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Integrating Artificial Intelligence Internet of Things and 5G for Next-Generation Smartgrid: A Survey of Trends Challenges and Prospect

EBENEZER ESENOGHO, (Member, IEEE), KARIM DJOUANI, (Senior Member, IEEE), AND ANISH M. KURIEN, (Member, IEEE)

Department of Electrical Engineering, French South African Institute of Technology (F'SATI), Tshwane University of Technology, Pretoria West, Pretoria 0001, South Africa

Corresponding author: Ebenezer Esenogho (drebenic4real@gmail.com)

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ABSTRACT Smartgrid is a paradigm that was introduced into the conventional electricity network to enhance the way generation, transmission, and distribution networks interrelate. It involves the use of Information and Communication Technology (ICT) and other solution in fault and intrusion detection, mere monitoring of energy generation, transmission, and distribution. However, on one hand, the actual and earlier smartgrid, do not integrate more advanced features such as automatic decision making, security, scalability, self-healing and awareness, real-time monitoring, cross-layer compatibility, etc. On the other hand, the emergence of the digitalization of the communication infrastructure to support the economic sector which among them are energy generation and distribution grid with Artificial Intelligence (AI) and large-scale Machine to Machine (M2M) communication. With the future Massive Internet of Things (MIoT) as one of the pillars of 5G/6G network factory, it is the enabler to support the next generation smart grid by providing the needed platform that integrates, in addition to the communication infrastructure, the AI and IoT support, providing a multitenant system. This paper aim at presenting a comprehensive review of next smart grid research trends and technological background, discuss a futuristic next-generation smart grid driven by artificial intelligence (AI) and leverage by IoT and 5G. In addition, it discusses the challenges of next-generation smart-grids as it relate to the integration of AI, IoT and 5G for better smart grid architecture. Also, proffers possible solutions to some of the challenges and standards to support this novel trend. A corresponding future work will dwell on the implementation of the discussed integration of AI, IoT and 5G for next-generation smart grid, using Matlab, NS2/NS3, Open-daylight and Mininet as soft tools and compare with related literature.

INDEX TERMS 5G, artificial intelligence (AI), Internet of Things (IoT), next-generation smartgrid, network slicing.

I. INTRODUCTION

Digitilization has transformed our current world through the introduction of disruptive technologies such as IoT, artificial intelligence, and 5G just to mention a few [1]–[3]. The application of these technologies into the ecosystem has given birth to a more robust intelligent models with unequal capacity and functionalities. To this end, it finds applications in smart cities, smart factories, smartgrid, etc. Although, these applications require higher data rates and huge bandwidth but delivers increased capacity, low latency, and high spectral efficiency. On one hand, the IoT centric concepts like smart wireless sensor network (SWSN), vehicle to vehicle (V2V), nano-communications, machine to machine (M2M), smart environment, e-health care, have an ubiquitous presence currently. Moreover, IoT has transformed the our ecosystem by providing seamless connectivity between heterogeneous sensor networks. For smartgrid, the ultimate aim of IoT is to

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introduce the plug and play strategy by providing the end-user, ease of operation, remote access control configurability, and scalability [3], [4].

Since digitization prompted the workforce to migrate from the old-fashioned and manual way to automation and intelligence, AI/ML on the other hand, attempt to demonstrate the natural intelligence of humans for efficiency. This intelligence is needed in the design of the next-generation smart grid which involves a lot of accurate decision making based parameters, and the ability to cognitively adjust to past and present environmental changes within the grid [4], [5]. For instance, the next-generation smart grid should be able to, through its machine learning algorithm, learn the patterns of activities within grid such as real-time monitoring and detection of faults with the corresponding solution without human interference. This will in turn make humans focus more on what is called the *"second skill"*. The second skill implies those abilities that an AI machine may not be able to carry out. For instance, autonomously identifying problems within the grid infrastructure and developing algorithms to solve them. In addition, for every system to go smart, it means it is connectable to the internet. This implies that securing the grid is paramount hence AI/ML are necessary for the securing of the smart grid especially hidden (masking) patterns of a cyber-attack [6].

It is generally misunderstood that cyber-threats merely emanates from cyber-attacker or hacktivist with a mischievous intention. Personnel within the grid infrastructure can sabotage the security protocol/process hence present a risk since they have legitimate access to several components of the grid and are aware of sensitive information and their location. For instance, passwords, cryptologic keys and others defence tools stored in grid database could be compromised to coordinate an attack [7]. Nevertheless, very few security breaches are mischievous, several of which emanates from unintended misalignment, to adhere to specific guideline and procedures. Power grid vulnerability could be in the form of system-level threats, theft attempts to electric service, and compromise of data privacy. Furthermore, every proposed model has building blocks that make up the system and are connected by an enabler [8]. Thus, in this paper, the enabler is the fifth generation (5G) network since it supports the integration of AI and IoT (Artificial Intelligence of Things or AIoT) for the enhancement of the current smartgrid which is the focus of this review.

The main attribute of 5G technology stands with the concept of hardware-agnostic aspect, virtualization at a different level from access level, transport and core network to the orchestration at a different level, making use of different cutting edge technologies such as the SDN and NFV on the cloud-based platform. Therefore next-generation smart grid is not only a new paradigm, built to respond to the growing demand on the network capacities but rather a network slice within the 5G/6G networks thus, makes it different from all other generations of the cellular network. In plain context, the idea of a next-generation smart grid integrates several technologies, customer-driven solutions and speaks to various strategies and business models with the digitalization of infrastructures toward the delivery of electricity network performance, control and optimize systematically with full interoperability [7]. The highlights and the problem statements of this work is predicated on the premises of enhancing or upgrading the current smartgrid to a more robust next generation smart grid (future grid) through the integration of disruptive technologies such as artificial intelligence, Internet of Things and 5G which are prime mover of the fourth industrial revolution. To be specific, since grid components (feeders, substations, sensors, control center etc.) can be interconnected via IoT then, it possible to infuse AI into those components to make them truly intelligent. Secondly, since current mobile network are facing spectrum crunch and scarcity, then, 5G network slicing (multi-tenanting of service) will be handy to solve that issue.

Without ambiguity, several literatures [9]–[10] have made good attempt to integrate other disruptive technologies like block chain and AI to enable 5G IoT. Infact, the relationship between our solution and past literature like [9] and [10] is that both try to enhance the functionalities and performance and the contemporary challenge (security, interoperability, privacy, programmability scalability) of the current smart grid however, this review work is specific in the application of these technologies on smart grid. Blockchain could be very important when issue of security and privacy is the cardinal point of the work but in this regards the 5G SDN with multi-controller is considered. Therefore, the major contributions of this paper are as follows:

a) To provide a holistic review of the smartgrid concept and the future trend.
b) Discuss the integration of AI, IoT and 5G for the next generation smartgrid.
c) Discuss a road map on how the next generation smart grid will look like in terms of architecture, design, compliance, and compatibility.
d) Bring to the know the benefits of integrating disruptive technologies like AI, IoT and 5G for the next generation smartgrid.
e) Give a detailed examination and exposition of 5G network slicing as it relates to the next-generation smart grid.
f) Discuss the possible challenges of this integration and proffer possible solutions.

The rest of the paper is organized as follows: Evolution from the classical grid to the next generation smartgrid is captured in Section II. Section III discussed AI/ML for next-generation smart grid. Section IV dwells on the IoT in the smart grid, Section V, looked at 5G as an enabler for next-generation smartgrid while section VI presents the architecture for the next generation smartgrid. Section VII discussed the challenges and solutions of the next generation smartgrid. Section VIII present the prospect of AI on next-generation smartgrid. The limitation of the survey is found in Section IX and finally, the paper is concluded in section X.

II. EVOLUTION FROM CLASSICAL GRID TO NEXT-GENERATION SMART GRID

Electricity grid design has evolved over the decades. The section presents a chronological evolution of existing to the present smartgrid.

A. CLASSICAL GRID

The power utility grid has come a long way from the classical configuration which is hardwired to semi-automatic network as shown in figure. 1 and 2. Currently, grid design has scaled up to a full smart network with a future projection of a software-driven grid that integrates AI, IoT and is powered by 5G which this paper is discussing. The present power grid is a response to rapid industrialization and infrastructural growth in several parts of the globe in the last decades. However, power grid exists in different topographies, the power-utility corporations have largely implemented similar technologies. The growth of the electric power system, though, has been affected by fiscal, partisan, and terrestrial issues that are exclusive to each utility company [8]. Despite such variances, the architectural component of the current grid has remained unchanged. from inception, the energy industry has functioned with clear distinctions between its generation, transmission, and distribution subsystems and consequently has formed diverse planes of automation, progression, and transformation in all phases [11]. From Figure 1 and 2 the existing power grid is an absolute hierarchical architecture where power plants located at the uppermost part of the value chain ensures power distribution to customers at the bottommost of the value chain. The scheme is fundamentally a simplex-pipeline kind of interaction where the source been the central generation has no real-time information about the facility constraints of the transmission and distribution respectively.

The grid is hence completely hard-wired (mechanically operated) to withstand maximum estimated peak demand across its combined load. Subsequently, since the peak demand is an occasional occurrence, the system is inherently ineffective. Furthermore, an unprecedented increase in the demand for electric power, in addition to the inadequate financial support in the power grid infrastructure, has mitigated system stability. With the tolerant limit reached, any unanticipated upsurge in demand or irregularities across the distribution network is it industrialization or urbanization will result in component collapse could initiation catastrophic shutdowns. To enable auto-diagnosis and maintenance of the expensive upstream assets, the power utility corporations have proposed at several levels, a central controller. An example of such is the commonly deployed supervisory control and data acquisition system. This is a technique that intends to supervise and self-control field devices (sensors or smart agents) at your remote sites.

B. SMART GRID

Smart electricity/power grid, also known as; intelligent grid, intelligent, advanced grid or inter grid, is an improvement of the twentieth-century energy grid. The conventional energy grids as shown in figures 1 and 2 are mostly used to convey electricity from a central generator to a large number of users, or customers/consumers.

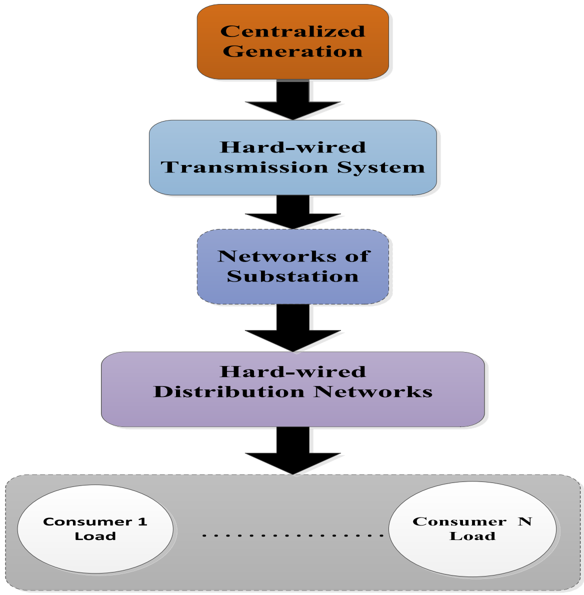

FIGURE 1. The classical grid block diagram [7], [8], [12].

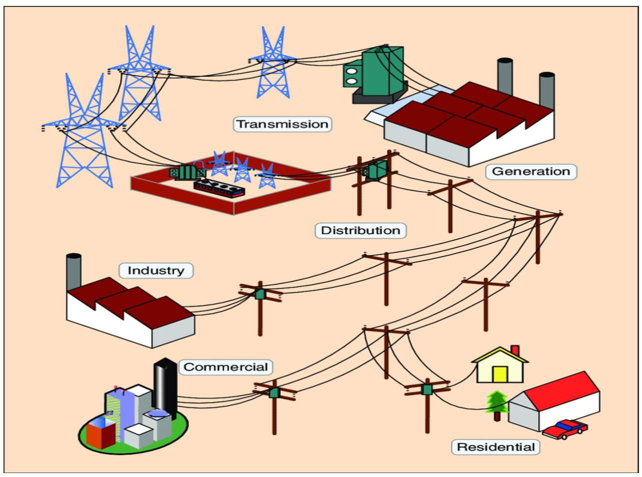

FIGURE 2. A classical grid [12].

To be precise, The idea of a smart grid implies the switching from the conventional power grid that is an electromechanically controlled network to a more digitally system that is automated with distributed control as illustrated in figure 3. figure 3 also shows the metering part of the distribution network which has been the focus of most latest infrastructure investment. The previous plans in this sector witnessed the initiation of automated meter reading (AMR) schemes in the distribution network. AMR allows the utility companies to read the utilization data, warnings/alarms, and status from customers premises equipment remotely [13], [14]. The report in [15], indicate that the smart grid comprises

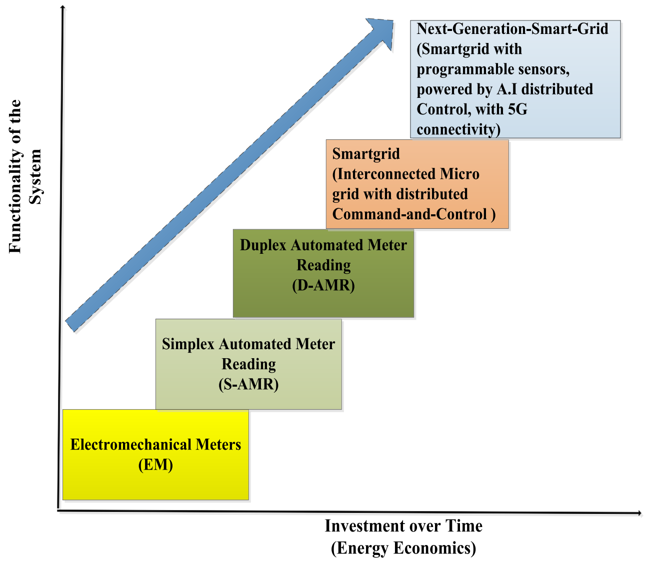

FIGURE 3. The evolution from the traditional grid to nextgeneration smart grid [12].

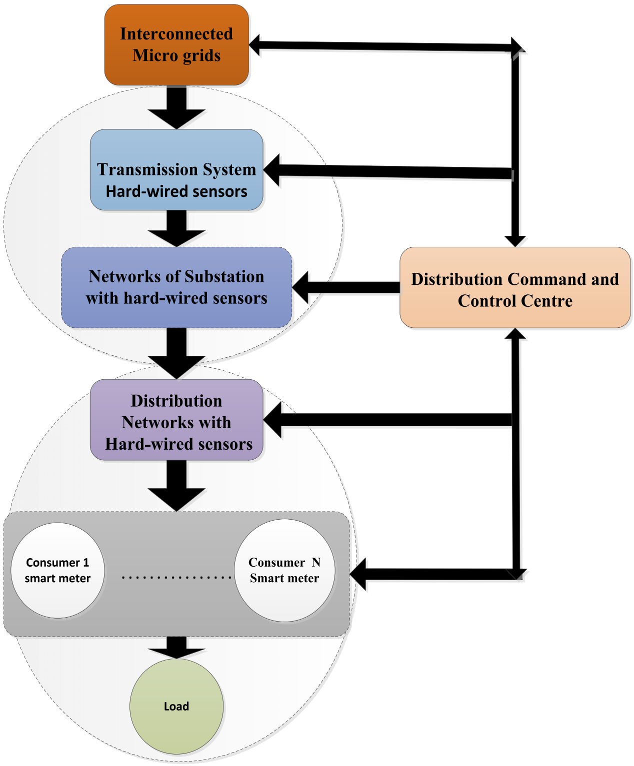

FIGURE 4. Functional diagram of the smart grid.

FIGURE 5. Smart grid architecture overview [15].

control technologies, sensor field devices that function to coordinate multiple electrical activities, information/network management, electronic-based sensing and communication technologies. These smart grid technologies and capabilities have altered the traditional grid architecture and operation challenges in three key parts, mostly in the capacity to; firstly, monitor and measure processes, transmit information back to management and control centres through a feedback mechanism and frequently respond automatically to fine-tune the response as shown in figure 4 and 5. Secondly, share information between field devices and systems. Lastly, process, evaluate, and support operators gain access to and utilize the information which comes from the automated technologies all through the power grid. Several of the associated problem areas in smart grids are; load predicting and balancing grid reliability evaluation, fault detection and monitoring, and grid security from cyber attacks. These crucial elements are permitting substantial volumes of high dimensional multi-class data to be collated regarding the electric grid activities and operations. Nevertheless, there are several drawbacks associate with the conventional optimization, modeling, and control techniques. Therefore, the incorporation of artificial intelligence (AI) and machine learning techniques into the smart grid turn out to be more obvious [16].

Considering the number of challenges that the current smart grid has presented or faced over the few years of its existence, couple with ICT at the edge, issues such as absolute compatibility of equipment or devices, interfacing with the cloud seamlessly, data security and privacy, internet protocol compatible devices and applications, rise in energy consumption due to population explosion and industrialization, the introduction of programmable/intelligent sensors, deployment AI/ML for apt control with precision like real-time monitoring, decision and analysis just to mention a few. There is a need to look into the future for the "Next Generation Smart Grid (NGSG)" that will be software-driven and powered by the next generation network like 5G.

