meter voltage data," presented at the Proceedings of the Seventh International Conference on Future Energy Systems Poster Sessions - e-Energy '16, 2016.

[21] Y. B. Qin, J. Housell, and I. Rodero, "Cloud-Based Data Analytics Framework for Autonomic Smart Grid Management," presented at the 2014 International Conference on Cloud and Autonomic Computing, 2014.

[22] L. Lin, A. Dagnino, D. Doran, and S. Gokhale, "Data Analytics for Power Utility Storm Planning," The Ohio Center of Excellence in Knowledge-Enabled Computing, Kno.e.sis Publications2014.

[23] X. Daqing and H. Yinghua, "An Adaptive Data Management Model for Smart Grid," presented at the 2015 8th International Conference on Intelligent Computation Technology and Automation (ICICTA), 2015.

[24] M. Edwards, A. Rambani, Y. Zhu, and M. Musavi, "Design of Hadoop-based Framework for Analytics of Large Synchrophasor Datasets," *Procedia Computer Science,* vol. 12, pp. 254-258, 2012.

[25] *SCADA Supervisory Control and Data Acquisition*, 978-1-936007-09-7, 2010.

[26] X. He, L. Chu, R. C. Qiu, Q. Ai, and Z. Ling, "A Novel Data-Driven Situation Awareness Approach for Future Grids—Using Large Random Matrices for Big Data Modeling," *IEEE Access,* vol. 6, pp. 13855-13865, 2018.

[27] D. P. Mandic, S. Kanna, Y. Xia, A. Moniri, A. Junyent-Ferre, and A. G. Constantinides, "A Data Analytics Perspective of Power Grid Analysis-Part 1: The Clarke and Related Transforms [Lecture Notes]," *IEEE Signal Processing Magazine,* vol. 36, no. 2, pp. 110-116, 2019.

[28] J. T. C. Neto;, P. H. M. d. Andrade;, J. M. Vilanueva;, and F. A. O. Santos, "Big Data Analytics of Smart Grids using Artificial Intelligence for the Outliers Correction at Demand Measurements," *IEEE*, p. 6, 2018.

[29] B. N. Silva, M. Khan, and K. Han, "Integration of Big Data analytics embedded smart city architecture with RESTful web of things for efficient service provision and energy management," *Future Generation Computer Systems*, 2017.

[30] S. Santoso and D. D. Sabin, "Power Quality Data Analytics: Tracking, Interpreting, and Predicting Performance," *IEEE*, p. 7, 2012.

[31] J.-H. Shin, S. Y. Han, and S.-H. Choi, "Cross-domain approach for operation support in smart grid," *IET Generation, Transmission & Distribution,* vol. 9, no. 11, pp. 1151-1159, 2015.

[32] Y. Simmhan *et al.*, "Cloud-Based Software Platform for Big Data Analytics in Smart Grids," *IEEE Computing in Science & Engineering*, p. 10, 2013.

[33] H. V. Haghi, M. A. Golkar, and H. Haeri, "Model-driven software design for smart grid data analytic,"

