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A Systematic Survey on the Application of Artificial Intelligence (ai) Baseline Networks on Grid Computing Techniques - Challenges, Novelty and Prospects

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***Abstract:** A smart grid is a contemporary electrical system that supports two-way communication and utilizes the concept of demand response. To increase the smart grid's dependability and enhance the consistency, efficiency, and efficiency of the electrical supply, stability prediction is required. The true test for smart grid system designers and specialists will therefore be the increase of renewable energy. To integrate the electric utility infrastructure into the advanced communication era of today, both in terms of function and architecture, this program has made great strides toward modernizing and expanding it. The study reviews how a smart grid applied different deep learning techniques and how renewable energy can be integrated into a system where grid control is essential for energy management. The article discusses the idea of a smart grid and how reliable it is when renewable energy sources are present. Globally, a change in electric energy is needed to reduce greenhouse gas emissions, prevent global warming, reduce pollution, and boost energy security.*

***Keywords:** Deep learning, Electricity Consumption, Power Distribution Smart Grid, etc.*

I. INTRODUCTION

A developing idea in today's power infrastructure, the smart grid (SG) allows data and electricity to move back and forth between peers in electricity system networks (ESNs) and their clusters(Kumar et al., 2020; Nallapaneni et al., 2020). Thanks to SG's self-healing properties, peers can actively participate in ESN. Generally speaking, distributed energy resources (DER) will take the role of the fossil fuel-heavy conventional grid in the smart grid (Kumar et al., 2020).

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It does this by combining a variety of current and developing know-how, such as digital communications and information technologies, to manage a multitude of operations. By doing this, the SG will be able to handle various problems and "detect, react, and pro-act" to changes in usage, guaranteeing timely grid operations. However, the full potential of DER-based SG's "detect, react, and pro-act" capabilities can only be realized with the utilization of cutting-edge technologies such as Blockchain (BC), Internet of Things (IoT), and Artificial Intelligence (AI) (Kumar et al., 2020; Nallapaneni et al., 2020) [21]. Some of the AI approaches are neural networks, fuzzy logic, and knowledge-based systems. They have improved the control of SG based on DER. Numerous services, including data sensing, data storage, and safe, transparent, and traceable digital transactions between ESN peers and its clusters, have also been made possible by the Internet of Things and BC. Over the last ten years, these promising technologies have undergone a rapid technological evolution, and the applications of these technologies in ESN have grown significantly (Kumar et al., 2020) [12]. Massive data sets are used in artificial intelligence (AI) approaches to build intelligent machines that can perform tasks that need human intelligence (Omitaomu & Niu, 2021) [22]. AI includes machine learning (ML), however the terms are sometimes used synonymously. ML is only one method, though, of creating AI systems. Neural networks, robotics, expert systems (ES), fuzzy logic (FL), and natural language processing are other, more comprehensive approaches to creating AI systems (Foruzan et al., 2018; Omitaomu & Niu, 2021) [8]. In general, AI methods facilitate quick and precise decision-making. Artificial Intelligence (AI) in smart grid applications refers to the computer mimicking the cognitive functions of grid operators to attain self-healing capabilities. In other situations, AI might not be able to take the role of grid operators, though (Karimipour et al., 2019; Omitaomu & Niu, 2021) [11]. While AI systems have the potential to be more accurate, dependable, and thorough, the smart grid's application of AI technology still faces numerous obstacles (Foruzan et al., 2018; Zhang et al., 2019).In the smart grid, virtual and physical artificial intelligence (AI) systems are both feasible. Informatics is one aspect of virtual AI systems that can assist grid operators in carrying out their duties (Omitaomu & Niu, 2021).

Self-aware AI systems that can optimize and manage particular grid activities with or without human intervention are examples of physical AI systems.

Artificial narrow intelligence (ANI) and artificial general intelligence (AGI) are two further classifications for AI systems in the smart grid (Omitaomu & Niu, 2021). Artificial neural networks (ANIs) are AI systems designed to accomplish certain tasks within relevant requirements and limitations. An example of an ANI would be a system that uses various datasets to forecast load (Karimipour et al., 2019). AI systems created to learn and evolve on their own, much like humans, are referred to as AGI systems. In the future, creating AGI systems may aid in the realization of actual smart grid systems (Karimipour et al., 2019; Zhang et al., 2019) [35].