The next-generation smart grid also called the future grid was not only born out of advancing science and engineering or solving the challenges of the current smart grid but investor and investment push which in turn solve problems [11]. The beauty of NGSG network architecture is that it incorporates some advancements made in the course of the current smart grid. The trajectory in figure 6 suggests the advance meter reading (AMR) scheme appears to be at first attractive in

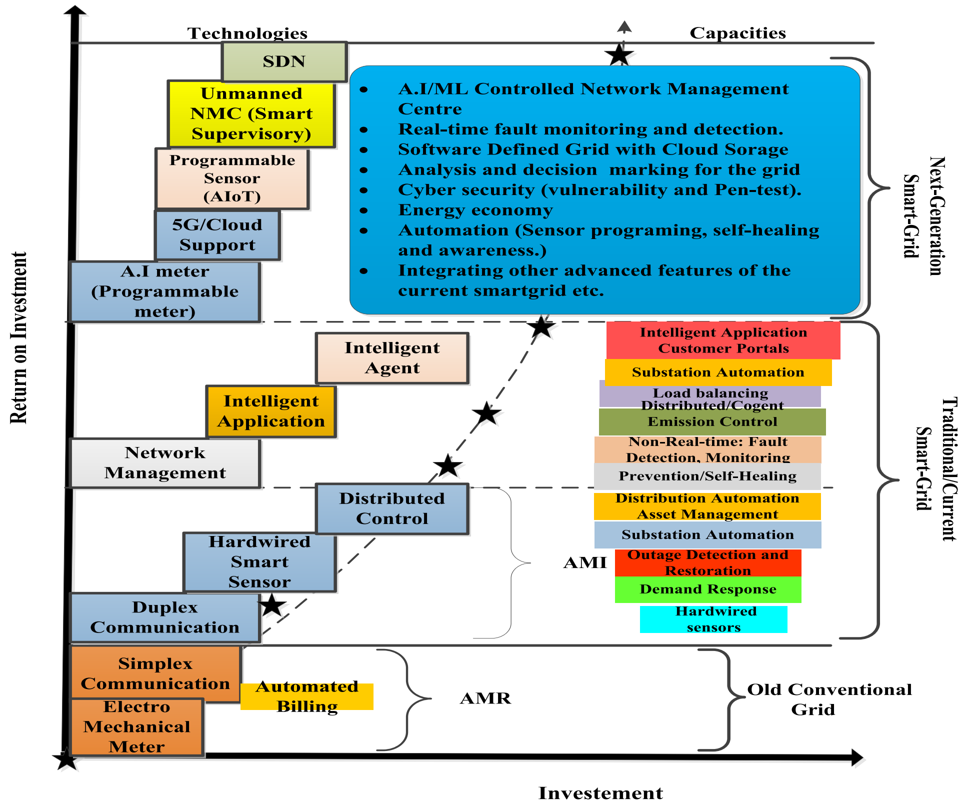

FIGURE 6. Trajectory from the old fashioned grid to the proposed next generation smart grid.

terms of functionality and investment. However, power utility companies have realized that AMR does not address some of the major challenges that are needed to solve the demand side of management [15], [16]. As a result of its simplex communication exchange architecture, the AMR ability is limited to meter reading with any form of data logging. This limitation does not allow the power utility corporations to take corrective decisions based on the data collected from the meters. This implies that the AMR systems hinder the possible migration to the smart grid, where ubiquitous self-control and management at all levels from generation to distribution is a fundamental requirement thus, the AMR technology did not stand the test of time. Instead of investing more in AMR, power utilities around the globe shifted in the direction of advanced metering infrastructure (AMI) which of course is the first phase of the smart grid as shown in figure 6. AMI being perceived as smartgrid phase I (semi-smartgrid), is unique in the sense that it has a distributed control, with mechanical sensors which help for sensing/measuring physical quantities and sending them through its full-duplex communication system to the meter, coupled with the capability to adjust consumers' service-level constraints. Through AMI technology, power utility establishment can meet their basic targets for capacity management, return on investment as well as revenue protection [13]. In AMI, utility companies not only can obtain instantaneous information about specific and accumulated demand but however they can also enforce specific limits on energy consumption or utilization, as well as introduced a variety of revenue generation models to manage their costs since it is a profit-driven venture [6], [7]. The advent of AMI signaled a collaborative push by investors around the world to further enhance the ever-changing ideas about the smart grid. Furthermore, one of the key metrics which the power utility corporations employ in deciding amongst AMI technologies to adopt is if they will be onward compatible with the proposed next-generation smart grid technologies and topologies which this paper will de be dwelling on. The second phase of the smart grid which will be referred to as full-scale smartgrid (smartgrid-2) will be more automated than phase I which deploy the AMI technologies. In this phase, network management is automated, sensors are not just hard-wired but smart (smart-sensor), the application is intelligent (customer portal) and the field devices are supported by the intelligent agent which helps for precision, monitoring and reporting. In addition, transmission (substation) and distribution are fully automated with reliable outage and detection response. The current smartgrid also support load balancing if it notice uneven load on the generation line [17].

As earlier mentioned, the proposed NGSG will be software-driven or software-defined. This implies that unlike the current smart grid, whose sensors are simply smart, the sensors deployed in the NGSG will be programmable. In other words, AI is incorporated into the sensors since they

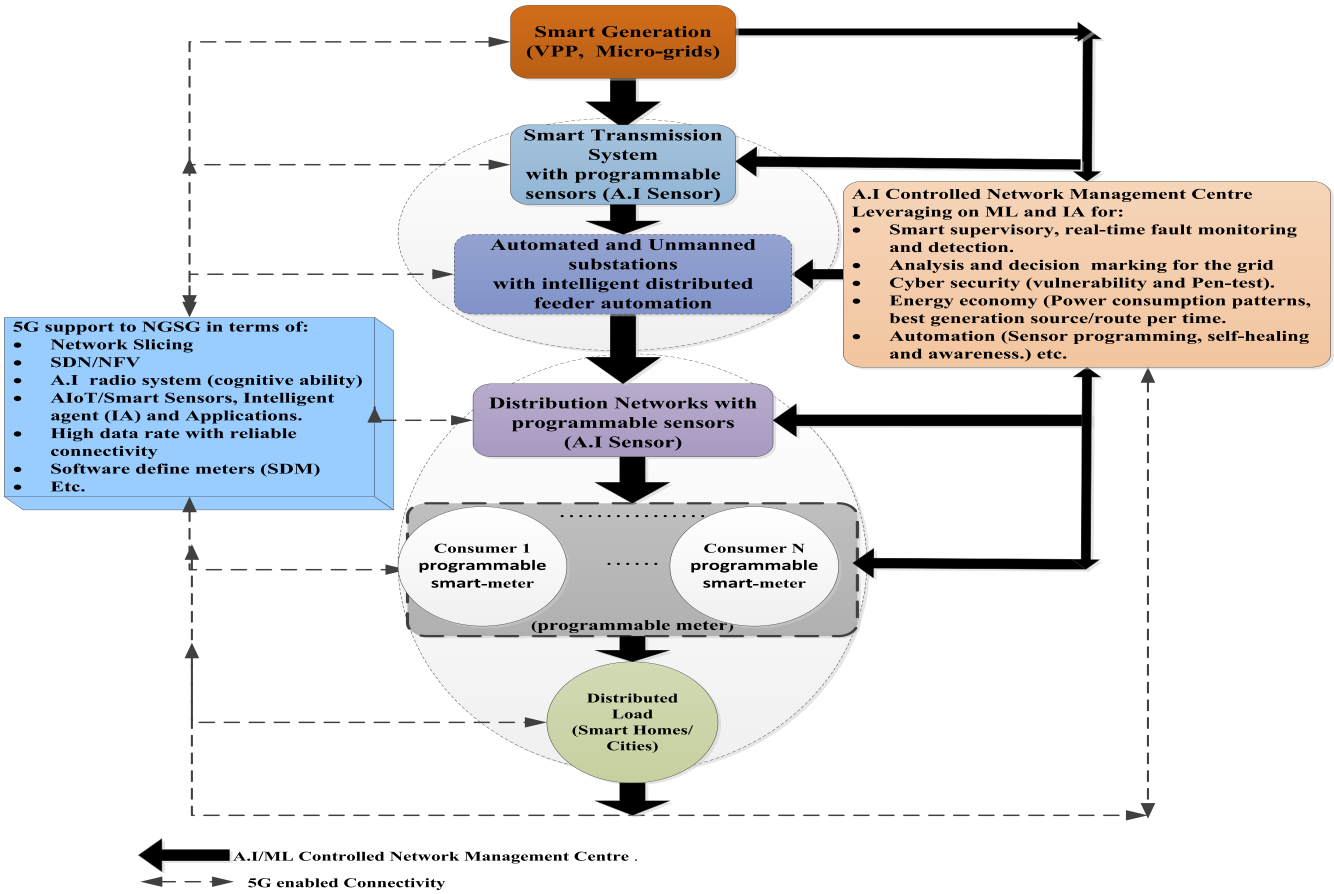

FIGURE 7. Functional schematic of the next generation smart grid (future grid).

form the foundation on which the IoT will be built. It, therefore, means that: (a) sensors within the NGSG can perceive and make mini-decision with its jurisdiction, (b) from the AI-controlled management centre which will be unmanned, a specific IoT sensor can interact or be upgraded with the latest version of code or isolated if faulty. These unique features will enable the programmable sensor to interface with any platform, be it cloud, 5G etc. In addition, unlike the traditional smart meter found in the customer buildings, the next-generation smartgrid NGSG will have an AI-meter installed in all homes, particularly smart homes since rollout will not be at once. The essence of proposing an AI-meter is predicated on some factors: firstly, the current smart meter is not smart as it is commonly assumed since it can not make micro-decisions like remotely monitoring users consumption level and reporting to the authority or suggesting which appliance needs to be disconnected to save energy for the user independently. From the customer end, the current smart meter used in today's smartgrid can be hacked by cybercriminals by malicious code/bug injection hence security and data privacy is sure using an AI-oriented meter [18]. From figure 7, the NGSG do not only use a duplex communication system that is common to the current smart grid but a more advanced communication system that is robust, like network slicing, network function virtualization (NFV) etc. This implies that only an intelligent network like 5G and beyond that is software-defined or software-driven with network slicing and NFV capabilities or functionalities can support the NGSG. From the network or service provider viewpoint, the choice of 5G as an enabler is not only based on the fact that it is heterogeneous but also can be supported by elastic compute clouds (EC2) instances like cloud computing and storage [19]–[21]. These are part of the artificial intelligence-enabled services which integrates machine learning, natural language processing and other advanced technologies. This is the interesting aspect that the NGSG which we are proposing to replace the current smart grid will bring to bear. Last, the details of this proposed next-generation smartgrid will be dissected in the next section of the paper and the proposed principle of operation will also be explained. In addition, the network architecture will also be discussed.

C. NEXTGENERATION SMARTGRID

Figure 7 illustrate the functional schematic of the proposed next generation smart grid. The proposed futuristic grid illustrated in the figure above is made up of eight functional and fundamental blocks. Which will be explain in this subsections below.

1) SMART GENERATION

In power system engineering, generation is the key factor upon which all other components depends on, including customer/user experience. There are several models of power generation which includes the centralized generation used in the traditional grid system, decentralized generation employed in the current smart grid model and the micro-grid/virtual power plant system otherwise known as the smart generation model proposed for the next generation smartgrid system as shown in figure 8, 9 and 10.

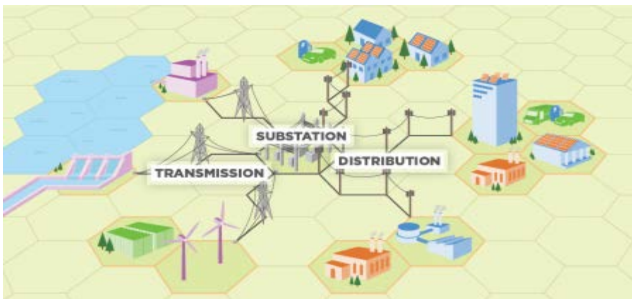

FIGURE 8. Centralized generation [22].

Centralized generation means a large-scale generation of power at a centralized facility. This facility is typically sited away from end-users and connected to a network of high-voltage transmission lines. The power generated by centralized generation is distributed through the power grid to multiple customers. Examples of centralized generation include thermal power plants, nuclear power plants, hydro-electric dams, wind farms, etc. Centralized generation is often unclean, costs are increasing and transmission and distribution are susceptible to both natural and human disruption [22]. Distributed power generation implies a combination of power models that generate energy by or close to where it wants to be utilized, for instance, solar panels and combined thermal and wind as shown in figure 9. Distributed generation could serve up a specific building, such as an individual home or industry. It could also be a part of a microgrid. This model is handy such that once tied to the customers lower voltage distribution lines, it can help boost the supply of clean, reliable energy to other users and lessen power losses along transmission and distribution lines. However, distributed renewable are costly and the combined heat and power (CHP) is hardly optimized [22].

In this paper, smart-generation is presented in two forms, microgrids and virtual power plants. The microgrid in figure 10 is a new concept of energy generation engineering. It represents a drastic shift from traditional remote centralized power plants to a more localized, independent and intelligent distributed generation especially, in metropolises, districts, etc.

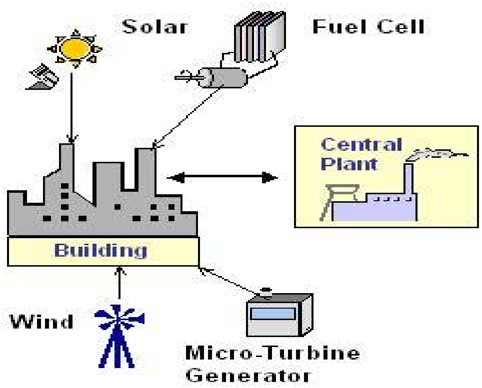

FIGURE 9. Distributed power generation [17].

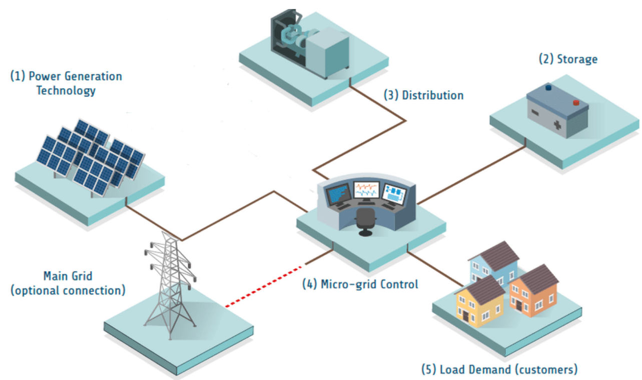

FIGURE 10. Smart generation (microgrids) [23].

The ability to smartly detach from the larger grid makes microgrids robust, flexible and the capacity to conduct concurrent tasks allows delivery of services that make the grid more sustainable. By islanding or isolating from the grid in times of crises like a natural disaster or any unanticipated occurrence, a microgrid can both continue serving its included customer when the power grid is down and serve its neighbouring users by delivering a strategy to sustain critical services from hosting first respondents and administrative purposes to offering vital services and backup protection. Another unique feature of microgrids is that they provide efficient, affordable, clean energy, boost local resilience, and enhance the operation and reliability of the regional power grid. It also delivers dynamic awareness extraordinary for an energy source [24]. Lastly, smart generation can present itself as a virtual power plant (VPP) which is a bit different from microgrids as shown in figure 11. A virtual power plant is a newer concept proposed for the next generation grid since it is a cloud-based distributed power plant that aggregates the capacities of heterogeneous distributed energy resources to boost power generation, as well as trading power on the electricity market [24].

Basically, a virtual power plant (VPP) is an aggregation of distributed generation treated as a unique unit. Usually, the different entity is in small-scale, however, once

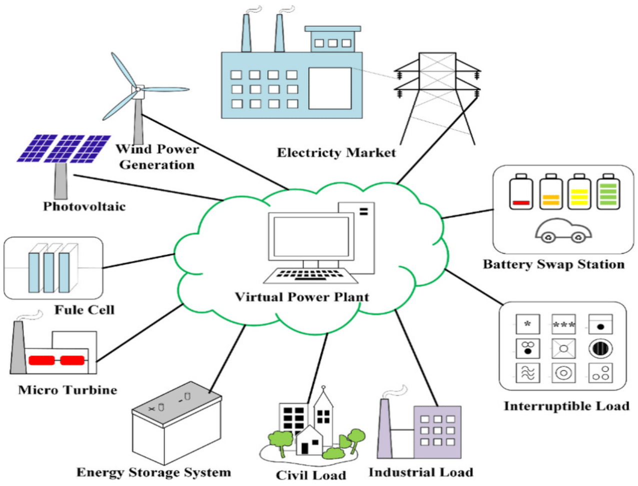

FIGURE 11. Smart generation (virtual power plants) [25].

aggregated, it becomes significant to deliver and support peak power demand. Regardless of their various sites, it is easier to control and harmonize a cluster of low-scale, scattered energy generating sources using ICT. According to [26], the idea of VPP is support the bigger utility players with large, centralized power plants by way of creating new suppliers with small, distributed power sources connected to create computer-controlled power network which can be managed from a grid control centre. Such pool (computer-controlled power network) can be capable of combine all sources of energy generation, along with large energy users to operate as a single supplier. For the convenience of the reader, it is pertinent to differentiate VPP and microgrid. Firstly, VPPs are incorporated into the power grid system while microgrids are normally off grid, and in an on grid setting, it intend to cut-off (islanded) for it to work autonomously irrespective of circumstance or state of the grid-like grid experiencing downtime. Secondly, a VPP is built utilizing resources linked to any part of the grid, while microgrids are naturally restricted to a specific location, such as a region. Thirdly, the two models use different systems for control, operation, and procedure. VPP is cloud-based and are managed by aggregated software system, presenting roles meant to emulate those of a conventional power management center. Microgrids on the other hand, depend on extra hardware-based inverters and switches for islanding, on-site power flow and power quality management. Lastly, an additional variance is the markets strategy, policy and regulation. VPP are aimed at wholesale markets and do not usually require specific regulation whereas, microgrids, in contrast, are more concern with power supply at customer end [27]. However, to cover the gap between the wholesale market and end-user, the next-generation smart grid will be adopting both concepts for robustness base on their respective advantages.

2) SMART TRANSMISSION LINE

The classical SG is faced with numerous challenges to effectively convey energy from the generating source to the customer end. Therefore, a robust real-time monitoring and detection system is crucial for the pylons, transmission, and distribution lines. Several advanced methods have been proposed in the literature that timely and accurately detect faults [28]. The proposed next-generation smart grid will have a state of the art smart transmission line [29]. This implies that the lines are designed/embedded with intelligent sensors or better put, with programmable sensors as shown in figure 12. The essence of this kind of concept is to help for the capturing of first-hand information about the status of transmission lines in real-time. Also, it will enable the AI-controlled network management centre to have a grasp of the entire grid considering the challenges of cable theft and other vandalization associated with transmission lines globally. Secondly, since sensors or sensor networks are the premises upon which IoT is predicated, this approach will launch the transmission lines to be internet-oriented making detection and monitoring for the utility companies convenient [30]. Another approach that helps to deepen the smartness of the next-generation smart grid is the installation of smart agents along the transmission lines. This application, despite monitoring of transmission line can also serve for overhead transmission line inspection and maintenance [29]. In a nutshell, the concept of technological approach allows for two-way communication between the utility and its customers, and the intelligent sensing along the transmission lines is what makes the grid smarter [31].