presented at the 22nd International Conference on Electricity Distribution Stockholm, 2013.
[34] C. Fernandes, P. Frías, and J. M. Latorre, "Impact of vehicle-to-grid on power system operation costs: The Spanish case study," *Applied Energy,* vol. 96, pp. 194-202, 2012.
[35] M. C. Falvo, R. Lamedica, R. Bartoni, and G. Maranzano, "Energy management in metro-transit systems: An innovative proposal toward an integrated and sustainable urban mobility system including plug-in electric vehicles," *Elec. Power Sys. Research,* vol. 81, no. 12, p. 12, 2011.
[36] C. Guille and G. Gross, "A conceptual framework for the vehicle-to-grid (V2G) implementation," *Energy Policy,* vol. 37, no. 11, pp. 4379-4390, 2009.
[37] A. M. A. Haidar, K. M. Muttaqi, and D. Sutanto, "Technical challenges for electric power industries due to grid-integrated electric vehicles in low voltage distributions: A review," *Energy Con. and Mng.,* vol. 86, pp. 689-700, 2014.
[38] S. K. Mullen, "Plug-in hybrid electric vehicles as a source of distributed frequency regulation," doctor of philosophy, University of Minnesota, ProQuest LLC, 3373412, 2009.
[39] K. BAO, "Battery charge and discharge control for energy management in EDV and utility integration," Master of Science, Electrical and Computer Engineering, The University of Alabama, 2012.
[40] D. P. Ghosh, R. J. Thomas, and S. B. Wicker, "A Privacy-Aware Design for the Vehicle-to-Grid Framework," pp. 2283-2291, 2013.
[41] B. Arellano, S. Sena, S. Abdollahy, O. Lavrova, S. Stratton1, and J. Hawkins1, "Analysis of electric vehicle impacts in New Mexico urban utility distribution infrastructure," *IEEE,* p. 6, 2013.
[42] A. Di Giorgio, F. Liberati, and S. Canale, "Electric vehicles charging control in a smart grid: A model predictive control approach," *Control Engineering Practice,* vol. 22, pp. 147-162, 2014.
[43] S. Müller, F. Möller, J. Meyer, A. J. Collin, and S. Z. Djokic, "Characterisation of harmonic interactions between electric vehicle battery chargers and PV inverters," *IEEE,* p. 5, 2014.
[44] J. L. C. Lagares, J. M. R. Fernández, M. B. Payán, and J. M. R. Santos, "Synergy of photovoltaic generators and electric vehicles in a low voltage distribution grid," in *The 2011 IEEE Trondheim Power Tech*, 2011.
[45] J. S. Marshall, P. D. Hines, J. D. Zhang, F. Minervini, and S. Rinjitham, "Modeling the impact of electric vehicle charging on heat transfer around underground cables," *Electric Power Systems Research,* vol. 97, pp. 76-83, 2013.
[46] D. Q. Oliveira, A. C. Zambroni de Souza, and L. F. N. Delboni, "Optimal plug-in hybrid electric vehicles recharge in distribution power systems," *Electric Power Systems Research,* vol. 98, pp. 77-85, 2013.
[47] W. Kempton and J. Tomić, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *Journal of Power Sources,* vol. 144, no. 1, pp. 268-279, 2005.
[48] Y. Ota, H. Taniguchi, J. Baba, and A. Yokoyama, "Implementation of autonomous distributed V2G to electric vehicle and DC charging system," *Electric Power Systems Research,* vol. 120, pp. 177-183, 2015.
[49] S. Weckx and J. Driesen, "Load balancing with EV chargers and PV inverters in unbalanced distribution grids," *IEEE Transactions on Sustainable Energy,* vol. 6, no. 2, pp. 635-643, 2015.
[50] J. P. Lopes, F. Soares, and P. R. Almeida, "Identifying management procedures to deal with connection of electric vehicles in the grid " *IEEE Power Tech.,*, pp. 1-8, 2009.
[51] M. Q. Raza and A. Khosravi, "A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings," *Renewable and Sustainable Energy Reviews,* vol. 50, pp. 1352-1372, 2015.
[52] I. S. Jha, S. Sen, and V. Agarwal, "Advanced Metering Infrastructure Analytics -A Case Study," *IEEE,* p. 6, 2014.
[53] K. Zhou, S. Yang, and Z. Shao, "Energy Internet: The business perspective," *Applied Energy,* vol. 178, pp. 212-222, 2016.
[54] W. Chen, K. Zhou, S. Yang, and C. Wu, "Data quality of electricity consumption data in a smart grid environment," *Renewable and Sustainable Energy Reviews,* vol. 75, pp. 98-105, 2017.
[55] F. Ye, Y. Qian, and R. Q. Hu, "An identity-based security scheme for a big data driven cloud computing framework in smart grid," *IEEE,* p. 6, 2015.
[56] Y.-J. Kim, F. Feather, and M. Thottan, "Implementaton Aspects of On-line Grid Data Analytics Systems," *IEEE,* p. 5, 2015.
[57] D. Aggarwal, E. Curry, and K. C. Davis, "Employing Virtual Power Analytics and Linked Data for Enterprise IT Energy Informatics," presented at the Proceedings of Semantic Web Information Management on Semantic Web Information Management - SWIM'14, 2014.
[58] S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou, and M. Nijim, "Machine Learning Approaches for EV Charging Behavior: A Review," *IEEE Access,* vol. 8, pp. 168980-168993, 2020.
[59] Z. Qu and S. Zhang, "References to literature from the business sector in patent documents: a case study of charging technologies for electric vehicles," *Scientometrics,* vol. 124, no. 2, pp. 867-886, 2020.
[60] A. B. De Souza *et al.*, "Computation Offloading for Vehicular Environments: A Survey," *IEEE Access,* vol. 8, pp. 198214-198243, 2020.