II. TECHNIQUES FOR ARTIFICIAL INTELLIGENCE IN SMART GRID

Due to the modern power system's rapid revolution, a larger electrical power network and the underlying communication system are encompassed by more distributed smart grid components, such as distributed energy resources, smart metering infrastructure, communication infrastructure, and electric vehicles (Omitaomu & Niu, 2021). These components are tightly integrated into the power system (Omitaomu & Niu, 2021). These components provide enormous volumes of data to enable a wide range of applications, including distributed energy management (Foruzan et al., 2018), cyberattack security (Karimipour et al., 2019), system state forecasting (Zhang et al., 2019), FD (Jiang et al., 2014) [10][36][37][38], and automation of the smart grid. Artificial intelligence (AI) techniques have garnered significant attention due to their capacity to process the massive amounts of data supplied by smart grid systems, a capability that conventional computational techniques lack. (Omitaomu & Niu, 2021)These artificial intelligence (AI) techniques were the focus of a lot of research efforts because they leverage large-scale data to further enhance smart grid performance. The following categories can be used to broadly group the AI methods used in smart grid systems (Omitaomu & Niu, 2021).

1. ES: A human loop technique expert utilized for certain issues. 2021's Smart Cities: 4,550
2. Supervised learning: An AI paradigm wherein the outputs of fresh inputs are predicted by studying the mapping of inputs and outputs.
3. Unsupervised learning: A machine learning lesson that uses unlabeled data to identify similarities and differences in the data.
4. Reinforcement learning: Its intelligent agent technique, which tries to optimize the idea of cumulative reward, sets it apart from supervised and unsupervised learning.
5. Ensemble model: To get around an algorithm's shortcomings and outperform it overall, combine the output of other AI systems.

III. SMART GRID (SG) AND AI

The distributed generating units (DGUs), energy storage systems, smart meters, smart home appliances, and other components are dispersed among several sites and serve as multiple ports of entry to the grid. For cybersecurity to endure mild calamities, the grid's physical security is just as important. SG is making every effort to guarantee the security of distributed components through the use of ICTs, utilizing an advanced control and communication system (Erol-Kantarci & Mouftah, 2013) [7]. McLaughlin et al. describe how critical information such as user authentication keys can be compromised and how malicious programs can be implanted into smart appliances to get access to any area of the grid (McLaughlin et al., 2010) [18]. Every system in the actual world has weaknesses and complexity, even the SG. The cyber-physical system (smart grid) can be made secure against cyberattacks by using AI techniques like ANN (Dogaru & Dumitrache, 2019b) [6]. Individual privacy, security, dependability in terms of performance and communication, and denial of service are important SG issues.