3) DISTRIBUTED AUTOMATED SUBSTATIONS WITH INTELLIGENT FEEDERS SYSTEM

This subsection deals with two inextricable characteristics concepts of the proposed next-generation smartgrid, which are the distributed automated substations and an intelligent distributed feeder system that is automated. In other words, the proposed next generation (future) smart grid can only be tagged smart when all the components that make it up are smart. In the same light, this paper is proposing a smart substation with intelligent distributed feeders for the future grid. Before this paper proceeds, let us not misunderstand a

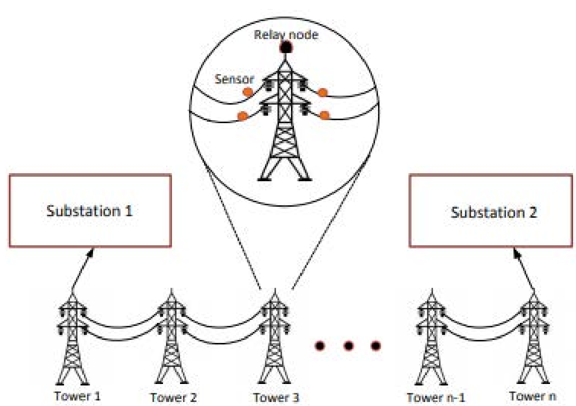

FIGURE 12. Smart transmission line with intelligent/programmable sensors [28].

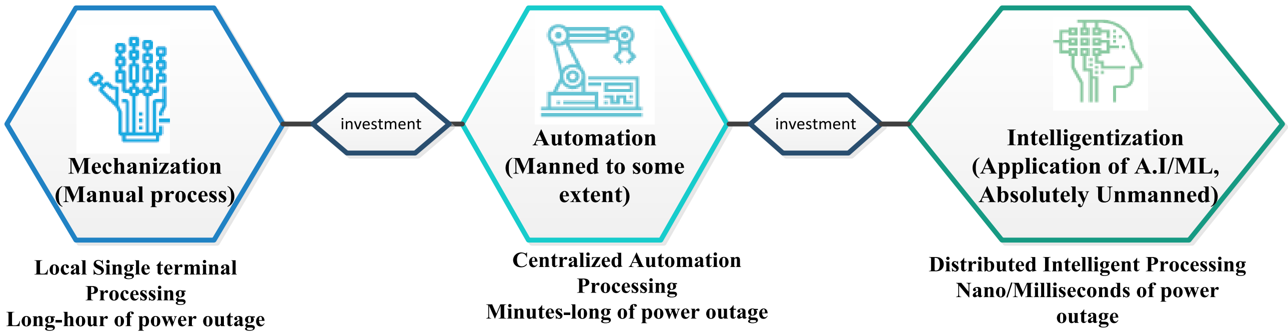

FIGURE 13. **Advancement in distribution automation [32].**

feeder and a transmission line. A feeder transmits power from generating end or sub-station to the distribution stations.

To be precise, a feeder is a power distribution network that conveys power from substations to consumers, while transmission lines are current-carrying lines that transmit power from generating end to the substations. Specifically, a transmission line starts from generating point and ends at the electric grid and this could be long, medium or short transmission lines. Having made that clear, distribution automation is an integrated data management scheme that utilizes artificial intelligence and machine learning algorithms, 5G full-duplex data communication network, intelligent agent, smart feeders and sensors. It is used in enhancing the reliability of energy deliveries and the quality of utilization, offer quality services to consumers, lower operating, and labour expenses. Driven by investment, distributed automation are in three phases as shown in figure 13. Firstly, the intelligent switching devices (reclosers, sectionalizers and load break switches) work collectively, with robust IoT-sensor networks and applications. Unlike the previous model [14], where switching devices do not require a communication link or any form of computerization. The essence of this proposed model is that if a fault occurs in real-time, the smart switching devices isolate the neighbourhood in which the fault occurred and keep on delivering energy to other regions while AI sensors monitor and learn the pattern of failure or causes of the fault via its ML algorithms for future references. Furthermore, throughout this process, smart reclosers and emergency reserved auto-switch on devices are used couple with other smart operations and supervision. Thus, eliminates the labour-intensive operations that are currently in use by the current smartgrid.

This system will be adopted for the next-generation (future) smartgrid. Secondly, radiocommunication network, intelligent feeder terminal units (IFTU), and backend embedded system are employed. When the energy distribution network is running perfectly, the distribution smart supervisory agents monitor the operating status of the power distribution grid in real-time and modify the operational parameter remotely, allowing swift fault detection in real time [32]. Also, the dispatcher can cut off the affected neighbourhood remotely and restore the power supply in other areas as earlier mentioned. Communication network which 5G plays a part, mainly conveys information service traffic comprising telemetry and tele-indication data which are uploaded from IFTU to main locations, subroutine commands to remote control commands for line-fault isolation and restoration in line or segment locating that is conveyed from primary sites to substations). The intelligent distributed feeder system is developing to be one of the trends of energy distribution system automation which the next-generation smart grid will be adopting. In intelligent distributed feeder automation, the processing logic of the main locations goes to intelligent power distribution mode via the AI-enabled backend embedded system. Through the mesh interactions (peer-to-peer communication) among IFTU, intelligent decision, analysis, exact fault location, fault isolation, and power supply recovery in non-faulty areas can be executed. This makes the diagnosis process completely automated, reduce the time interval, possibility of power failures and the diagnostic time from milliseconds to nanoseconds. Lastly, as backend embedded systems are integrated and deployed, intelligent control functions are enabled. These functionalities allow an integrated automation system that uses the smart supervisory controller and data collation system which is a bit superior to SCADA since it uses AI/ML algorithms. It also integrates power distribution geographic information management system (PDGIMS), dispatcher scheduling simulation, fault call service system, and work management. Other functions comprising substation automation, feeder segment switch controller, capacitor bank parameter controller, customer load controller, and remote meter reading. The distribution automation system for the next-generation smartgrid will have the capacities and functionalities mentioned above.

4) DISTRIBUTION NETWORK WITH PROGRAMABLE SENSORS

In this study, it has been well established that distributed network architecture is the panacea for a reliable and robust smartgrid. Also, the embedding of wireless sensors within the grid from generation to distribution is another good stride for a grid to be smart. There are a lot of sensors both wired and

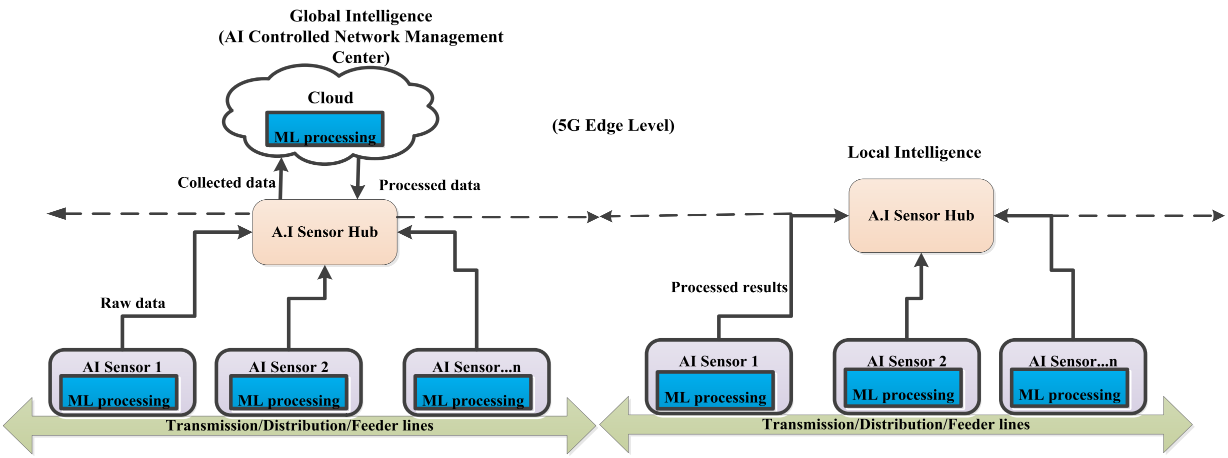

FIGURE 14. AI/Programmable sensor architecture showing global and local intelligence [33].

wireless that have been developed over the years and a lot of these reliable sensors have worked well independently [32]. However, decision-making always requires human input, and this is what this study is proposing an AI sensor for the next generation (future) smart grid as shown in figure 14. AI-powered sensors are the future, and what this suggests in this study is a sensor that is programmable and is decision-making enabled. Just like sense organs are important in the human body, so also will the AI sensors play a vital role in "local intelligence" gathering within the space in which they are embedded from generation, transmission up to the distribution value chain of the next-generation grid. As earlier mentioned, the network management centre is AI-controlled and as such, for it to get accurate feedback of the grid status in real-time, the sensors within the lines must be AI-powered. These sensors which form the foundation of IoT will develop local intelligence, which does not only means the acquisition of raw data (status of the grid: faults, outage, etc.). The raw data are extracted from the sensors and transmitted to another with more computationally capable within the grid called the sensor hub as shown in figure 14. The receiving-end AI sensor collects the raw data and performs pre-processing to present relevant results for analysis by the AI-controlled network management centre which act as the "global intelligence" of the grid located in the cloud [25]. Normally, the raw data of the sensor needs to be processed using a machine learning (ML) algorithm for classification. All these are possible because the sensors are programmable and if updates (new version of codes) are required from the network management centre, this update can be sent via the 5G SDN cloud network to the sensors. This is what the next generation smart grid this paper is brought to the fold.

5) CUSTOMERS PREMISES WITH SOFTWARE DEFINED METERS

The classical smartgrid have the smart meter installed at the customer premises. This implies a meter that can digitally read energy consumption, wirelessly transmit information about the customer within a neighbourhood and can be logged. It should be emphasized that there is no urgency on the complete abandoning of the conventional smart meters, because of the ongoing regulatory process, which has affected interoperability. In this regard, this paper proposes the adoption of "software-defined" meters for the next generation smart grid [34]. This is for ensuring global visibility of all the smart elements (sensor, meter, feeders) on the grid. To the best of our knowledge, the key benefits of introducing this kind of approach to the metering system for the next generation smart grid are:

a) To function over a wide range of frequency bands like TVWS, mm-Wave, with various data rates. The utilization of spectrum agility and the ability to perform different tasks, with the capacity to adapt to different circumstances within the customer neighbourhood.
b) Robustness, reliability, sustainability and especially scalability required by smart metering can be successfully supported by a software-defined approach due to its flexibility, re-programmability [34].
c) Introducing a software-defined meter or better still AI meters for the next generation smart grid is predicated on the fact that the current smart meter is not truly smart as it is generally assumed since it can not make decisions within its jurisdiction like remotely monitoring of user's energy consumption level and reporting to the utility companies if any violation of protocols, or suggesting/recommending via its mobile app or SMS, which gadgets need to be disconnect from the grid to save energy for the user. Then the user can execute the recommendation irrespective of the location. This makes the customer a stakeholder in the value chain.
d) Lastly, the current smart meter used in today's smartgrid can be hacked by cybercriminals hence security and data privacy will guarantee using an AI meter [34].

6) DISTRIBUTED LOAD (SMART HOMES AND CITIES)

The next-generation smart grid is perceived as a futuristic concept that adopts disruptive technologies. This implies

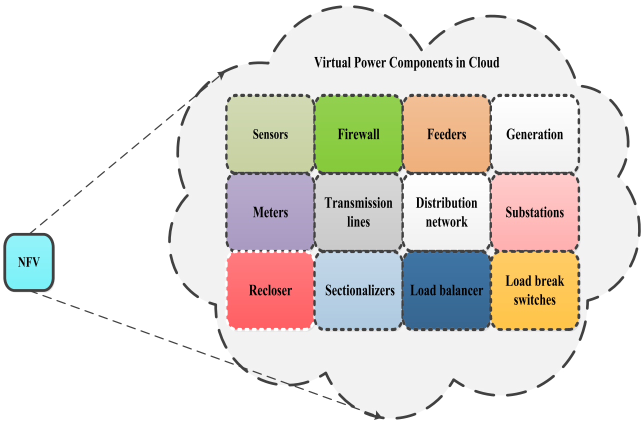

FIGURE 15. NFV-based approach in next generation smart grid.

that the kind of load/customers that will be serviced by the proposed future grid must be first, distributed and secondly, smart. In this context, smart load implies smart cities, smart colleges and campuses, smart homes etc. The smartness of the environment (cities, homes, and colleges and universities) is predicated on the kind of pervasive gadgets that is been used by these customers. For example, homes or colleges that are equipped with pervasive gadgets or equipment like smart TV, smart board, software-defined meters, amazon-Alexa, energy management apps etc., can easily form a cluster of wireless sensor networks and this is the foundation of the internet of things. Furthermore, with this kind of smart customer/loads, the power utility companies deploying the next generation smartgrid been proposed can effortlessly, interfaced load.

7) ARTIFICIAL INTELLIGENT CONTROLLED NETWORK MANAGEMENT CENTRE

The envisaged transition from the classical smartgrid to the propose next generation smartgrid (future grid) with all its functionalities make the ecosystem more complex for human to man alone, especially the network management center which is the heart of the grid [36], [37]. Critical services and applications such as energy resource allocation through virtual power plant (VPP), load balancing, grid's real-time fault monitoring and detection, security enforcement (vulnerability and pen-test), smart supervisory, smart decision-marking, and energy economy (power consumption patterns, best generation source or distribution route), requires real-time Al/ML algorithms for online analysis as well as efficient strategy for offline deep analysis of big data from the grid. So, proposed in this paper, software-defined networking (SDN) and network function virtualization (NFV) as the key candidate for the network management center to function optimally. As illustrated in figure 15, the SDN [38] divides the entire grid into three planes which are;

- *The infrastructure layer* which comprise of different generation sources (solar, wind, hydro etc.), meters, feeders, sensors just to mention but a few. In fact, it could be referred to as hardware layer or data plane since it houses all the programmable power components that are interfaceable with the application layer through the southbound interface open-flow system of the control layer or plane.
- *The control plane or layer* is the heart of the entire system. It seats in between the infrastructure or hardware layer and the application layer. It houses the AI/ML algorithm, the communication and control functions. To be precise, all the command line (codes), global intelligence are seated in this layer hence is called the controller. The control layer interface the infrastructure layer and the application layer. It is described as the hub of the artificial intelligence of the NGSG thus have access to all field devices and components.
- *The grid application layer* is the abstraction of the entire system. This means that, if human are to be involved, this is the only place they can interact with. The grid application layer is taken into higher abstraction through the help of the network function virtualization (NFV). In this paper NFV is a network architecture concept that applies the technologies of ICT abstraction that virtualize the entire sections of grid node functions into building blocks that can link, or connect together, to create seamless services. The beauty of adopting this feature into the next generation smart grid architecture is to reduce cost. For example, if the grid need more security, instead of buying physical hardware firewall, code can be used to that effect. Lastly, with the NFV node functions load balancing, sensor status, firewalls, intrusion detection, faults, generation, etc., can be seen at a glance and with a click of a button as presented in figure 16.

8) 5G SUPPORT SERVICES TO THE NEXTGENERATION SMARTGRID

Based on the features and functionalities like intelligence and autonomy proposed by the next generation smart grid, it is only logical to support it with an intelligent network like 5G. Of a truth, the 5G as an enabling network have the various attribute that benefit the next generation smart grid hence it is adopted to support the communication side of the grid. Features like network slicing, ultra-high data rate, reliable connectivity, security, network function virtualization, intelligent radio system with cognitive ability, the artificial intelligence of things (AIoT) just to mention but a few are all needed to realize the complete architecture of the next-generation smart grid [32]. This paper discussed in detail some of the support that 5G will be rendering to the proposed next-generation smart, however, emphasis will dwell more on network slicing which is a pioneer and cardinal feature of 5G [39]. The 5G network slicing has shown remarkable characteristics. Normally, a network slice is an occupant-skewed virtual network (tenant-oriented). It is intended to handle precise service requirements, meets different service level agreements, and hence builds an isolated network instance on request. 5G network slicing provides end-to-end network assurance

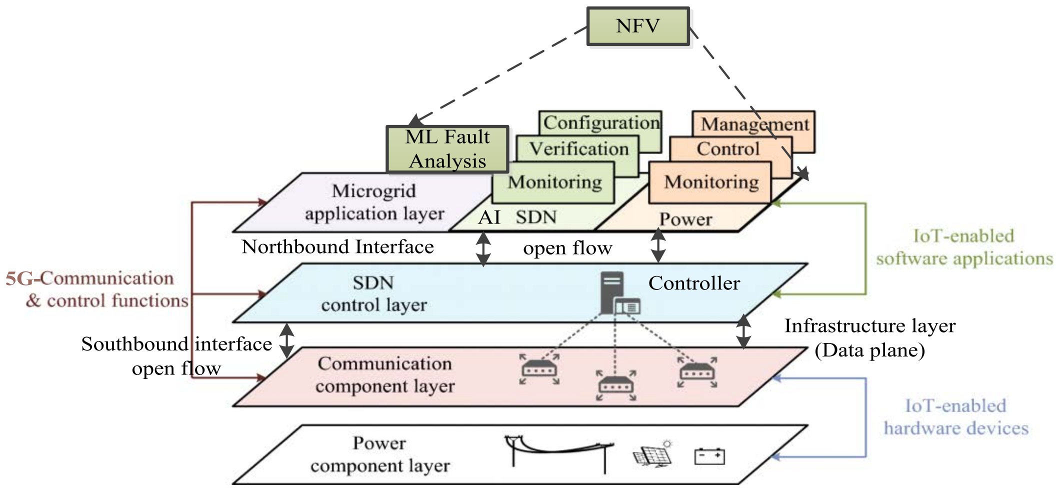

FIGURE 16. **Internal schematics of the AI/ML controlled network management center [35].**

for different service level agreements, service isolation, on-request network function customization, and automation. It allows service providers to flexibly allocate network resources and deliver a network as a service (NaaS). Also, it provides extra nimble services, stronger security isolation, and a more dynamic business concept for industry clients [32].

