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Review

A Conceptual and Systematics for Intelligent Power Management System-Based Cloud Computing: Prospects, and Challenges

Ahmed Hadi Ali AL-Jumaili [1,2,*], Yousif I. Al Mashhadany [3], Rossilawati Sulaiman [1,*] and Zaid Abdi Alkareem Alyasseri [1]

1 Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, Bangi 43600, Malaysia; zaid.alyasseri@ukm.edu.my
2 Computer Centre Department, University of Fallujah, Anbar 00964, Iraq
3 Department of Electrical Engineering, College of Engineering, University of Anbar, Anbar 00964, Iraq; yousif.mohammed@uoanbar.edu.iq
* Correspondence: ahmed_hadi@uofallujah.edu.iq (A.H.A.A.-J.); rossilawati@ukm.edu.my (R.S.)

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Abstract: This review describes a cloud-based intelligent power management system that uses analytics as a control signal and processes balance achievement pointer, and describes operator acknowledgments that must be shared quickly, accurately, and safely. The current study aims to introduce a conceptual and systematic structure with three main components: demand power (direct current (DC)-device), power mix between renewable energy (RE) and other power sources, and a cloud-based power optimization intelligent system. These methods and techniques monitor demand power (DC-device), load, and power mix between RE and other power sources. Cloud-based power optimization intelligent systems lead to an optimal power distribution solution that reduces power consumption or costs. Data has been collected from reliable sources such as Science Direct, IEEE Xplore, Scopus, Web of Science, Google Scholar, and PubMed. The overall findings of these studies are visually explained in the proposed conceptual framework through the literature that are considered to be cloud computing based on storing and running the intelligent systems of power management and mixing.

Keywords: power management; state of charge; battery aging; dc-device; power consumption; renewable energy; cloud computing

1. Introduction

In the last decade of industrial progress, the world economy has shifted from cheap energy to expensive fuel consumption. However, industrialization necessitates an increasing amount of energy, which is a condition for humanity's economic prosperity and sustainability [1]. Awareness of the relative constraints of traditional energy resource exhaustion is essential; however, the restricted energy supply from RE sources is necessary. Thus, these two factors have not only a two-fold influence on energy and economic development only, but also on the environment. A cyber-physical system in which electrical components are controlled by a computer and connected to a network of other computer-controlled physical equipment is known as a power grid [2]. The power grid includes the movement of electricity and information between the power grid and control centers [3]. Safe and reliable grid operation requires controlling the energy flow such that the supply and demand can be well balanced in real-time [4]. It is necessary to ensure that information flows as intended as any disruption in information flow will affect the correct conduct of energy flow and the system's safe and dependable functioning [5,6]. In traditional power networks, the supply and demand balancing are generally achieved by adjusting the output of centralized generating units [5]. When consumption rises, the production must increase to keep up. Similarly, as demand falls, the created production must be reduced [7].

The power system has witnessed significant modifications in recent years due to the rapid growth of a distributed generation (DG). DG, unlike centralized generators, are mostly weather-dependent and hence have limited controllability to meet demand. Due to their various sizes and network tiers to which they are attached, they also add more unpredictability to the entire operation [8]. Recent environmental worries about growing carbon dioxide emissions (CDE), expanding energy needs, and the liberalization of the electrical industry have drawn the world's attention to renewable energy technology [9]. Although the integration of intermittent RE generation into electrical power systems is still relatively new in the evolution of electrical systems, it is popular all over the world due to its technical advantages such as improved voltage profile, power quality (PQ), voltage stability, reliability and grid support [8]. According to the modern grid initiative study from the United States Department of Energy (USDOE), a modern smart grid (SG) must be capable of self-healing and distributing high-quality power in order to avoid wasting money due to outages [9].

This study focuses on the uses of a variety of RE sources, including unlimited and other power sources. Moreover, it focuses on conserving energy and spending it wisely following its direction and location. Furthermore, reducing costs by using suitable energy sources depends on prioritizing using a multi-heuristic technique for intelligent power systems. All these processes and data will be saves and controlled by a cloud computing framework using a cloud sim. Cloud computing can be a great addition to any system aiming for an optimal solution for power distribution to reduce cost and waste power and time.

1.1. Smart Energy Systems

Societies on a global scale have reached a tipping point from fossil fuel power generation to sustainable alternatives. However, wireless connectivity plays a critical role in this transformation by enabling innovative smart energy systems (SESs) [9]. SES is a novel solution, which integrates energy generating and storage technologies with 'intelligent' applications, regulating and optimizing their usage. Cloud computing can use combined multiple energy sources with storage systems to manage them [10]. Furthermore, significant points to improve SES require real-time performance decisions based on technical features and climatic data, surplus renewable power generation, and building decentralized energy systems with excellent efficiency and lower cost [11]. In addition, to reduce rising environmental hazards such as increasing global mean temperature and greenhouse gas emissions, energy systems are experiencing a rapid transition toward low-carbon intelligent systems [12]. Unlike traditional energy systems, which dispatch various generators to meet changing demand, future energy systems include two-way energy flows between providers and consumers and active engagement of customers as prosumers in various electrical markets [13]. Under the suggested micro-market, not completely controllable loads were rescheduled by changing specific lectures, research timelines and optimization by a self-crossover genetic algorithm (GA) [14]. The numerical findings revealed that the suggested micro-market and algorithm efficiently increased load flexibility and resulted in increased cost savings for intelligent energy systems [15,16], as shown in Figure 1.