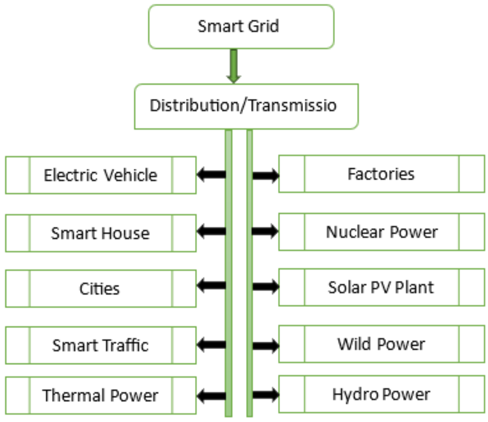

Fig. 1. Smart Grid Application in Different Technologies

Dogaru et al. employ a deep neural network to successfully pinpoint the assault location through a case study and lessen the effects of cyberattacks on the power system at various levels (Dogaru & Dumitrache, 2019a) [5]. Threats are any number of potential events, whether man-made or natural, that have the potential to affect how well a system operates (Mendel, 2017) [19]. If the necessary steps are not taken promptly, these threats could be dangerous. Electronics 2020, 9, 1030 16 of 25 breaches of customer data privacy and malevolent control of smart home equipment and devices are the most common threats (Goel et al., 2015) [9]. Because of the complexity of the system and the fact that sophisticated attacks are difficult to identify, it is impossible to include every potential hazard in the SG. Malicious threats are divided into three categories by Lu et al. according to their objectives: network availability, data integrity, and information privacy (Lu et al., 2010) [17]. In addition to its technical difficulties, the SG presents regulatory difficulties. Changes are anticipated at random because politicians and stakeholders compete for domination (Pearson, 2011) [23]. Designers of smart devices must guarantee compliance with SG standards (Ali & Choi, 2020) [2].

IV. NOVELTY IN AI BASELINE NETWORKS

AI technologies have been steadily advancing in a variety of VPP applications in recent years (Wang et al., 2020). The economic dispatch was approached by the studies by utilizing either a non-dominated sorting genetic algorithm or reinforcement learning (RL) (Lin et al., 2020) [16].

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There have also been other variations of intelligent energy management techniques based on RL and recurrent neural networks (RNN) (Kuzlu et al., 2020; Wan et al., 2018; Xu et al., 2020) [31]. For solar photovoltaic power prediction, the studies used explainable AI tools and artificial neural networks, whereas suggested an ensemble learning-based model for wind energy forecast. (Kuzlu et al., 2020; Wan et al., 2018; Xu et al., 2020) [28][29]. For solar photovoltaic power prediction, (Kuzlu et al., 2020) [13] the studies used explainable AI tools and artificial neural networks, whereas suggested an ensemble learning-based model for wind energy forecast (Lee et al., 2020) [14]. Based on a multilayer perceptron, demand-side energy management with a price forecast was proposed in (Zhang et al., 2020) [33]. (Najafi et al., 2019) [20] combined the EV bidding technique with the RL method. To estimate EV energy consumption, a unique centralized energy demand learning system was presented in (Saputra et al., 2019) [26]. Given that the majority of these works conduct their tests on a single, centralized server, the system will inevitably run into the following issues. The center's collection and learning of all the distributed data may first cause latency and cost constraints. Second, the centralized server plays a major role in maintaining the stability of the entire system. That is, all distributed nodes' requests will stop receiving responses once the server fails. Furthermore, it is simple for attackers to get or alter sensitive data once they have access to the centralized server. Conversely, in certain edge computing models, the processing is shifted from data centers to nearby devices (Da Silva et al., 2019; Saputra et al., 2019) [4]. However, the edge nodes' speed and storage capacity are still constrained (Wang et al., 2020).

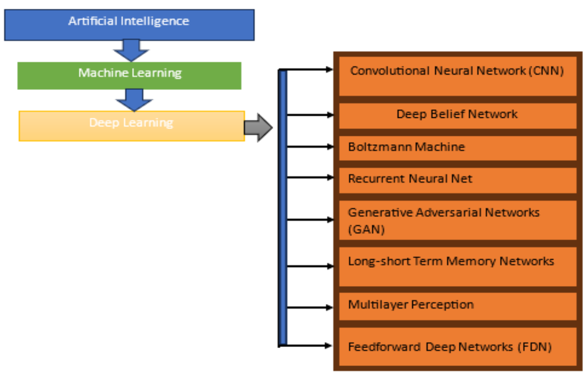

Figure 2. Techniques Associated with Deep learning

With the aid of strong computer technology and a growing volume of data, new AI algorithms have emerged, propelling AI into the so-called AI 2.0 stage (Zhang et al., 2018) [34]. AI is now able to address increasingly complicated issues. First applied to image processing, deep learning (DL), a subset of machine learning (ML), started with multilayer deep neural networks (DNNs). In recent years, deep learning (DL) techniques have advanced quickly. Several effective structures, such as deep belief networks (Wei et al., 2018) [30], convolution neural networks (CNNs) (Li et al., 2017) [15], recurrent neural networks (RNNs) (Abdel-Nasser & Mahmoud, 2019) [1]. AI has advanced into the so-called AI 2.0 stage because of the development of new algorithms and the availability of an increasing amount of data (Zhang et al., 2018). AI can now handle problems that are getting more and more complex. Multilayer deep neural networks (DNNs) were the foundation of deep learning (DL), a branch of machine learning (ML) when it came to image processing. Deep learning (DL) approaches have made rapid progress in the last few years. To address issues with smart grids, several efficient structures have been proposed, including generative adversarial networks (Abdel-Nasser & Mahmoud, 2019) [1].