An end-to-end (E2E) assurance, the 5G network slice comprises of several subdomains, which includes the wireless network transport network and the core network. The service level agreements of the network slice are guaranteed by the E2E network comprising of several sub-domains. The network slice employs cooperation between various subdomains, such as network requirement breakdown, service level agreements breakdown, and deployment and networking collaboration. For service isolation, network slices are employed to create different network units for different applications and functions. Realistically, isolated dedicated networks guarantee that services of dissimilar slices do not impinge on one another. This simply implies that interference or overhearing would be eliminated thus the beauty of 5G on NGSG. On-request function customization and flexible orchestration ensure that service-based restructuring and service-based architecture of the software system facilitate network orchestration abilities on 5G networks [39]. To meet up the diverse network needs for different industries like energy, on-request orchestration abilities on 5G networks deliver distinct network resources peculiar to each application. In Addition, 5G networks slice permit services to be implemented in various sizes to meet diverse latency constraints. Automation is one of the conceptual features of 5G network slicing. It is the goal of network development and a such, makes it different from a conventional traditional network. 5G employs slicing to split up one network into several networks. Hypothetically, 5G proliferation will improve operation and maintenance complexity. Consequently, automation is an unavoidable requirement for 5G networks, and it is tricky to deploy full-scale automation simultaneously. Operations of each phase in the life cycle of a network slice can be done manually, semi-automatically, and then automatically, step by step. Full-scale automation is attained slowly along with the advancement of network design capabilities and the flattening and generalization of networks. Network slicing permits a particular renter, such as the power utility industry, to use customized network services. Each renter has its capacity for operating and maintaining its networks, but the level of proficiency of the renter operation and maintenance personnel are distinct from those of traditional operators. Hence, operation and maintenance graphic user interfaces (GUIs) that are simple to monitor, manage, and operate are usually necessary for renters to self-manage their networks.

a: 5G NETWORK SLICING ENABLING THE SMART GRID

No doubt, a characteristic case of the vertical industry (an industry where vendors offer narrow applicable products and services to customers) as energy grid will pose new challenges to communications systems. The multiplicity of the next generation smart grid services needs an adaptable and orchestrated system, high reliability needs isolated networks, and nano/millisecond-level ultra-low latency requires networks with optimum capabilities. For instance, when the 4G network is lightly overloaded in capacity, its ideal latency can only be between 35-45ms, which generally does not meet the nano/millisecond-level latency conditions for the proposed next-generation smart grid control services [32]. Moreover, the entire services on the 4G network are running on the same network, and such services could disturb each other, which does not meet the service isolation requirements of the next generation smart grid. In addition, the 4G network provides similar network functionalities for all its services, which again does not meet the differentiated service requirements of the next generation smart grid. Hence, the 5G network slicing is introduced to address these challenges and thus meet the diversified network connection requirements of vertical

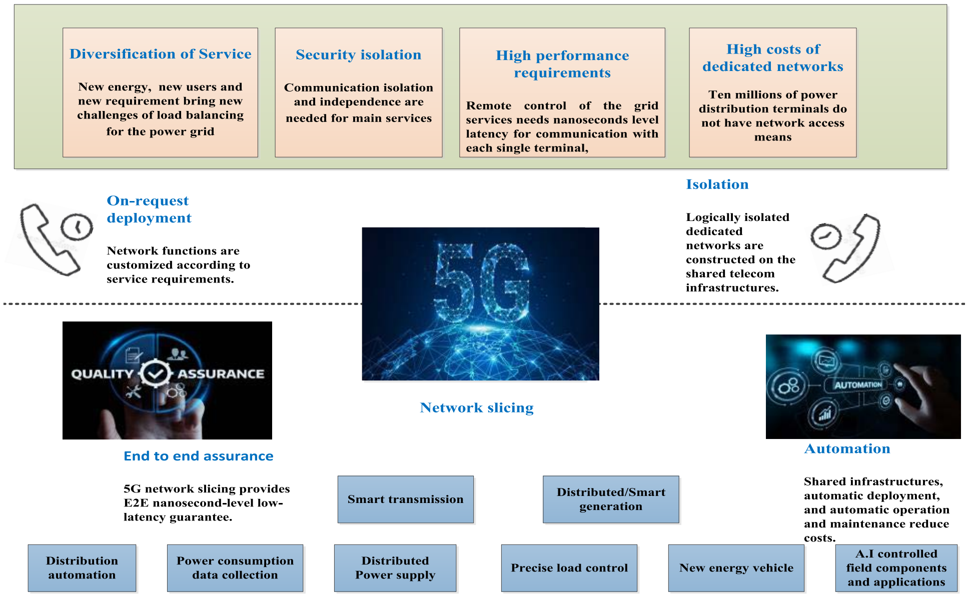

FIGURE 17. Smart grid enabled by 5G network slicing [32].

industries like the energy grid. Conclusively, the 5G network slicing can be viewed in four different perspectives which are technical, service and deployment respectively as shown in figure 17. From the technical perspective, the 5G network slicing can meet the connection requirements of core industrial control services of next-generation grids. 5G being the new enabling wireless communications network, is designed to take into account the scenarios of not only the human-to-human communication in terms of mobile phones but also the things-to-things and human-things communication as in the case of artificial intelligence and IoT in this case. The ultra-low latency of 0.5ms and massive access of 100 million connections per square kilometre network capabilities can well meet the link requirements of core industrial control services on the next-generation smart grid [39]. The network slicing technology, which was original introduced by 5G networks, can realize security and isolation together at the same level as dedicated systems with a significant reduction in design and complexity costs when likened to a dedicated fiberoptics network built by companies. On the other hand, the 5G edge computing technology allows distributed gateway servers placement to execute local traffic processing and logical computing, which is economical for both bandwidths and latency [40]. This, in addition, adheres to the ultra-low latency requirements of industrial control services on the next-generation smart grid proposed. From the service characteristics perspective, typical smart grid service scenarios are generally considered in two categories which are the industrial control services, this includes the intelligent distributed feeder automation and nano/millisecond-level specific load control. However, there is another slice particularly meet for the ultra-reliable and low-latency communication service. Secondly, the information collection services which comprises information acquirement of low voltage distribution networks, distributed power supplies, and massive machine type communication are services that require precise slice. Furthermore, for these two typical slice categories, the next-generation grid will also require enhanced mobile broadband which is a typical service scenario for remote inspection using drones, robots and other intelligent agents powered by AI. Lastly, voice slicing is a typical service scenario for manual operation, maintenance, and inspection. From the viewpoint of service deployment and utilization, 5G network not just supports new future power grid industrial control services, nonetheless, inherits the information gathering services supported by the current 1G/2G/3G/4G public networks. This way, several slices of the power grid can be utilized, managed, and maintained in a cohesive way, which in turn helps consumers of the power grid industry to be cost-effective. The generalized network slicing is seen in figure 18 while table 1 summarises how 5G network slices meeting various requirements of different next-generation smart grid scenarios.

b: 5G MULTI-SLICE ARCHITECTURE FOR NEXT/FUTURE GENERATION SMART GRID

Based on the application, various requirements of the next-generation smart grid scenarios and the architecture of 5G network slicing, the general architecture of 5G next-generation smart grid design and management is found in figure 19. The slices of intelligent distributed substation/feeder automation, intelligent distributed sensor automation, nano/millisecond-level precise load control, information acquirement of low voltage distribution systems, distributed power supplies, distributed generation / smart VPP, are used

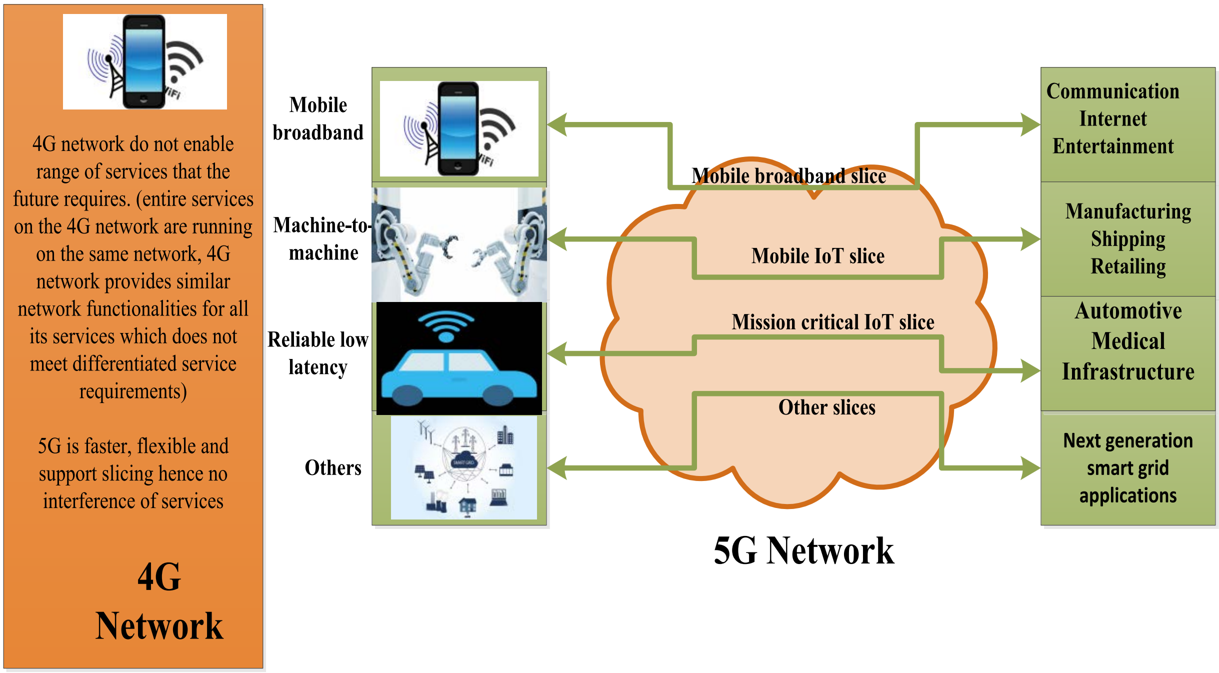

FIGURE 18. General overview of 5G network slicing [40].

TABLE 1. Summary 5G network slices meeting various requirements of different next generation smart grid scenarios [32].

Service Scenario	Communication Latency Requirement	Reliability Requirement	Bandwidth Requirement	Terminal Quantity Requirement	Service Isolation Requirement	Service Priority	Slice Type
Intelligent distributed substation/ feeder automation	High	High	Low	Medium	High	High	URLLC
Intelligent distributed sensor automation	High	High	Medium	Medium	High	High	URLLC + mMTC
Millisecond-level precise load control	High	High	Medium/low	Medium	High	Medium / High	URLLC
Information acquirement of low voltage distribution systems (Software defined meters)	Low	Medium	Medium	High	Low	Medium	mMTC
Distributed power supplies	Medium/High	High	Low	High	Medium	Medium /low	mMTC+ URLLC
Distributed/Smart/VPP generation	Medium/High	High	Low	High	Medium	Medium /low	mMTC+ URLLC
Note that URLLC and mMTC denotes **Ultra-reliable and low-latency communication and Massive machine type communication**							

to meet the real-world specification requirements of diverse provision scenarios. Furthermore, slice management which is based on domain orientation and integrated E2E are also used to meet service requirements in these scenarios [32]. Lastly, since the next generation smart grid will power smart cities, edge-DC is deployed in this architecture. This is to ensure distributed data centres since huge computing and storage power is required. edge-DC offers low latency and evades other factors that may interfere with proximity, operation, and availability. Another use of the Edge DC is to distribute the load over several smart nodes and connections. Altogether, these features make substantial enhanced security and availability throughout the network. For example, if a fault occurs in one Edge DC, services are transferred to another one nearby and this is the beauty of global intelligence. In a conclusion, to the next generation smart grid, the 5G network slicing will fully integrate the software-defined networking (SDN) and network function virtualization (NFV) technology [40]–[42]. This is to flexibly match service requirements with network resources, adhering to the precise function requirements of diverse vertical industries in the 5G regime. For wireless network service providers, 5G network slices will better build a nimble and adaptable network and broaden services to vertical markets. Network service provider communication infrastructures are shared, which significantly enhance network resource optimization. Furthermore, wireless network service operators provide diverse slicing capabilities to meet the real-world requirements of separated services in vertical industries. The adaptable and open network architecture can offer autonomous process capabilities for vertical industries to ensure adaptable and modified service provisioning. For vertical industry customers, 5G network slices drive network service providers to gain on-request service assurance exclusive of building mobile private networks. This way, vertical industry customers can expand their capabilities of swift design and develop a more customized service and increase service markets in the shortest possible time [32]. The application scenario analysis of the next-generation smart grid in figure 17 and table 1 shows that the service requirements based on real-world specifications differ significantly affording to scenarios. Power utility companies and network equipment providers (vendors) must also quantify network technical specifications and architectural plans built on the real-world specification requirements of these industries, including:

1) Additional quantifying slice security, service isolation, and E2E service latency requirements, respectively.
2) Negotiating network capability exposure requirements and network management GUIs.
3) Discussing business partnership modes and future ecological settings.
4) Delivering a complete solution that meets different requirements of multiple scenarios in the energy industry.
5) Conducting practical verification and demonstration of the solution.

D. FUNDEMENTAL DIFFRENECE

Several challenges contribute to the inability of both the old traditional grid and current grid to capably meet the rising demand for power supply globally. Agreed the current smart grid has contributed and improved some functionalities immensely. However, the characteristic difference of the three grids (existing grid, classical smart grid and next-generation grid) is still wide due to the era of technological advancement and user/customer experience which investors want to see. This section highlights some of these characteristics in table 2.

III. ARITIFICIAL INTELLIGENCE AND MACHINE LEARNING FOR NEXT GENERATION SMART GRID

AI/ML are two pair that plays key roles in enhancing the electric grid system. What makes the next-generation smart grid unique from the classical smart grid system is the incorporation of disruptive techniques and technologies. Their relevance and application cut across subdomains of the next-generation grid architecture which includes the AI radio system (though for 6G), network control centre powered by AI, intelligent substation and feeders, intelligent sensor and sensor hubs, smart distribution transmission, and smart power generation just to mention but a few [14], [32]. As a cyber-physical system, the next-generation smart grid is internet-oriented, hence it is exposed to attacks. To take care of cyber and other malicious attacks, a machine learning approach is deployed which will be discussed in detail in the course of the study [6], [14]. Apart from securing the grid, the other reasons for deploying AI/ML for the proposed next-generation smart grid are human inaccuracy, building an automated, robust, and autonomous system that is a self-learning system that can make a decision based on statistics and information available from current and previous experience. Thirdly, enable personnel attached to the facilities to develop the second skill (coding and updating the AI/ML system algorithms to be smarter) and lastly, cost-effective and customer-friendly in terms of GUI of the AI/software-defined meters installed in neighbourhoods.

A. GENERAL ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNIQUES IN SMART GRID

Several AI/ML techniques can be applied to the proposed next-generation smart grid. This subsection highlight and generally classified each into the following categories. They include:

1) EXPERT SYSTEM TECHNIQUE FOR SG

An expert system (ES) is a computer program or system, that utilizes an AI/ML algorithm to simulate and emulate the decision and behaviour of a human expert or an establishment that has expert knowledge and experience in a specific domain, for example, autopilot in aviation/maritime sector, auto cruise in shipping/maritime sector, Autotrader in stockbroking/forex analysis, etc.). It is developed to solve complex problems by reasoning through bodies of knowledge (database), represented mainly as if-else, then rules rather than through traditional routine code [47]. As illustrated in figure 20. Expert system is the pioneer smart system, built to supplant the human expert in a particular subject using Boolean algebra. In the conventional smart grid system, the response to challenges relating to intelligent control, fault diagnosis, real-time monitoring and detection, self-determined power routing, etc., still hinges on the ES technique [48]. The subject knowledge gained from the subject expert is denoted in the knowledge base which is made up of the database and expert knowledge of the ES. As earlier mentioned, expert

TABLE 2. Comparison between the old grid, current smartgrid and the proposed nextgeneration smart-grid.

Author Ref.	Features	Old Grid (Related work)	Current Smart Grid (Related work)	Next Generation Smart Grid (Proposed)
[43]	Communication/Antenna orientation	Uni-directional (Simplex)	Bi-directional (Duplex)	Omni-directional /Beam forming
	Supporting Network	Not Supported	Up to 4G	5G and beyond
	Device/Application Types	Not Supported	Supported MBB only	• eMBB • URLLC. • mMTC • Hybrid (eMBB+URLLC)
	Network slicing	Not Supported	Not Supported	Fully supported
	EC2 supported	Not Supported	Not Supported	Supported: • Virtual power plant. (Cloud based distributed power plant)
[44]	Control	Manual	Automated	Proposed AI Controlled
	Customers/Users side Interaction	Limited	Extensive	Unlimited due to AI enabled CPEs/UPEs
	Instrument type	Electrical	Numerical	Numerical and Software define/driven/programable
	Flow control	Limited	Universal	Ubiquitous/Pervasive
[45]	Customer participation	Limited	Extensive (to a large extent, the current smart grid permits users to play a part in optimising the operation of the system with limited contribution.	• Unlimited (NGSG automatically makes the customer a shakeholder in the value chain • It allows consumers full participation in optimising the operation of the system. • Provides utility companies with greater information and choice of supply)
[46]	Metering system	Electromechanical	Digital	AI Enabled (Software defined/drivem, programable)
	Reliability and Protection	Prone to failure and cascading outage, estimate reliability	• Adaptive reliability. • Real-time protection and Islanding.	• Predictive reliability. • Preemptive based on ML capacity, • Realtime protection and Islanding.
	Power restoration	Manual/Blind	Self-healing	Self-aware/healing, autonomous
	Topology	Radial	Network	Network
	Generation	Centralized	Distributed	Smart generation with distribted architecture.
	Transmission style	Traditional	Maintained Coventional Transmission line	• Smart transmission (transmission line with programable sensors and smart robots)
	Response to action	Slow	Very fast	• Ultra fast
	Operation and maintenance	Physical equipment check, time based maintenance	Remote monitoring, predictive and condition based maintenance	• AI monitored with smart supervisory. • Predictive condition based maintenance.
	Number of Sensor	Small number of sensors	Many sensor	• Sensor based
[43]	Sensor type	Electromechanical sensors	Smart sensor/hardwired sensor	AI sensors/programable sensors
	Latency	Very low (seconds)	Low (milliseconds)	Ultra-low latency(nanoseconds)
	Simulation Tools & Testbeds .		Lot of them are available	Need to develop simulation tools and testbeds.