[61] Y. Zhou, A. Ravey, and M.-C. Péra, "A survey on driving prediction techniques for predictive energy management of plug-in hybrid electric vehicles," *Journal of Power Sources,* vol. 412, pp. 480-495, 2019.

[62] G. Sankaran, S. Venkatesan, and M. Prabhahar, "Range Anxiety on electric vehicles in India -Impact on customer and factors influencing range Anxiety," *Materials Today: Proceedings,* vol. 33, pp. 895-901, 2020.

[63] S. C. Mukherjee and L. Ryan, "Factors influencing early battery electric vehicle adoption in Ireland," *Renewable and Sustainable Energy Reviews,* vol. 118, 2020.

[64] D. Alahakoon and X. Yu, "Smart Electricity Meter Data Intelligence for Future Energy Systems: A Survey," *IEEE Transactions on Industrial Informatics,* vol. 12, no. 1, pp. 425-436, 2016.

[65] L. Russell, R. Goubran, and F. Kwamena, "Sensor Node to Improve Resiliency and Monitoring in Smart Grids: Taking the Lab to Field in Industry," presented at the 2015 International Conference on Distributed Computing in Sensor Systems, 2015.

[66] D. Caicedo and A. Pandharipande, "Sensor Data-Driven Lighting Energy Performance Prediction," *IEEE Sensors Journal,* vol. 16, no. 16, pp. 6397-6405, 2016.

[67] P. D. Diamantoulakis, V. M. Kapinas, and G. K. Karagiannidis, "Big Data Analytics for Dynamic Energy Management in Smart Grids," *Big Data Research,* vol. 2, no. 3, pp. 94-101, 2015.

[68] A. Yeow, C. Soh, and R. Hansen, "Aligning with new digital strategy: A dynamic capabil-ities approach," *Strategic Information Systems,* vol. 27, no. 1, pp. 43–58., 2018.

[69] B. Shen, G. Ghatikar, Z. Lei, J. Li, G. Wikler, and P. Martin, "The role of regulatory reforms, market changes, and technology development to make demand response a viable resource in meeting energy challenges," *Applied Energy,* vol. 130, pp. 814-823, 2014.

[70] S. Prasad and A. S. B, "Application of Polyglot Persistence to Enhance Performance of the Energy Data Management Systems," presented at the International Conference on Advances in Electronics, Computers and Communications (ICAECC), 2014.

[71] L. Gelazanskas and K. A. A. Gamage, "Demand side management in smart grid: A review and proposals for future direction," *Sustainable Cities and Society,* vol. 11, pp. 22-30, 2014.

[72] M. Goulden, B. Bedwell, S. Rennick-Egglestone, T. Rodden, and A. Spence, "Smart grids, smart users? The role of the user in demand side management," *Energy Research & Social Science,* vol. 2, pp. 21-29, 2014.