Table 1. Merit and Demerits of Various Deep Learning Techniques

Techniques	Merits	Demerits
CNN	CNNs are strong, very competitive supervised deep learning techniques. Its scalability is increased with the addition of CNN features, and the length of its training when paired with ANN features is improved. Because CNNs may dynamically learn functionality from raw data on protection, they provide potential uses for IoT privacy.	CNNs have substantial computational expenses. As such, their implementation to provide onboard safety features on commodity-constrained platforms is difficult.
RNN	In many situations, RNNs perform better than their equivalents when dealing with serial data. Serial data can occasionally be seen in IoT security data. RNNs could therefore be useful for IoT security.	The primary drawback of RNNs is the issue of gradients blowing up or disappearing.
AE	Theoretically, AEs are important for functionality extraction. Without any prior knowledge of the data, AEs can be used to minimize dimensionality and train features for representation learning that are superior to the manually constructed features used in conventional ML.	A lot of computer power is used by AEs. Even while AEs are easily trained to capture the properties of training data, they will not be able to reflect the qualities if the training dataset is not representative of the test data set. Instead, they will merely confuse the learning process.
RBM	Multiple key features can be recovered using an unsupervised approach using a feedback mechanism on RBMs.	RBMs have significant computational expenses. Therefore, it is difficult to integrate them to enable onboard protection systems on IoT devices with limited resources.
DBN	DBNs are iteratively trained with unlabeled data to represent relevant features in non-supervised learning scenarios.	Because the lengthy initialization process generates a huge number of parameters, DBNs have substantial computing costs.
GAN	Similar to DBNs and RBMs, where the Markov network needs an arbitrary number of iterations, the only option to generate a sample with GAN is to go through the model.	GAN is erratic and requires planning. Learning how to use a GAN to create discrete data is a challenging undertaking.
EDEN	Combining different DL optimization algorithms can produce a wider range of models, improving the generalization and efficacy of the models.	The temporal complexity of the system can be greatly expanded.

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V. SMART GRID'S ADVANCES AND REFORM

Through the integration of modern metering infrastructure, control technologies, and communication technologies, the smart grid is making it possible to collect vast amounts of high-dimensional and multi-type data regarding the operations of the electric power grid (Omitaomu & Niu, 2021). The limits of traditional modeling, optimization, and control technologies in handling data have led to increasing recognition of the smart grid's potential for utilizing artificial intelligence (AI) techniques (Omitaomu & Niu, 2021). Technological progress has led to a transformation of power systems, bringing about institutional adjustments. The implementation of the smart grid necessitates cooperative processes involving technological, institutional, economic, and social issues (Veldman et al., 2010) [27]. Since their founding, the RTOs and ISOs have battled to create an effective market-based decision-making structure that keeps all parties informed. The main concept is to open up the electricity market to new ISOs and RTOs, allowing them to enter the market and increasing the accessibility of electricity for medium- and small-scale consumers(Ali & Choi, 2020). This would stimulate new market competition, which could result in breakthroughs and aid in the transition from centralized fossil fuel generation to green and clean energy as well. Energy-related problems are directly related to the consumer's lifestyle (Ali & Choi, 2020). (D'Oca et al., 2014; Sagebiel et al., 2014) [3] [25] use numerous technical breakthroughs, including SM, to highlight pro-sustainability attitudes and values of power transition and consumption. The energy industry has seen significant changes as a result of market liberalization with far-reaching technical and financial ramifications. Policymakers and industry participants are working hard to implement effective strategies to keep up with the improvements as a result of rising digitization. Xu et al. (Xu et al., 2019) [32] suggest an energy market design architecture that can integrate, coordinate, and manage intricate power sector systems thanks to AI technology and big data. To provide new services, SM and ICT gather vast amounts of consumer and utility service management data, which are then used in conjunction with advanced communication equipment. It will also assist in controlling market prices for electricity(Ali & Choi, 2020). Investors in the power sector are becoming more and more interested in the ongoing liberalization of the energy market, or the transition from monopoly to competitive market structures (Ali & Choi, 2020). The virtual power plant (VPP) idea gives distributed energy resources (DERs) visibility and access to all energy markets. Businesses can maximize their location to increase the potential for their revenue creation by utilizing VPP market knowledge (Saboori et al., 2011) [24].