TABLE 2. *(Continued.)* **Comparison between the old grid, current smartgrid and the proposed nextgeneration smart-grid.**

[32]	Security	Less security issue	Secured but vulnerable to modern day cyber attack (DDoS)	Cyber defense system. (AI grid monitoring, self enabled vulnerability/Pen-test)
	Standardization on		Not much of work is done on smartgrid standardization.	Need more efforts for AI specific next generation smart grid standards
	Protocol Compatibility/ Connectivity	Non	Not with all protocols	• Compatible with internet protocols and others protocols like PLC, SCADA. • Connect with more field device. enabled mobile internet
	Interoperability		Difficult to cope with different vendor specific devices and protocols.	• 5G and beyond. • Technology is not vendor specific and operates on open standards. So, various types of communication network devices can be easily managed and designed, and their interoperability is not a challange.
	Platform/Data center type)	Non	Central DC	• Edge DC (distributed data centers)
	Cost	Less expensive	More expensive	Most expensive
	Return on Investment (ROI)	Less attractive to investor	More attractive to investor	Most attractive to global investor due to higher ROI.
	IoT with smart sensing	Non	To a large extend	Full scale IoT oriented.
[38]	Resilience	Not expose to cyberattack but prone to failures	Not too much resistant to attacks and failures.	Resilience against failures and malicious attacks can be achieved by using AI alogorithm .
	Network Management	Complex, time consuming, and Manual	Complex, time consuming, and Manual	Straightforward, automatic and AI driven, and faster.
	Energy economy			
	Granularity	Not attainable	Dependent upon proprietary hardware	AI controllers can identify the traffic at every flow and packet level.
	Scalability	Very limited	Limited to finite servers	Unlimited due to cloud support and cost effective
	Energy Pricing	Fixed	Stakeholder decides	Dynamic: both customers and investors are stakeholder
	Power consumption	Consume more power	Consume power relatively	Reduced power consumption
	Programmability	Not possible	Not programmable	With SDN capability, it now easily programmable.
	Protocol independence Protocol	Non protocol independent	Not truly protocol independent	Independence can be easily achieved through AI Controllers

knowledge and databases produce the knowledge base, which is the underlying element of ES. In the knowledge base, rules and regulations are well-defined in a manner such that an "if" statements follow a "then" statement which is linked with algebraic operations [16]. Furthermore, knowledge can be obtained directly from subject experts or the results of an in-depth investigation. The ES draws inferences from the challenge at hand by analyzing the "if-then" rules through the user-input knowledge that interact with the intermediary rule engine as shown in figure 20. Fuzzy logic was recommended to manage the hypothesis of incomplete accuracy for instance when a device in the grid is faulty but is still working within an acceptable limit, how does the AI in the network management centre perceive its performance.

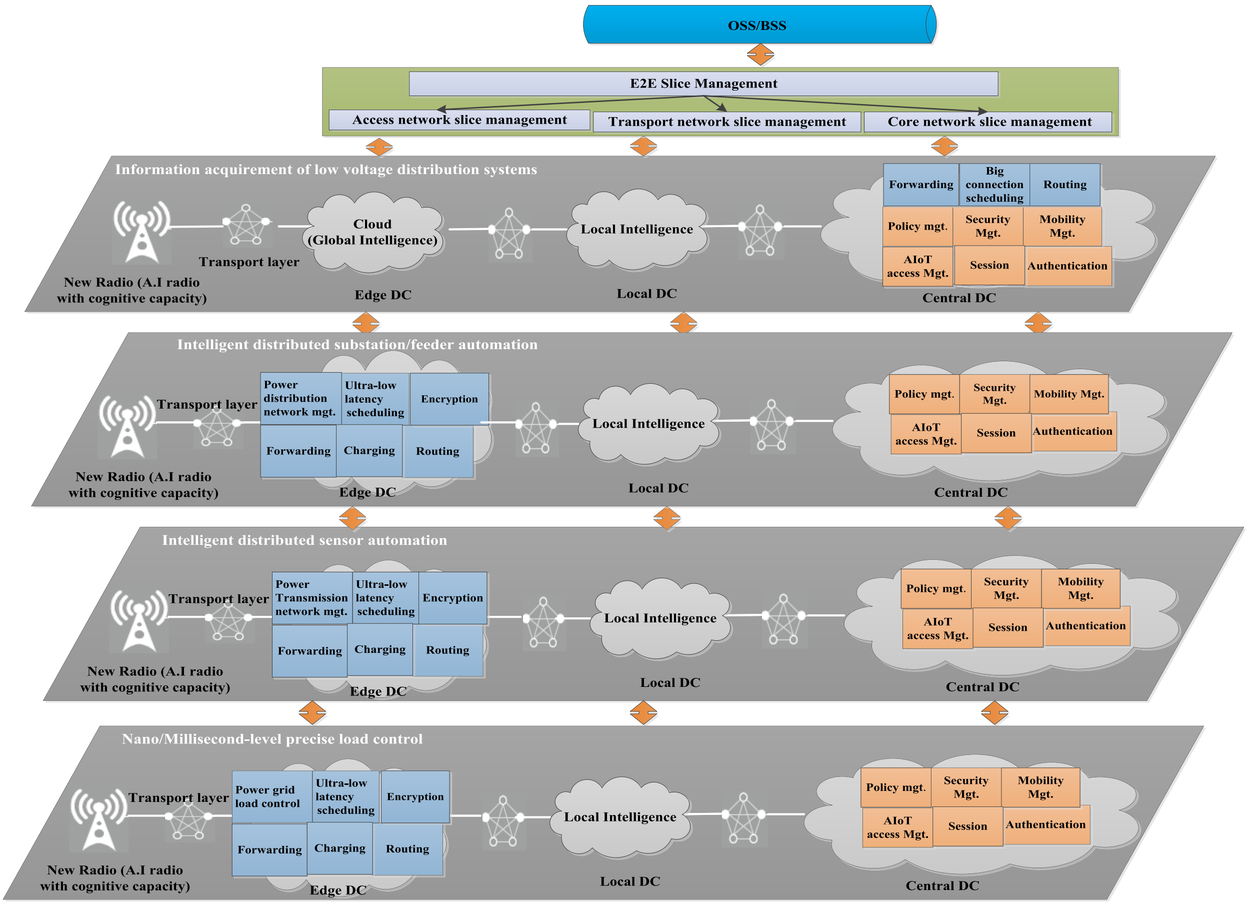

FIGURE 19. 5G network slicing architecture of the next generation smart grid [32].

Contrasting the Boolean reasoning employed by ES, fuzzy logic is a technique developed to compute based on values that fluctuate between 0 and 1. For instance, an efficiency of 0.1 to 0.9. Fuzzy logic developed in the hypothesis of fuzzy sets offers a level of participation, usually a value between 0 to 1. For example, the fuzzy logic can use 0 to indicate false, while 1 to signify true, and the numbers between 0 and 1 to denote incomplete truth or incomplete false, by allocating levels of truthfulness to the recommendation. Finally, it is generally assumed in a very inclusive logic, that a fuzzy inference system initially moves input crispy variables into fuzzy variables [14]. Later, employing the input variables to fuzzy operators in the "if" part of the rule, subsequent results can be extrapolated from the "then" part of the rule. The last step of the fuzzy inference system is defuzzification, which transforms the output to crisp values. This is a valuable technique that can be adopted for the next generation smart grid in terms of decision making by AI-controlled devices and systems.

2) SUPERVISED LEARNING TECHNIQUE FOR SG

Supervised learning (SL) is an AI/ML concept in which the mapping (label data) of inputs and outputs has been studied to predict the outputs of new inputs. It mostly requires training the AI system with data set for the machine to learn and make a prediction. It is an ML responsibility of developing universal premises for input and output trained by linking classified exterior input and output sets [49]. After training, the labelling and mapping functions can then be utilized for forecasting future information subsequently. Studies have shown that several SL algorithms have been built in the previous decades and are extensively deployed to enhance the energy grid systems. The diagram in figure 21 highlights the generally used SL algorithms in power grid system strategy.

The artificial neural networks (ANNs), which mimic the human nervous system [50], have hugely been applied in several areas of research domains in recent times. Programming in ANN approaches, like several other ML approaches, is simply not necessary, however, use a set of rules (algorithm) like weight to predict based on the quality and quantity of the data set. Most often, ANNs technique is best for solving pattern recognition and image processing problems, which are tricky to resolve by the outdated approaches.

For instance, intelligent drones with HD cameras use image processing techniques for monitoring the transmission and feeder lines in a grid facility. This helps it to compare and make a decision if lines have been damaged as a result

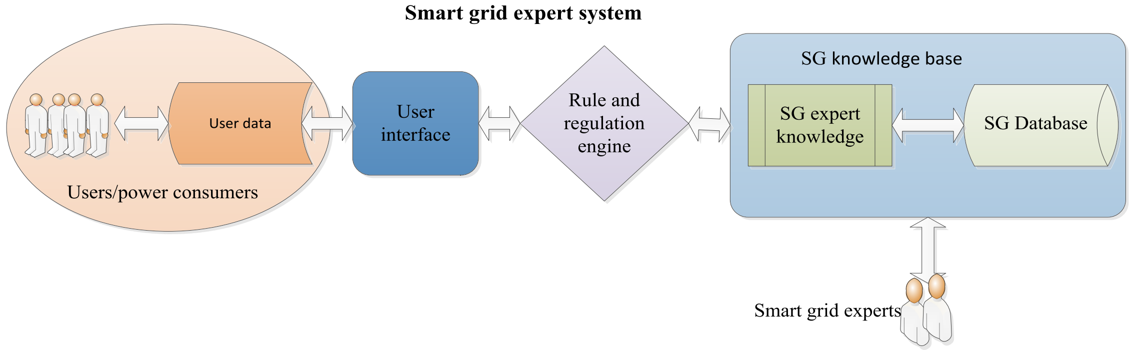

FIGURE 20. Expert system for smart grid.

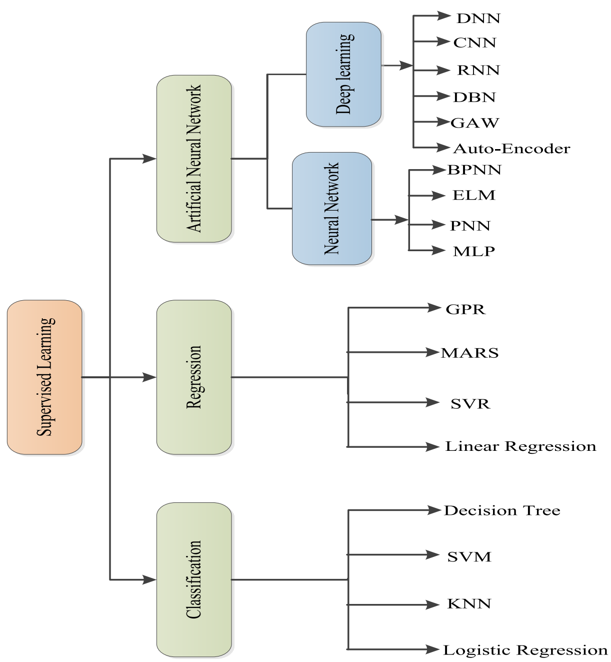

FIGURE 21. Supervised learning techniques used in the next generation smart grid.

of theft or warn out. The pattern recognition aspect could be employed for security purposes because data generated and transmitted by IoT devices on-grid have patterns and if these patterns are out tolerable limit, it decides on abnormalities.

Other ANN techniques used to solve smart grid problems, like fault detection [51]–[53] and power system stability assessment is the extreme learning machines (ELMs) that utilized the hidden layer feedforward neural [54]–[56]. The back-propagation neural network (BPNN) was proposed by [57]. This algorithm is designed such that the knowledge process of neural networks is achieved by constantly altering the network weights till the error between the output and ground truth gets to a confident level. Also, the multilayer perceptron neural network (MLP) is a feedforward algorithm used to solve problems stochastically [58]. The probabilistic neural network (PNN) is another sophisticated approach that uses the feedforward neural network method, where the parental probability distribution function of the individual class is used to guesstimate the class to input data [59]. The deep learning (DL) technique, being a subset of ML, was initially applied for image processing, beginning from multi-layered deep neural networks (DNNs). DL techniques have experienced rapid development in recent times. Several tested and proven models for solving smart grid challenges have been proposed. Some of which are convolution neural networks (CNNs) [60], autoencoder [61], recurrent neural networks (RNNs) [62], generative adversarial networks (GAN) [63], deep belief networks (DBN) [64]. Apart from the novel algorithms mentioned above, several robust AI/ML approaches are also used for regression and classification challenges. For example, the Support vector machine (SVM) technique is one of the best classification models proposed [65]. The decision tree (DT) learning technique and logistic regression approach, are another simple to develop and understand algorithms and have also been extensively modified to find application power grid systems [66], [67]. The k-nearest neighbours (KNN) system is one of the fastest algorithms in terms of training data set. It is mostly used for regression and classification purposes in power grid systems [68]–[70]. Regression approaches which include support vector regression (SVR) [71], multivariate adaptive regression spline (MARS) [72], [73], Gaussian process regression (GPR) [74], and linear regression (LR) [75], all serve as a solution for problems associated with power grid fault detection, demand response predicting, just to mention but a few. The proposed next-generation smart grid will generate a lot of data. Motivated by Big data, and the necessity to resolve complex problems in a cyber-physical system like the next generation smart grid, there has been the advent of new AI algorithms with the help of robust computer hardware, enabling AI to migrate to the artificial superintelligence (ASI) mode, so-called AI 2.0 stage [76]. This simply implies ''use data to answer complex questions and build predictive smart grid applications.

3) UNSUPERVISED LEARNING TECHNIQUE FOR SG

Unsupervised learning is an ML approach in which the unlabeled data are used to capture the similarity and

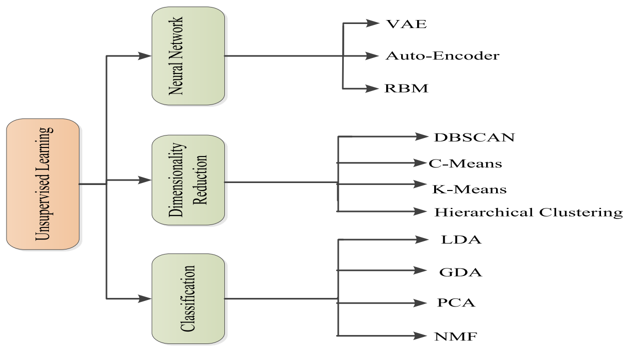

FIGURE 22. Unsupervised learning techniques diagram.

differences in the data. It is an algorithm that has shown tremendous improvement over the years of development. However, it is most useful when the users have some benchmark or know what patterns to look out for (ground truth) which is not always certain in a practical sense. This characteristic renders the unsupervised learning technique helpful since it can be applied to deduce and extract possible information or discover concealed patterns from data without tags or mapping, unlike the supervised learning algorithm. There are three categories of Unsupervised learning with about eleven sub-branches as shown in figure 22. These categories are unsupervised neural networks, clustering, and dimensional reduction. The Unsupervised neural network for instance includes variational autoencoder, restricted Boltzmann machine and the autoencoder. All of these have found application instability assessment [77], anomaly detection [78], [79] and load forecasting [80]–[82] of the power grid. Clustering, on the other hand, is the unsupervised task of assembling the data points into a set of clusters, in which data in the same clusters are alike with one another. hierarchical clustering, DBSCAN (density-based spatial clustering of applications with noise), fuzzy c-means, K-means, find application in load prediction [83]–[85] and fault detection [86]. The dimensional reduction converts the set of data from a high to low dimensional space. It is often vital when processing or preprocessing smart grid data to lower unused/idle features. Some of the dimensional reduction approaches generally used in the smart grid comprise linear discriminant analysis, principal component analysis (PCA), non-negative matrix factorization, and generalized discriminant analysis [81], [87]–[89].

4) REINFORCEMENT LEARNING TECHNIQUE IN SG

Reinforcement Learning is gradually becoming a popular algorithm for solving smart grid problems. RL differs from supervised and unsupervised learning, due to its intelligent agents' strategy, which aims at maximizing the concept of cumulative reward, and action. The robustness of this technique is based on the fact that with partial knowledge of the grid ecosystem and partial feedback on the fineness

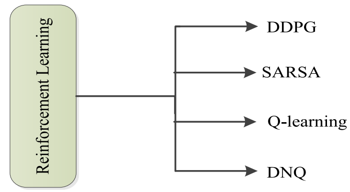

FIGURE 23. Reinforcement learning method.

of the decisions, RL can respond to unpredicted situations. Some commonly used RL algorithms are listed in figure 23. The deep deterministic policy gradient and deep Q network are current algorithms of RL in smart grid systems. SARSA (state action reward state action) and Q-learning are commonly used in energy management [80], [90], attack detection and identification in cyber-physical systems like smart grids [91]. Deep reinforcement learning (DRL) is another robust technique that synergizes the insight of DL with the decision making of RL [92]. For instance, [92]–[97] showed the achievement of DRL by the application of the valuable insight of high-dimension input and strategy control.

5) ENSEMBLE TECHNIQUE IN SG

As the name implies, ensemble techniques have a way of aggregating outcomes (results) from various learning sets of rules (algorithms) or diverse original data to get improved general performance. In figure 24, bagging or bootstrap aggregating handles every single model in the ensemble poll with the same weight and trains them by utilizing a random data subclass. Random forest is a popular bagging/bootstrap model that merges a high-classification algorithm with a random decision tree. In the smart grid, it is mostly deployed for anomaly detection [98], [99], load forecasting [100], and stability assessment [101]. For clear understanding, bootstrap is a robust front-end framework used to build modern websites and web apps. It is open-source and free to use however, includes numerous hypertext markup language (HTML) and cascading style sheets (CSS) templates for user interface (UI) elements such as typography, forms, buttons, navigation. If finds application in interfacing components for the software-defined next-generation smart grid in conjunction with network management centre. The boosting technique, on the other hand, is an ensemble method that develops a different model that tries to rectify the misclassification issues from the earlier model and demonstrated favourable results in smart grid challenges [102]–[104]. Stacking as an ensemble learning method that aggregate the forecasts of various regression or labelling algorithms, is sophisticated for cyber-attack detection [105], load prediction [106], anomaly detection [107].

6) DEEP/TRANSFER LEARNING TECHNIQUE IN SG

The absence of label data set is still a major issue for power grid analysis and evaluation. Transfer learning reduces the requirements of pre-training of data set, which motivate scientists and engineers to make use of them to solve the

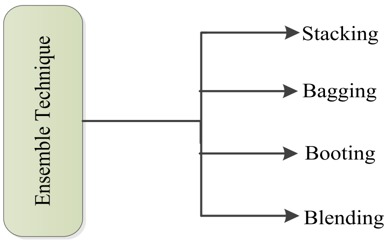

FIGURE 24. Ensemble technique.

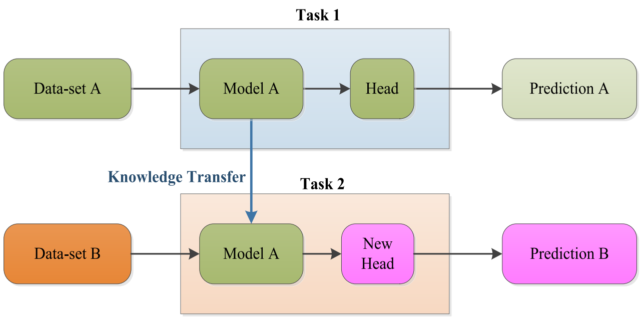

FIGURE 25. Deep/Transfer learning method.

problem of insufficient data which is often faced. In this light, transfer learning is a machine learning technique that focuses on accumulating knowledge earned in the course of solving one challenge and utilizing it in a unique way but connected domains. It is an ML technique where a model built for a task is used again as the basis for a model on the next task as shown in figure 25. For instance, knowledge gained while learning to predict or detect a fault in transmission lines is applied when attempting to predict or detect a fault in a feeder line of the smart grid facility.