VI. CONCLUSION

The study reviewed how a smart grid applied different deep-learning techniques and how renewable energy can be integrated into a system where grid control is essential for energy management. The article discusses the idea of a smart grid and how reliable it is when renewable energy sources are present. Globally, a change in electric energy is needed to reduce greenhouse gas emissions, prevent global warming, reduce pollution, and boost energy security.

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DECLARATION STATEMENT

The authors declare that none of the work reported in this study could have been influenced by any known competing financial interests or personal relationships. After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

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AUTHOR'S PROFILE

Fidelis Nfwan Gonten Msc., PhD in View (Computer Science, With a strong focus on prolific research (in AI) and global learner development, I am deeply committed to contributing to the research community and advancing the overall body of knowledge through a systematic approach. My expertise lies in building vision-based systems using advanced deep-learning algorithms. Over the past 13 years, I have been actively engaged in the teaching and learning process. Through extensive and rigorous studies, I am well-prepared and equipped to establish and uphold computing standards at a high level. I married my beautiful wife, Chongdah Fidelis Nfwan. I held from Lur Village, Kanke Local Government of Plateau state Nigeria.

Jimmy Nerat Jakawa, Bsc, and Msc. Computer Science from the University of Jos and Abubakar Tafawa Balewa University (ATBU), Bauchi, Nigeria respectively, and also a lecturer at Khal Kum University, Plateau State, Nigeria. Having more than seven (7) years in teaching and research. Major research areas include Machine Learning algorithms and deep learning with seven reputable Journals.

Mr. Datti Useni Msc and PhD. In view. I held from Gung village in Pankshin local government, Plateau State of Nigeria. I was born forty-seven (47) years old, married to Mrs. Datti Nanpan Plang, and blessed with three (3) kids. I reflect a varied personality including ambition and qualities of generosity and thoughtfulness. I am also a well-determined and vigorous individual, yet pleasantly calm. I encourage fighting for what you desire and believe in and doing it through God because nothing great comes easy and with God everything is possible.

Dakur Atiku Pandok is a dedicated and passionate individual. I hold a National Diploma in Computer Science from Plateau State Polytechnic Barkin Ladi, also hold a BSc. Computer science and MSc. Given Plateau State University Bokkos, Plateau state. I have a strong foundation in technology and a drive for continuous learning, I am committed to expanding my knowledge through intensive education pursuit. My academic prowess also augmented my desire to contribute positively to the global technological arena. I have a keen interest in management information systems (MIS), ICT, AI, and Data science.

Ponfa Canfa Maikano Bsc Ed. (Computer Science) currently working in the ICT Department, Plateau State Polytechnic Barkin Ladi, Plateau, Nigeria. I have a strong foundation in technology and a drive for continuous learning, I am committed to expanding knowledge through intensive education pursuit. My academic prowess also augmented my desire to contribute positively to the global technological arena. I have a keen interest in management information systems (MIS), ICT, AI and Data science.

Goteng Kuwunidi Job, Bsc and Msc. Computer Science from the University of Jos and Abubakar Tafawa Balewa University (ATBU), Bauchi, Nigeria respectively, and Post Graduate Diploma in Education at College of Education Gindiri, Plateau State, also a lecturer at Memorial College of Nursing Science, Jengre, Bassa LGA of Plateau State. I have more than seven (7) years in teaching and research. Major research areas include Machine Learning algorithms and deep learning with seven reputable Journals.