B. AI/ML APPLICATION TECHNIQUES FOR NEXT GENERATION SMART GRID

From this survey, it is logical to say that the proposed next-generation smart grid will be different from the current smart grid through the combined application of disruptive technologies such as IoT, AI, and 5G. Having mentioned the general AI/ML techniques used in smart grid, this section discusses in detail some specific areas in which AI/ML techniques have and will help in improving the overall performance of the smart grid system. To be specific, AI/ML technique has been found to be effective in grid security, real-time faults detection and monitoring, load prediction, grid stability assessments to mention but a few.

1) LOAD FORECASTING

One characteristic of the next generation smart grid is the integration and management of several kinds of energy generation as in the case of microgrid and virtual power plants. However, the ambiguity of the planning and operation of the grid given the exponential rise in the demand for electricity due to urbanization is becoming gradually more difficult. Load forecasting is one of the main factors that ensure the power grid is stable and intelligent. Predicting the load on the grid is important for scheduling and strategy because it will help to reduce energy generation costs and save electric power especially in a situation when the load is unstable [108]. LF is categorized into three which are short-term LF (STLF), which forecasts the load from second to minutes to hours, mid-term LF (MTLF), which forecasts the load from hours to a week and the long-term LF (LTLF), which forecasts the load from months to years [109]. Furthermore, LF could also be influenced by a variety of factors which includes, time, type of users, weather, season, event, and the algorithm in place. Normally, MTLF and LTLF prediction are patterned in line with past data of power consumed, alongside other components, such as customers, population data, and weather conditions [110]. STLF has largely been applied in areas for example energy transfer planning, demand response and real-time control [111]. The MTLF and LTLF are deployed for next-generation smart grid planning, designing, and showing the changing aspects of the power grid [110]. Based on the data supplied by software-defined meters, several methods are recommended and utilized for power grid LF.

a: SHORT-TERM LOAD FORECASTING

Several AI/ML techniques can be applied specifically to smart grid short term load forecasting. For instance, [112] proposed and implement an ensemble approach that combines three base techniques for STLF. The study demonstrates that the model's efficacy for STLF. Though, the choice of base techniques in the ensemble method requires more verification. Reference [81] applied a hybrid technique utilizing a restricted Boltzmann machine (FCRBM) as a training component and genetic wind-driven (GWDO) as an optimization processor. This paradigm is proven to outperform other advanced algorithms. A DBN embedded with parametric copulative models was proposed to predict the minutes and hourly customer load of a particular grid in urban cities. The findings indicate the efficacy of the technique by evaluating it with other methods like SVR, ANN, and ELM [113]. Reference [114] developed a blended clustering technique predicated on ANN and wavelet neural network (WNN) systems. The result demonstrates a higher performance of the proposed model over other clustering methods. To addressing the laborious technique of developing an optimum DNN, that defines the number of hidden layers in the DNN model, [102] applied an ensemble technique that integrates various DNN algorithms with various numbers of hidden layers to attain total improved performance by removing the badly achieved models. Nevertheless, the processing overhead is a constraint, since several CNNs are involved. Many DL-based techniques are applied in solving LF challenges. In recent times, DNNs have found application in obtaining the possible knowledge for a predicting paradigm. However, the ANN technique is habitually stuck in local minima [115] and this hence fails to forecast future load consistently. Hence [116] proposed a deep RNN for STLF to tackle the over-fitting problem by enhancing volume and data multiplicity in the smart grid.

In a nutshell, by using the ensemble technique, the effectiveness and precision of STLF can be enhanced in a smart grid.

b: MEDUIM-TERM LOAD FORECASTING

In general, LF is a proactive and very vital strategy for steady and efficient power delivery. The MTLF on the one hand is employed to manage maintenance planning, load balancing, load demand and dispatch, and generation [117]. Contrary to the STLF, which normally match data to a model, MTLF and LTLF have unique challenges that are mostly overlooked owing to their unpredictability and complexity [118], [119]. Unlike STLF, the MTLF and LTLF are affected by obvious factors, like weather data and previous load, and other implicit factors like demographic data and local economy which implies appliances in use and population distribution [117]. The STLF on the other hand considers all weather variables equal in terms of weight, whereas, in MTLF and LTLF, weather variables such as humidity, precipitation, temperature, and wind are given decremental consideration [120]. Reference [121] developed dynamic Bayes network (DBN)-based MTLF template to predict the peak power load for the subsequent year. [122] implemented a DNN paradigm with an enhanced training algorithm that consists of two search algorithms for MTLF in the power grid and shows the efficacy of the method. In [123] an integrated neural network-based model with particle swarm optimization (PSO) technique was proposed. The model demonstrated viability and strength over other models. Reference [124] provide a solution based on CNN and LSTM methods for MTLF. Reference [125] developed a hybrid DL model for MTLF which integrate advanced LSTM, exponential smoothing, and the ensemble technique. This is a competitive method that also uses the ensemble approach. In general, MTLF has a pool of AI techniques that can be adapted or improved for the next generation smart grid.

c: LONG-TERM LOAD FORECASTING

LTLF is specifically developed for predicting grid planning, power consumption and upgrade of the generating unit of the power grid. Usually, it covers over a decade depending on the requirement. Though, it involves massive investment to build a modern power generating facility, hence, prediction accuracy and efficacy is paramount in this regard. Several AI/ML methods have been developed over time to tackle LTLF problems. Reference [72] demonstrated that the multivariate adaptive regression spline (MARS) technique as earlier mentioned, provide more precision and consistent outcomes than the ANN and LR paradigms when forecasting the link between load request and other ecological variables. Reference [126] proposed an innovative concept called the hybrid fuzzy-neuro model for LTLF. In addition, the Long Short-Term Memory (LSTM) model also find application in this area because of its ability to learn long-term dependencies in forecasting difficulties. In furtherance, [109] applied the LSTM-based RNN for the long-term dependencies in the electrical load time sequence for LTLF, where the technique had a positive index. Reference [127], [128] suggest too that an LTLF model with minute-hourly fine-tuning can have high accuracy when the LSTM network is applied. In other to resolve the challenges of exploding and vanishing gradient problems, [129] introduce a hybrid technique that combines gated recurrent unit (GRU) and LSTM. This hybrid technique showed superior performance for LTLF. Also, [130] proposed an LSTM-RNN model for this same task mentioned earlier. To get a holistic view in terms of performance and superiority, [131] compared several universally used AI/ML techniques which include the generalized regression neural network (GRNN), GPR, RNN, ANN, SVM, KNN, and ANN. The ANN displayed superior performance over the other techniques for LTLF as summarizes in Table 3 of the AI methods for LF.

2) REAL TIME FAULTS MONITORING AND DETECTION

There are some AI/ML approach which have been found useful in electric grid performance enhancement. These techniques were specifically proposed and developed to solve the problem of real-time faults monitoring and detection (RTFMD) in smart grids. To be precise, [132] developed an ELM-based technique for the real-time fault location detection of the grid following the extraction of features by deploying a wavelet transform (WT) then contrast it with ANN and SVR algorithms. Reference [133] introduced a GPR-based general probability ratio test to improve the RTFMD performance in solar PV grid systems. In [134], two ensemble approaches were employed to detect surreptitious false data infusion with a supervised and unsupervised classifier, respectively. In [135], an ensemble framework that integrates several AI/ML models for power grid disruptions rate analysis was proposed. The concept can detect faults in real-time with three layers of the degree of seriousness. Reference [136] is centred on high-impedance RTFMD in the power grid and suggested an ANN-based technique for resolving the dilemma with an accuracy of 98.7%. Reference [137] ELM is also employed for high-impedance RTFMD and is usually predicated on wavelet packet transform[138] recommends a technique for line trip fault projection in a power grid system that uses both the LSTM networks and SVM. An AI/ML-based discrete wavelet transform, and double channel extreme learning machine method was proposed in [139], to locate, detect and classify the faults in both feeder and transmission lines. To enhance the precision of line trip fault forecasting, [140] developed a stacked sparse auto-encoder-based system through PCA and SVM validating the applicability in practical data. The introduction of VPP and microgrids, which are cloud-based, proffer an effective and robust solution for the ever-growing alternative energy sources. However, in short/midtem, fault monitoring and detection in VPP and microgrids continue to raise serious concerns [141].

As such, [143] proposed a hybrid technique that integrates feedforward neural networks and S-transform for fault detection in the distribution side of the grid. In [145],

TABLE 3. Summary of methods for load forecasting.

Ref.	Aims and objectives	Method
[116]	STLF	RNN
[113]		DBN
[112]		Ensemble, statistic models
[106]		CNN, Ensemble
[80]		FCRBM
[114]		WNN, ANN
[112]		Ensemble
. [121-123]	MTLF	DBN
[123]		SVR
[124]		CNN, LSTM
[125]		LSTM, ETS, Ensemble
[129]	LTLF	LSTM, GRU
[72]		MARS, ANN, LR
[128]		LSTM, GRU
[130]		LSTM, RNN
[109]		LSTM
.[126]		LSTM
[127]		ANN Fuzzy
[131]		ANN, SVM, RNN, KNN, GPR, GRNN.

an ANN-based approach was proposed, and the outcome showed the efficacy of detecting the time and spot of faults. To deal with labelled and unlabeled data set, [146] recommend a hybrid-supervised ML algorithm consisting of DT and KNN model, for fault detection at both the distribution and transmission side of VPP and the microgrid network. To solve the challenge of isolation, islanding, and fault detection in smart grid, [142] developed an SVM-based system. The outcomes demonstrated improved indices compared to the conventional experiment-based techniques of a photovoltaic generating station [147] applied a PNN classifier for fault monitoring, detection, and diagnosis in the direct current side of a PV scheme. [148] developed a fault detection technique for PV built on ANN with over 95% accuracy. Realtime condition monitoring in wind turbines is crucial for enhanced protection by early detection of faults. Reference [149] investigated the efficacy of deep ANNs CNN AND RNN in wind turbine fault detection. In [150], the ensemble technique was presented as an effective method in energy theft detection. Table 4 gives a general summary of the various techniques for real-time faults monitoring and detection in the power grid.

3) POWER GRID STABILITY ASSESSMENT

Another area where AI/ML techniques can be deployed in smart grid is "grid stability". This is crucial because aside

TABLE 4. Summary of methods used in power grid FD.

Ref	Aims and objectives	Methods
[132]	Fault detection (FD)	ELM
[134]		Ensemble
[135]		
[142]		SVM
[147]	VPP, Microgrid FD	KNN, DT
[143]		ANN
[146]		
[148]	PV FD	PNN
[133]		GPR
[149]		ANN
[148]	Line trip FD	LSTM, SVM
[140]		AE, SVM
[136]	HIFD	ANN
[137]		ELM
[139]	Feeder/Transmission Line FD	ELM
[149]	WT FD	ANN
[150]	Energy theft	Ensemble
[146]	VPP/Microgrid FD	KNN, DT
[138]	Line trip FD	LSTM, SVM

from monitoring, and detecting a fault in the grid, stabilizing the grid is even more vital for optimal performance. The stability of the grid is in four categories which include frequency stability, small-signal stability, voltage stability, and transient stability [151], [152]. This is important for guaranteeing the safety and dependability of the power grid. Power grid stability can be described as the capability of the network to experience steady operation or to quickly adjust to steady-state operation after a disturbance. Disturbance in the system could be due to frequency and voltage spike, over/under load, theft, open circuit [153]. In addition, grid stability can be assessed however, conventional models for stability assessments are complicated and as such, involve substantial computational power since they depend hugely on precise real-time dynamic power grid models [127], [152], [154]–[156]. Due to the introduction of a wide-area measurement system (WAMS), and phasor measurement units (PMU), several AI/ML stability assessment approaches that are data-driven have been employed on power grid stability analysis.

a: SMALL-SIGNAL STABILITY ASSESSMENT

As the name implies, small-signal stability, or better put, oscillatory stability could be described as the robustness of the smart grid to withstand and maintain operation during or after an oscillatory perturbation, which is due to the magnitude of some factors earlier mentioned [157]. In the smart grid, this stability can be assessed using AI/ML approaches. In [158], a CNN-based technique was proposed for oscillatory stability assessment (OSA). The result, however, showed that the approach is effective to PMU noise with no reduction in performance even as the system expands in size. Reference [159] deployed a multivariate random forest regression (MRFR) approach for the OSA system with 18-lines and the outcomes presented how robust and precise the model was.

b: FREQUENCY STABILITY ASSESSMENT

Smart grid frequency stability is described as the capability of a grid to sustain operation or be at equilibrium frequency irrespective of the severity of the network upset or disturbance. Most often, instability of the grid is a result of a substantial discrepancy between load and generating source [152]. This, most times, becomes more obvious when there is a huge frequency deviation causing the facility to respond and eventually affect the system stability. To prevent this from occurring, some proactive and reactive measures have been proposed using AI/ML techniques. Reference [52] proposed and developed a hybrid paradigm that combined a frequency response concept with an AI/ML extreme learning model for frequency stability assessment (FSA). In addition, AI/ML algorithm could be deployed for frequency load shedding [175].

c: VOLTAGE STABILITY ASSESSMENT

Fluctuation can considerably affect the voltage stability of a power grid. Therefore, voltage stability assessment (VSA) techniques that can measure and predict the stability of the grid in real-time would be a proactive step for protecting the grid. Over the years, several AI/ML-based techniques have been proposed in VSA. Reference [121] develop a hybrid approach by combining the SVR and dragonfly optimization algorithm for real-time VSA. Reference [118] recommended a technique for VSA by utilizing an SVM. The findings revealed that the misclassification ratio of the SVMs is as low as 2% for practical power grids. In [119], a DT approach was employed for interactive VSA. Reference [117] developed an ANN algorithm to guesstimate the loading margin of the grid and showed the efficiency of the bus network. Table 5 summarizes the AI/ML techniques for the power stability assessment (PSA).

d: TRANSIENT STABILITY ASSESSMENT

Lastly on the power grid stability assessment is the transient stability assessment (TSA). The TSA ascertain if a power grid will remain harmonized following a substantial disruption internally or externally. Direct techniques and time-domain models are the two most generally deployed conventional techniques for TSA. Nonetheless, the rise in complexity of the current power grid poses a problem in making better choices on the conventional TSA techniques to be adopted. Luckily, the introduction of AI/ML techniques into TSA has provided an innovative approach to this problem through the utilization of big data gathered from the WAMS and PMUs. Reference [153] proposed ANN, decision trees and SVMs, as the three main AI/ML techniques for online TSA. These algorithms were compared using two sets of data. The findings demonstrate similarity in their performance indices for all three techniques, however, performance indices may differ concerning the granularity of the data set. In [165], two superior SVM techniques were built to resolve the conventional SVM constraint that lowers the occurrence of missed and false alarms respectively. Reference [176] deployed a trained ANN algorithm for forecasting online TSA. The results showed an encouraging performance. A hybrid technique that integrates ELM and trajectory fitting (TF) techniques was proposed for TSA. This approach demonstrated consistency and efficiency for the online TSA [160]. In [163], a deep neuro-classifier algorithm was proposed for TSA. The results showed the generality of the proposed concept. Another proposed method is the RNN-LSTM algorithm which has improved learning capacity from temporary data dependencies of the input dataset. A high precision supervised

TABLE 5. Summary of methods for the power stability assessment.

Ref	Aims and objectives	Methods
[144]	TSA	ANN
[160]		TF, ELM,
[161]		SAEs, CNN
[162]		NN, ELM ,Ensemble
[153]		SVM, ANN, Decision tree
[163]		ANN
[164]		RNN, LSTM
[165]		SVM
[166]		DBN
[158]		CNN
[167]	VSA	ANN
[168]		SVR, FL
[169]		SVR
[170]		SVM
[171]		Spectrum estimation method
[172]		Decision tree
[173]		Random Forest
[52]	FSA	ELM
[174]	OSA	PSO
[158]		CNN
[159]		MRFR

ML classifier which comprises the stacked autoencoders (SAE) and CNN was proposed by [161] for TSA related problems. Reference [162] proposed the use of an intelligent technique that ensembled neural networks, predicated on ELM with over 99% accuracy. The study of [166] explores the application of a deep belief network (DBN) algorithm for TSA with excellent precision, while the TSA solution for power system control was proposed by [158] using a trained CNN algorithm. These are possible techniques and algorithms that will be improved and adapted or adopted into the next generation smart grid.

4) AI/ML IN NEXT GENERATION SMART GRID SECURITY

Every cyber-physical system or network that is internet-oriented is susceptible to cyber threats and the next generation smart grid is not exempted. As such, to guarantee the stability of the grid, extra measures must be taken or put in place to secure such valuable assets. Several human orchestrated efforts have been deployed over the years, however, still shows some vulnerabilities hence advance approach such as AI/ML is proposed. The reasons for adopting AI/ML is obvious since personnel cannot work on the facility 24hours all through a year even when there is a shift in work schedules. Thus, need a system that can intelligently man, monitor and predicts the entire activities of the grid both online and offline, therefore rendering optimal security to the grid. Another reason supporting the deployment of the AI/ML approach is predicated on the fact that hackers or attackers ventures into developing codes, programs or bugs that alter the grid instructions codes and functional services hence, the grid is in dear need of an algorithm that can counter and predict hackers' activities. Furthermore, AI/ML algorithms can perform pen-test and alert the operators of the possible vulnerabilities in the system as a proactive measure. Security risk in smart grid is categorized into three broad classes which are: (a) attempts to compromise the confidentiality of data on the grid for instance false data injection into the software-defined smart-meter and substation concentrator (b) attempts to infuse threat services like operational failures, synchronization loss, power supply interruption, and (c) system-level threats that attempt to take down the grid, like hijacking the radio communication system, denial of service/distributed denial of service, and network barge-in by strangers (i.e. a hacker attempting to use the communication link to piggyback unauthorized traffic over the network or use a disguised radio to capture and transmit smart grid data). Other consequences of cyber-attack are complete blackouts, social welfare damages, and cascading failures just to mention but a few [191]. AI/ML approach to the smart grid are either statistical based or rule-based. But for the fact that this investigation is considering a soft approach, it will be looking more into rule-based or different algorithms for securing the smart grid. Several techniques on smart grid security have been proposed and develop over the years [188]–[192]. In [177], a combined game theory, fuzzy cluster, and RL agile model were proposed to analyze the security location and condition for the smart grid. Reference [184] proposed an intrusion detection paradigm for smart grid. This model is predicated on the whale optimization-trained ANN algorithm with only a single hidden layer. Reference [185] developed a stacked denoising autoencoder (SDAE) neural network algorithm to detect and label four types of cyberattacks in the smart grid. The techniques were found to be efficient with a precision of over 90%. To uncover malicious voltage control activities in the low-voltage distribution grid, the study proposed the use of an ANN-based technique in [181]–[182] while [185] employed an RL technique for detecting cyberattacks. The SVM method has also been found useful for detecting cyberattacks in [180]. In the study, an SVM-based technique for detecting covert cyber deception assault was proposed. The outcome of [178] showed the dominance of a quasi-supervised model built on domain-adversarial training to transfer the data of known cyberattack occurrences to identify recurring risks in dissimilar load patterns and hours. The isolation forest technique was used in [181] to detect the threat with superior performance while [182] contrasted various AI/ML-based techniques for securing the smart grid. Lastly, [190] integrated random forest and CNN algorithm for energy theft detection. This technique has positively affected power supply quality and operation cost considerably. Table 6 summarizes the AI techniques for smart grid security.

TABLE 6. AI methods for smart grid security.

Ref	Aims and objectives	Methods
[177]	Intrusion detection	FL, RL, game theory
[178]		Domain-Adversarial Learning
[179]	Detect malicious voltage control actions	ANN
[180] [181] [182]	Detect covert cyber deception assault	SVM, Isolation Forest
[156]	Attack detection	KNN, SVM
[183]		RL
[184]		ANN
[185]		SDAE
[186]	Review	Data-driven approach
[76]		DL, RL
[187]		Big data, ML
[188]		ML
[189]		AI
[190]	Power theft detection	random forests, CNN,

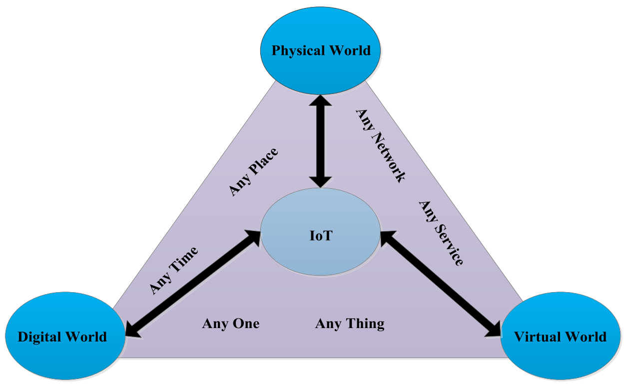

FIGURE 26. IoT with its connections and associated things [193].

IV. INTERNET OF THINGS IN SMART GRID

Internet of Things (IoT) as the name implies, is a pervasive technology that aid the interconnection of anyone or thing, any time or place, and any network or service respectively, as shown in figure 26. It is one of the disruptive technologies of the 21st century and a component of the fourth industrial revolution, which has found application in nearly every sphere of human endeavours. This section discusses the roles and benefits of IoT on the smart grid. The role of IoT in the smart grid is that it connects the grid elements such that the data from each element on the grid are extracted and used in analyzing the grid. These big data can be trained by an AI/ML algorithm as previously discussed and use for predicting any activity such as load balancing, security attack, and most importantly seamless communication between devices on the grid. This in turn, help the power utility companies for proper load shedding planning and other policy/regulations.

A. IoT APPLICATION AND SERVICES IN SMART GRID

As earlier mentioned in previous sections, IoT plays an integral role in supporting the power grid. For instance, the sensing and processing capabilities of IoT enhance smart grid functionalities like stability, accuracy, self-healing, processing, alerting, and disaster recovery. Integrating IoT into the smart grid has significantly helped the advancement of smart terminals like meters, sensors, data concentrators, and radio link devices. IoT also supports the reliability of data exchange in wireless link infrastructures within the smart grid facility from generation up to customer utilization. Several scenarios depict the usefulness of IoT within the smart grid value chain. On the generating side, IoT devices (sensors/transducers) are used in monitoring power generation from all kinds of energy sources (renewable, and nonrenewable) and forecast required power to deliver to the customers. Though, power forecasting requires AIoT capabilities which will be discussed later. IoT is used to obtain power consumed, monitor, dispatch, and protect transmission and feeder lines, substations, and pylons, manage and regulate equipment. On the customer end, IoT measures parameters like interoperability between different networks, power consumption, charging and discharging of EVs, and power demand. Other scenarios are its application in AMI [193], to collate data, measure anomaly, exchange information between smart meters, monitor electricity quality and distributed energy and analyze user consumption patterns using the AI/ML component. IoT enables smart homes to interact with users and the smart grid, control smart appliances, meet marketing demand, improve services, improve QoS, monitor renewable energy, and extract power consumption data collated by the smart meters. As mentioned earlier, IoT can help in transmission and feeder line monitoring through the support of 5G wireless broadband (slicing). In addition, faults in the transmission and feeder lines cannot be monitored but discovered and resolved.

1) IoT ARCHITECTURES IN SMART GRID

Various IoT network architectures have been developed for smart grids. These architectures fall into four categories of layers [87]–[90] as shown in Table 7. Reference [85] proposed a three layers architecture. In the design, network devices, smart meters, and communication protocols are found in layer 1. The radio device in charge of receiving data at the fusion centre is found in layer 2, while AI systems that support decision making and billing are located in layer 3. In [51], [52], a three-layer architecture that comprises the perception layer (device layer), network layer, and application layer was proposed as illustrated in figure 13. In the Perception layer (device layer), all types of sensors, readers, tags, and sensor equipment that are known for extracting grid data are found in this layer. The network layer, on the other hand, includes all classes of wireless communication networks standards but not limited to TVWS [5], ZigBee, private networks, Wi-Fi, fibre optics, cable broadband, public switched telephone networks (PSTN), GSM network up to 4G and the Internet, collate and transmit the data extracted from these IoT sensors in the device layer to the management and information centres which house the application layer for processing, analysis, control, and access to the backbone network. The main function of the application layer is to processes the data received from the network layer to monitor smart grid IoT devices in real-time as illustrated in figure 13. A variety of IoT technologies like SDN is used to achieve a wide range of IoT applications in the smart grid. Finally, the application layer is solely in charge of data processing, integration and interfacing other grid resources [193]. A four-layer was proposed in [89]. This includes the device layer, network layer, cloud management layer, and application layer. However, the device layer is subdivided into two sub-layers which are the thing layer (IoT sensors, actuators, smart meters, and smart tags) which intelligently sense grid ecosystem, collate information, and regulator user appliances. The gateway layer (which comprises a controller, radio link units, a display unit, and a memory unit) is responsible for interconnecting the grid component of the thing layer. The network layer functions remain unchanged as discuses previously. The cloud management layer is responsible for storage, analysis, and user management. In addition, the application layer delivers grid services to end-users such as

TABLE 7. Layer models for IoT architecture in a smart grid.

Ref.	Layer 1	Layer 2	Layer 3	Layer 4
[85–88]	Perception	Network	Application	Application
[89]			Cloud management	
[91]			Application	Social
[90]	Terminal	Field Network	Remote communication	Master station system

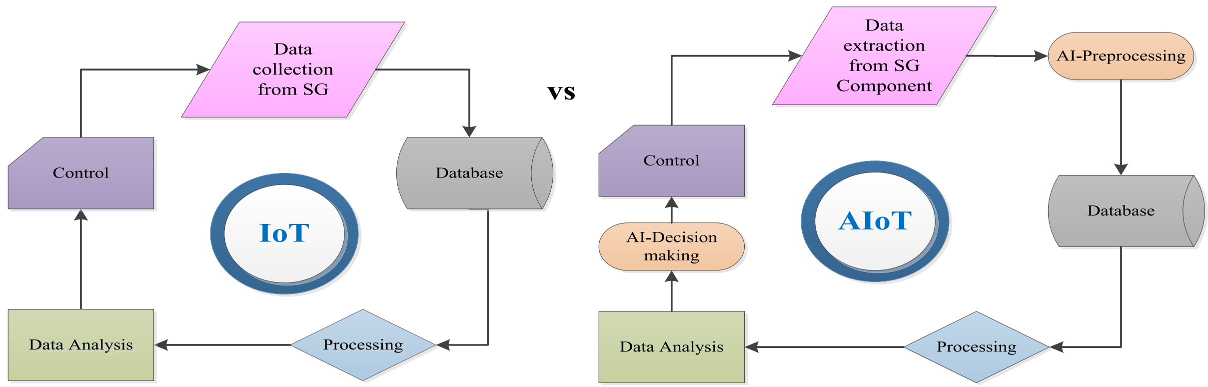

FIGURE 27. Artificial Intelligence of Things (AIoT) in smart grid [195].

dynamic pricing/billing, demand response management, and energy management. Reference [91] studied previous three-layer and four-layer models in [85]–[89]. However, proposed a four-layer concept that comprises the previous three layers with an additional social layer on top of these three layers. The responsibility of the social layer is policy, and regulation of the IoT applications to avoid any form of exploitation, abuse, or misuse to all parties in the value chain. Reference [90] proposed a four-layer which comprises the terminal layer, field network layer, remote communication layer, and master station system layer. As it is known, the terminal layer includes remote terminal units, smart meters, and all smart devices. The field network layer has the same functionalizes as the network layer previously discussed. The remote communication layer contains specifically, a wireless WAN such as TVWS [194], [195], 3G or 4G wireless cellular networks. These are services with enhanced spectrum efficiency. The master station system layer comprises the command-and-control structures for the different sections of a smart grid, from generation up to distribution end. In all of this, the next-generation smart grid will be deploying a 5G intelligent network, that is more software-defined.

B. ARTIFICIAL INTELLIEGENT OF THINGS (AIoT) IN SMART GRID

In this section, IoT is described as the connection and communication of smart grid elements with each other through the internet. However, as a key technology for the enhancement of both current and future smart grids, the incorporation of AI on IoT makes its applicability on the smart grid comprehensive as shown in fig. 27. AI has proven to be the real game-changer for the realization of smart systems with smart grids not excluded. In fact, what makes the next generation smart grid different from the current smart grid is the integration of AI in all components of the grid [195]. In this light, the names of the components of the next-generation smart grid thus become intelligent/AI sensor, meter, substation, feeders, network controlled network management centre and so on respectively. With AI, on IoT, the name changes to the artificial intelligence of things (AIoT), which implies that networked things need AI to become truly intelligent or, things become truly smart when AI is applied. The potential of IoT on the smart grid can be fully appreciated with analytics. For example, power consumers and personnel working on the grid facility can manage and monitor connected things (smart meters, sensors, etc.) remotely. Also, smart devices on the grid (smart meters, sensors, etc.) can learn from their activities as well as from each other and continue to evolve in this way. This means that smart devices are increasingly able to make their own decisions with their jurisdiction. For instance, with AIoT, the power component can heal itself during and after disturbance and reroute power to the neighbourhood based on its arrived decision. These, in turn, makes the grid more independently and safe through continuous self-optimization. Furthermore, AIoT creates added value from the huge data (big data) extracted from these smart grid devices. In practical terms, extracting and gathering data is only valuable if it is analyzed and put into context [196]. This is where AI comes to bear as a complement to IoT by processing and analyzing the data from the grid components. The outcome of the data analysis enables utility companies to draw precise inferences and ultimately improve service delivery, enhance processes, and secure their status as a major competitor in the energy sector. AIoT devices are becoming increasingly independent, providing huge data that can be translated and applied, thus increasingly becoming more useful for corporations. Other benefits of AIoT are the fact that the smart grid is a complex facility and as such, AIoT can aid personnel in a specialized department by multitasking with accuracy thus, saving the utility companies personnel expenses [196]. Lastly, communication with machines (system and devices) will turn out to be natural, moving away from the conventional display operation and to more human-machine interaction.

V. 5G AS AN ENABLER FOR NEXT GENERATION SMART GRID

The motivation for referring to the 5G network as an enabler for the next generation smart grid is predicated on many reasons as summarized in Table 2. Some of these reasons are but are not limited to its software-defined nature, cognitive or AI capabilities, network intelligence, self-healing, global-awareness, autonomous, etc. However, the few key motivations for integrating 5G into the current grid system which eventually gives birth to the proposed next/future generation smart grid are:

- *Network Management Become Simpler:* By integrating 5G into the current smart grid, network management become simpler [197]. The SDN/AI controller in the next generation smart grid will have a global view of the next-generation smart grid communication network. Based on the application requirement and other requirements like the hidden network traffic condition, the SDN/AI controller will alter the policy and regulation of processing packets swiftly and effortlessly in the infrastructure/data plane where switches, sensors, and other power components are found. Without an intelligent network like 5G which is software-defined, network orchestration and management will demand physical or human intervention by the utility companies to re-program all the components in the infrastructure/data plane to change their packet forwarding policy [38].
- *Isolation of Diverse Traffic Types and Applications:* In the next generation smart grid, different kinds of traffic classes are generated by different intelligent field devices e.g., sensors, AI agents, meters etc. These traffic classes are event-driven and are generated at regular intervals. By integrating 5G in next the generation smart grid, diverse traffic classes and applications are effortlessly isolated [198]. Furthermore, 5G oriented next generation can adjust power meter unit measurement (PMU) information traffic corresponding to the design specification of receiving field devices.
- *Traffic flow Ranking*: In the next generation smart grid ecosystem, crucial measurement information and instructions set must be sent on a well-timed basis and require high-level importance than the regular traffic. 5G can assist in this respect by ranking the traffic and give top priority to sensitive time crucial commands and measurement information in an adaptable way [199]. Also, as earlier mentioned, the 5G based programmable SDN controller in figure 13 will have a universal network view. Thus, will aid to orchestrate traffic flows (ranking) effortlessly.
- *Virtual Network Slices:* one attractiveness of the 5G network is in the creation of virtual network slices for the next generation smart grid based on domain or geographic consideration (generation, transmission and distribution or security zones) [200]. For example, there can be a slice for the metering side of the network. This implies that it can have its virtual network slice dedicated to the metering network or even sensor network. This will enable the metering system to have its security, policies, management, and quality of service (QoS) regulations.
- *Resilience:* Next-generation smart grid pliability can be easily attained via the 5G functionalities by switching the data traffic flow from breached wired link to wireless link [36]. By so doing, enables the next generation smart grid to be even more reliable. Similarly, the self-recovery process which helps to achieve a robust PMU network can simply be achieved using 5G. They are but are not limited to;
- *Ultra-Fast Failure/Fault Recovery:* The next generation smart grid largely depend on communication links. However, if there is a crunch (congestion, interruption, etc.) on the communication links, then the next generation smart grid will cease to function optimally. Hence, link failure/fault detection and recovery is vital. By introducing an intelligent network like 5G into smart grid architecture, it is possible to achieve ultra-fast link failure/fault recovery [199].
- *Avoidance of Voltage Failure and System Overload*: Sometimes in the electric grid system, It happens that the power network could be overloaded, and as such, voltage collapse is inevitable. It, therefore, implies that apt and timely load balancing through a load shifting or sharing mechanism will avert voltage failure in the grid. This can be achieved through the 5G's AI load balancer which is one of the features of the AI-controlled network management centre of the next generation smart grid [38], [92].
- *Standardization/Interoperability:* Currently, the 5G network technology is not network provider or manufacturer specific rather runs on an open standard, though a consensus is ongoing. However, several categories of communication network field devices can be simply

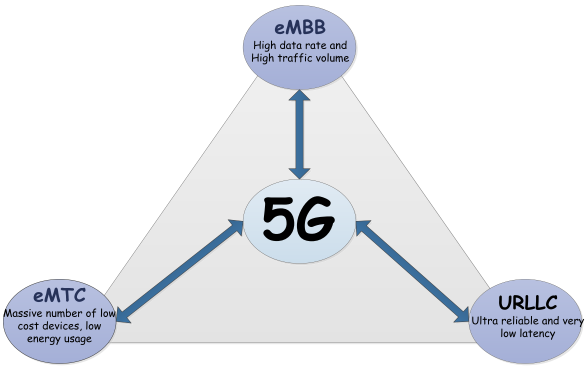

FIGURE 28. 5G network services for next generation smart grid.

managed, programed or re-programed, and their compatibility and connectivity is not a challenge within a next-generation smart grid [44].

- *Electric vehicle Integration in Next-Generation Smart Grid:* We cannot investigate next-generation smart grids as a proposed concept without discussing the electric vehicle. An Electric vehicle (EV) is considered a potential power plant on the move when deployed on a massive scale. Picture an EV moving on highways carrying battery stored energy. The energy stored in this EV can act as an emergency power source/plant for cities in times of urgency. Although, proper design of a robust energy management system for EVs is needed which easily update the state of these EVs, as EVs are generally movable. Nevertheless, the mobility of the EV and their status update will generate a lot of big data that could be used to analyze the EV behavioural patterns. Furthermore, connecting and re-connecting decisions of EVs will require software reconfiguration (coding/programming) in the next generation smart grid system. Through the assistance of SDN which is a component of the 5G, the management difficulty will be reduced substantially [197].
- *5G's Run/Execution time Configurability:* From inception, 5G is proposed to deliver speed both in code, command or program execution depending on the task at hand. With the assistance of 5G's SDN, runtime or execution time configurability, the quality of service (QoS) of the next-generation smart grid communication network between power nodes and terminals will be significantly enhanced, respectively.

In concluding this section, it is imperative to state that 5G roles as an enabler for the next generation smart grid are predicated on the fact that all intelligent nodes, terminals, feeders, substation, meters, etc., within the grid, need to communicate with another for synergy with little or no delay using enhance broadband strategies. As such, the 5G network services have been grouped into three major types by the International Telecommunication Union (ITU) which are Enhanced Mobile Broadband (eMBB), Ultra-reliable and Low-latency Communications (uRLLC) and the Massive Machine Type Communications (mMTC) [37]–[40] as shown in figure 28. The Enhanced Mobile Broadband (eMBB) is a service specifically for bandwidth-hungry applications and requirements such as real-time fault monitoring and detection with high-definition (HD) resolution. For example, internet equipped robotic drones with HD camera monitoring lines, feeders, substations, etc., from generation up to distribution thereby complementing the efforts of the AI sensors planted on the grid as shown in figure 10. Secondly, the essence of incorporating 5G is to deal with the challenges of delay therefore, the Low-latency Communications (uRLLC) service of the 5G is to address mission-critical services such as remote management of terminals, the software update for the controller and other intelligent applications, real-time analysis/decision making, EVs (self-driving cars) [39]–[42] etc. Machine Type Communications (mMTC) is a 5G service for high-volume communication between dense IoT nodes and applications such as intelligent metering, smart sensors, building, smart cities, smart homes and assert tracking of substations, feeders, and all field power devices to mention but a few.

VI. ARCHITECTURE FOR THE NEXT GENERATION SMARTGRID

The diagrammatic layout of the proposed next-generation generation smart grid is shown in figure 29. It is the incorporation of the entire ideas and figures discussed in the course of this survey. The three major components namely the AIoT (artificial intelligence and IoT) and 5G are illustrated in the diagram [195].

VII. CHALLENGES AND SOLUTIONS OF THE NEXTG-GENERATION SMARTGRID

The next-generation smart grid (future grid) is proposed to deliver a lot of benefits to the power consumers, utility companies and the government in both the short and long term. As earlier mentioned in this study, any complex cyber-physical entity that is internet-oriented is prone to a lot of challenges either by design or by eventualities. In this section, several challenges with possible and corresponding solutions will be x-rayed. The three most notable challenges of the next-generation smart grid include security (preserving data security and privacy), standards interoperability (equipment and protocol compatibility) and cognitive access to unlicensed radio spectra like TVWS [201]. Others are the incorporation of renewable energy, big data fast storage and analysis, explainability of AI algorithms, limitations of AI algorithms, government support, personal/consumer education.

A. SECURITY

Security is the most pressing issue begging to be addressed in the smartgrid system. This is because once the grid is digitalized (integration AIoT with duplex command and control ability), it is visible to the internet and as such, prone

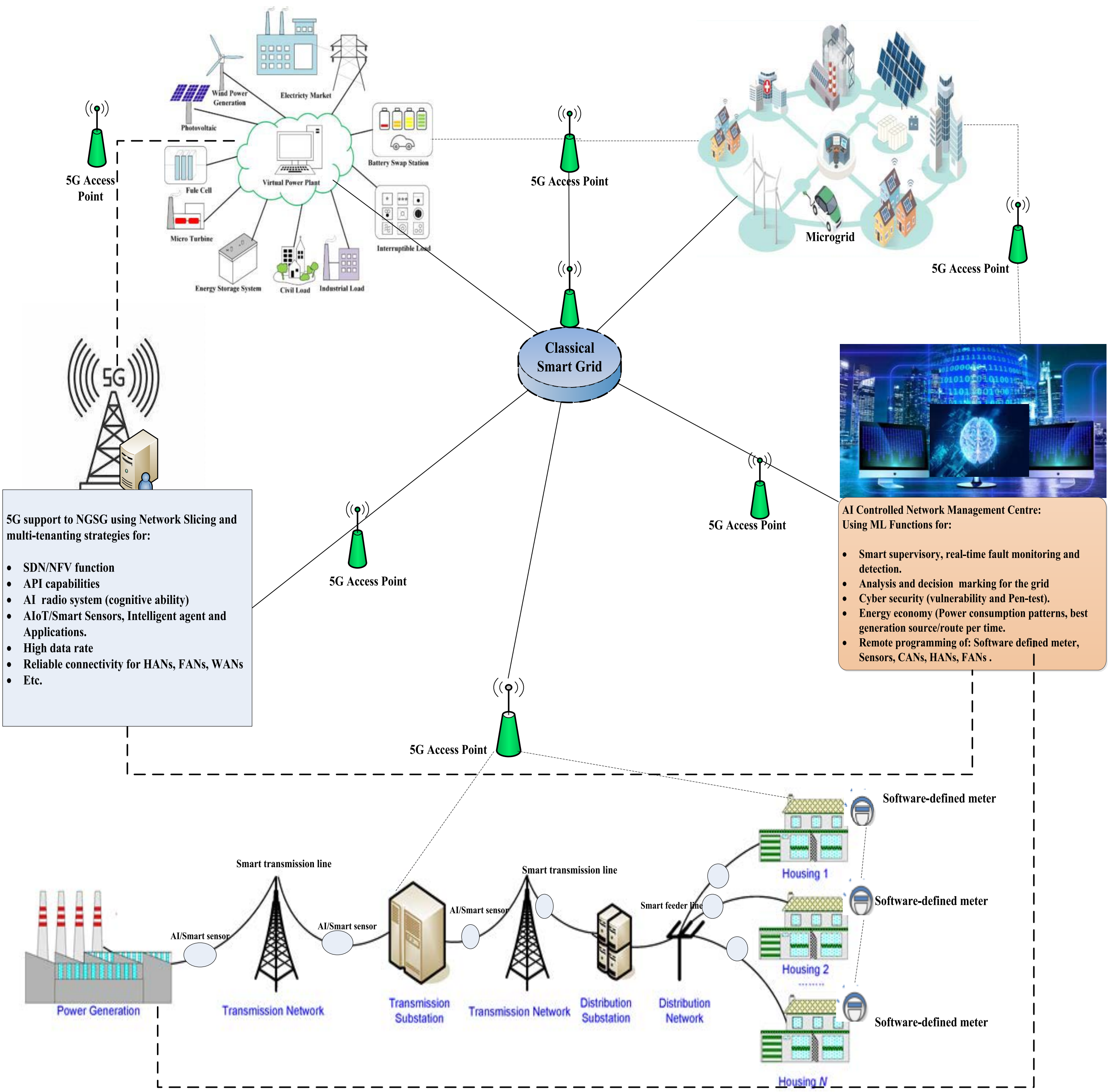

FIGURE 29. Network architecture for the next generation smart grid.

to all sorts of malicious attacks. These AIoT components within the smart grid that measure, and extract data must be put at alert. For instance, sensors, smart meters, substations, and intelligent feeders, if compromise, then it is possible for hackers to extract some vital information about consumers' behavioural patterns and therefore it must be assured of confidentiality. Reference [38], [202] have proposed how SDN can be employed to secure the smart grid. But, the SDN has some security problems as well. For example, notwithstanding the SDN control plane being the hub of security to the smartgrid, however, it could be affected by attacks and thus become susceptible. Besides, employing a sole SDN controller in a vast entity like a smart grid is a source of failure. Some approaches can be deployed to solve these pressing security issues in the smart grid. They include:

- *Blockchain:* Blockchain has shown potency for securing the grid as it did in the cryptosystem using decentralized authentication, authorization. The potential of decentralized databases to eradicate cyber-attacks has proven to be so efficient that even global institutions recommend its application. This is a good approach such that the grid operation is not in the hands of a single vendor, ISP, or supplier. The decentralized databases imply that an attack on a database of the grid, e.g., one generation plant, cannot affect the operation of the entire network.

- *Decentralized SDN controller:* One method to deal with this single point vulnerability of the SDN controller is to decentralize the SDN control plane. Such a distribution of the SDN control plane will lessen the menace of DoS attack to a large extent nevertheless another issue occurs that is connected with the interaction between SDN controllers [36], [200]. Picture a situation where a malicious terminal disguise as an SDN controller in a distributed SDN settings to gain access to the network. Then, such type of problem in this context, need to be dealt with using a *decentralized SDN Blockchain controller.* These intelligent solutions for smart grid security also have trade-offs between performance and security which is another area of research.

B. INTEROPERABILITY AND STANDARDS

The smart grid is a complex system by design and as such, to cover the entire grid structure, a lot of smart devices and equipment are needed, which must be compatible with one another. Therefore, standards provide a lingua franca (common language) that allow interoperability (exchange of information) between systems and devices from different vendors/manufacturers. Interoperability encourages an open architecture of technologies and their software systems to permit interaction with other systems and technologies. To achieve robust smart grid functionalities, technology implementations must link smart devices and systems involving hardware and software. In this regard, AI and SDN can assist a lot in interoperability challenges. Imagine a packet sent from a smart meter using ZigBee (IEEE 802.15.4g) to an intelligent substation using Wi-Fi (IEEE 802.11), if not data and communication driven interoperability proposed in [32], that would not have been possible. Other standards are IEC 61968 and IEC 61970 standards which provide models of transmission, distribution systems, as well as restricted models of power generation, known as the CIM (Common Information Model). IEC 61850 is a standard for substation automation system and renewable energy resources (PV, hydro & wind and other), a basis for field equipment communications. The EN 62056 standard for electricity metering (data exchange for meter reading, tariff, and load control). EN 13757-1 for communication systems for meters and remote reading of meters. The IEC 61968-9 for system interfaces for distribution Management (interface standard for meter reading and control) [202].

C. ACCESS TO UNLICENSED RADIO BANDS

A smart grid could be considered as a tenant network using the network slicing technique of 5G. However, it must surely use a radio spectrum for communication. Despite 5G network slicing, using unlicensed radio spectra like the Television White Space (TVWS) [204] is still one of the solutions to the problem of spectrum scrunch/scarcity. The TVWS if accessed by the 5G radio could solve congestion problems or over-dependence on the licensed band since mmWave beyoung 30GHz is a bit contentious in terms of health implications.

D. INTEGRATION OF RENEWABLE ENERGY

Highly integrated renewable energy is a key characteristic of smart grids. However, it presents several significant challenges due to the variability and unpredictability of renewable energy in which the power output can vary abruptly and frequently [44], [205]. This problem can be solved by embracing microgrid technology and VPP strategies. Islanding also could help in solving these challenges, but we cannot succumb to the disadvantages alone when the advantages out ways the disadvantages.

E. EXPLAINABILITY OF AI ALGORITHMS

Generally, AI algorithms have the black box problem, and they are not interpretable or explainable. A black box refers to a function where you know the signature of the inputs and outputs, but figure out how it determines the outputs from the inputs. This is an obstacle that AI algorithms currently face. [206] provide a comprehensive discussion on this domain. The development of the second skill will help in this regard. Imagine when personnel manning the smart grid facilities are trained on black-box analytics. This will eventually get read of the myth of black box in explainability.

F. LIMITATIONS OF AI ALGORITHMS

The development of AI/ML technologies has greatly influenced the deployment of AI on smart grid systems. However, every technique limitation should be considered before applying them to the smart grid. This is were standardization will play a major role because different AI/ML expert has its methodology. Thus, a consensus on the standard to use will go a long way to solve these issues. Take for instance the challenge of security in smart grid. While some AI algorithm expert will propose and deploy SVM, other will prefer ELM, KNN, CNN or DT as the case may be.

G. BIG DATA FAST STORAGE AND ANALYSIS

One more major problem is, by what means to continue enhancing the performance of storage and retrieving huge smart grid data for AI applications robustly. This problem can be tackled with the integration of edge technology like parallel cloud storage systems which includes EC2, Google cloud, i-cloud just to mention but a few.

H. GOVERNMENT SUPPORT

For the current smartgrid to evolve to the future grid, there must be an enabling environment provided by the government. Financial resources are not the only obstacle to initiate a future grid. The political will of the country play a significant role in this regard. It needs a government with strong political will with clear and effective energy policy for a successful implementation of next-generation smart grid.

I. PERSONNEL AND CONSUMER EDUCATION

Smart meters want to be software-oriented as such, consumer education and participation is an important component of the successful implementation of the smart grid. A significant portion of the smart meter benefits relies upon consumer engagement. So, the consumers have to be educated to get the maximum benefit. Also, personnel working in the smart grid facility need to be trained on coding (programming) since all the devices incorporate AI, hence the need for the ''second skill'' is inevitable.

VIII. PROSPECT OF AI IN SMART/FUTURE GRID

The objective of smart grids is to achieve a full self-learning system that will be responsive, adaptive, self-healing, fully autonomous, and cost-effective. Future directions and opportunities to achieve the advanced smart grid systems are predicated on the following:

- *Customer activities pattern forecast:* Fog computing has aided the evolution of next-generation networks and the energy demand management aspect is vital for handling the consumers' interaction in the power grid. The knowledge through the learning of consumer behavioural patterns in power utilization, significantly add value to the demand response tasks on the customer end.
- *Integration with cloud computing:* To achieve a fully self-learning smart grid system, the integration of AI with cloud computing can enhance security and robustness and minimize outages will play a more important role in smart grid systems [33].
- *Fog computing:* Fog computing attempts to clean up the raw data with its jurisdiction instead of forwarding it to the cloud. By providing on-request resources for computing, fog computing has numerous benefits like security [177], elasticity, energy savings and scalability of the grid [14]. Reference [207]–[209] investigated the incorporation of fog computing into the smart grid. Fog computing will play a greater role in the big data of the future smart grid system.
- *Transfer learning:* The absence of tag data has been one of the core problems for smart grid analytics. Transfer learning reduces the time frame for training the data set. This has encouraged investigators to adopt this technique to solving the dilemma of data set insufficiency. Also, deep transfer learning tasks have gain prominence as they could be applied in smart grid systems [210].

IX. LIMITATIONS OF THE SURVEY

This study has taken an extensive investigation of how to improve the current smart grid to the next generation smart grid through the integration of AI/ML, IoT and the 5G network. However, there is no way this study can exhaust all areas of these three major areas whose research domains are expanding daily considering, the rise in challenges facing the smart grid and the urgent need to proactively address it by proposing novel approaches that could be built on.

X. CONCLUSION

The fact remains that the electric grid has evolved from the old-fashioned electromechanical system to a more modern smart grid. There have been tremendous effort to enhance this transition with employment of several integrated solutions from blockchain to IoT, and 5G. This implies that both past solution and our proposed solution aim at addressing common challenges in a different way using different integrated techniques. However, it is a fact that no system is truly smart or intelligent without the infusion of AI/ML strategies. Hence, this survey discussed the next-generation smart grid (future grid) that leverage disruptive technologies like AI, IoT and 5G for robust reliability, security, resilience, and overall system performance. The next-generation smart grid comprises unique features like smart generation (which includes microgrid and VPP), smart transmission lines (lines with embedded AI-sensors), intelligent feeder and substation, programmable sensors (AI-sensor/intelligent-sensors), software-defined meters (instead of smart meters), AI-controlled network management centre (Unmanned), etc. Furthermore, instead of the usual not too flexible 3G, 4G network as the communication backbone, the next-generation smart grid will deploy 5G. The reason(s) for this is because the 5G network is an intelligent network with network slicing abilities that the grid can leverage by renting the slices. Secondly, the 5G is a software define network and that makes it robust to attack with the help of the controller security features, and the interoperability capabilities help to interface several AIoT-devices and components made by different vendors. Also, its NFV features make its operation, navigation and troubleshooting easier. The grid AI/ML algorithms empower it for load prediction, power and frequency stability, fault monitoring and detection, etc. All these make the next generation smart grid different from the classical smart grid. Of course, there will be challenges like the redundancy of personnel when AI devices/strategies are deployed on the entire power grid system. However, training and retraining of manpower on the ''second skill'' is inevitable. Our future work will dwell on the implementation feasibility through simulation, the discussed integration of AI, IoT and 5G for next-generation smart grid, using Matlab, NS2/NS3, Opendaylight and Mininet [211]–[216] with the corresponding comparison with existing literature.

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EBENEZER ESENOGHO (Member, IEEE) received the Diploma degree (upper div.) in computer engineering, in 2002, the B.Eng. degree (Hons.) (upper-div.) in computer engineering, in 2007/2008, the M.Eng. degree (upper-div.) in electronics/telecoms engineering from the University of Benin, in 2011, where he lectured, and the Ph.D. degree in electronic/telecoms (5G cognitive networks) from the University of KwaZulu-Natal, in 2016. He was involved in research and teaching with the Centre for Radio Access and Rural Technology, Centre of Excellence, University of KwaZulu-Natal, funded by Telkom SA, Eskom, Alcatel, Ericsson, and Huawei. He was previously hired into the prestigious Global Excellence and Stature (GES) Postdoctoral Research Fellowship at the University of Johannesburg, Auckland Park, under the Center for Telecommunication Research (CfT), Institute for Intelligent System (IIS), to pursue further research. He has authored/coauthored several peer-reviewed journals and conference papers, chaired sessions in conferences, and reviewed for some notable ISI/Scopus journals in his field. His research interests include but not limited to the fifth generation (5G) wireless networks, cognitive radio networks, networks security/cybersecurity, smart grid networks, the IoT/IoE, SDN/SDR, wireless sensor networks, artificial intelligence/machine learning, big data, and mobile/cloud computing, and visible light communication. He is a registered Engineer in Nigeria and a member of the South Africa Institute of Electrical Engineers (SAIEE) and IEEE Region 8. He was a recipient of several grants/scholarships/awards/fellowships, including the CEPS/Eskom's HVDC 2013, CEPS/Eskom's HVDC 2014, J. W. Nelson 2015, GES 2017, 2018, and 2019/20, and F'SAIT Fellowship 2021. He was a DST/NRF research delegate to the H2020-ESASTAP EU-South Africa STI Cooperation on Strengthening Technology, Research, and Innovation in Vienna, Austria, to woo investors.

KARIM DJOUANI (Senior Member, IEEE) was the Manager of the national and European projects with the LISSI Laboratory, in July 2008. From July 2008 to December 2010, he was seconded by the French Ministry of Higher Education to the French South African Institute of Technology (F'SATI), Tshwane University of Technology (TUT), Pretoria, South Africa. Since January 2014, he has been the DST/NRF SARChI Chair in enabled environment for assistive living. He was appointed as a Full Professor at F'SATI, TUT, in January 2011. He is currently leading the LISSI Laboratory, SIRIUS Team, University of Paris-Est, Champs-sur-Marne, France. He is also currently a Full Professor, a Scientist, and a Technical Group Supervisor of pattern recognition, soft computing, networking systems, and robotics. His research interests include development of novel and highly efficient algorithms for reasoning systems with uncertainty as well as optimization, for distributed systems, networked control systems, wireless *ad-hoc* networks, wireless and mobile communication, and wireless sensors networks as well as robotics.

ANISH M. KURIEN (Member, IEEE) received the D.Tech. degree in electrical engineering from the Tshwane University of Technology (TUT), Pretoria, South Africa, and the Ph.D. degree in computing (through co-tutelle) from the University of Paris-Est, Champs-sur-Marne, France, in 2012. He is currently the Node Director of the French South African Institute of Technology, TUT, where he is responsible for post-graduate programs with the Department of Electrical Engineering. He is also involved in research projects in wireless communications, radio resource management, and mobile networks optimization. He is involved in a number of industrial projects related to wireless networks and technology development. His research interests include feature extraction and pattern recognition algorithms applied to mobile networks subscriber classification.