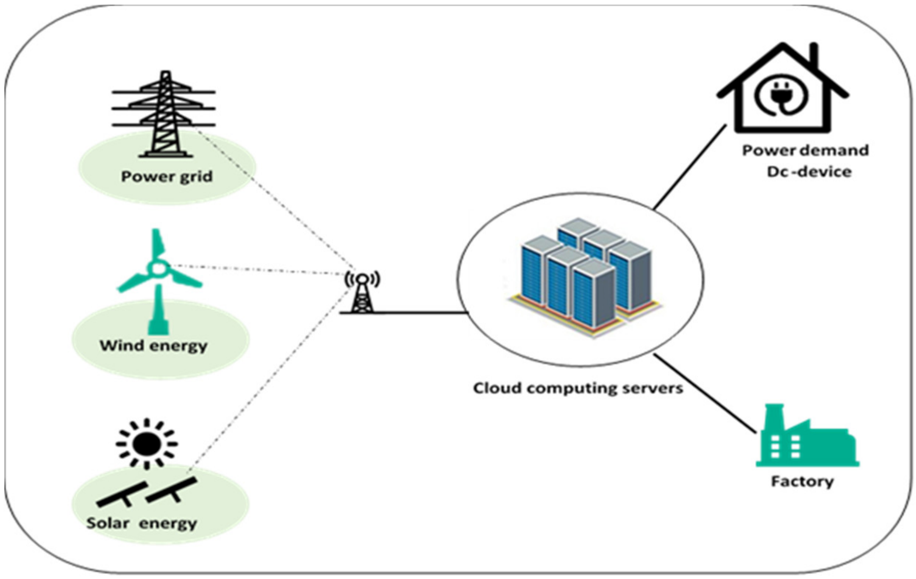

Figure 1. The schematic illustrates the smart energy system.

1.2. Background

The fast development of power stockpiling has received considerable attention lately [17]. The power stockpiling technique represents a popular system used in the most widely fixed and portable way [18]. Technique energy distribution consists of production, conveyance, allocation, scattered network methods, demand, administration [19]. Modern gadgets generally include many detectors to regulate and manage process variables directly. The detectors may recognize and prevent possible system faults. It is impossible to improve energy management strategies on the future route until accurate information is available [19]. As a result, the obvious visibility, high detection levels, and improved level of performance have attracted much interest. Artificial intelligence (AI) has become the focus of interest, particularly in industrial sectors, for its smart and precise natural deposit administration [20]. AI integration of fog will vastly improve the range of computing and execution speed of its base sensors in the industry [21]. However, a significant issue in using such energy-hungry gadgets, battery aging, and intolerable delays on the portable appliance is a traditional and inefficient fair distribution of precise natural trends. Demanding power management and control are critical to enhancing safety [20], reliability [17], performance, and cost [22]. Demanding power management is a choking technique due to a complicated process that is difficult to observe. Thus, it is a significant method for managing batteries to concentrate on developing a cloud-based battery for managing batteries based on an intelligent system that employs a machine-learning technique capable of operating consistently during changing environmental settings [23]. Enhanced freightage techniques are essential to later development predictions of more intelligent batteries, as the freightage efficiency has a significant impact on customer approval or rejection [24]. Technology-managing batteries on the cloud are proposed to enhance systems through enhancing arithmetic power ability, amount of data, and information stored on the internet. The internet-connected battery data is examined and analyzed and it is highly reliant on the supervision center framework for computation and connections and uses a cloud-based application server to assure procedure continuation independent of local infrastructure access and availability [21]. In addition, the growing demand for electricity worldwide, the environmental pressures, and the large-scale penetration of intermittent renewable energy sources (RESs) are compromising the operation of the electricity grid and creating new technical and economic challenges for network operators [25]. The worrying rise in power usage, natural pollution, global warming, and the exhaustion of coal and oil sources is pushing today's academics to make renewable electricity gathering easier [26]. The insertion of integrating solar panels in traditional electricity transmission lines has been proved fruitful [27]. However, variables such as solar irradiance, coverage of clouds, time of sunlight hours, and heat in the surroundings wreak havoc on renewable output power and total energy efficiency, which may be mitigated by combining renewable panels with energy storage devices [28,29]. The large penetration of solar power can cause significant voltage swings, through the use of energy storage devices. Solar power with a manageable energy storage system device also saves money for customers by reducing power consumption [30,31]. The collected information and data are conveyed to the cloud smoothly, which leads to creating a battery system's digital twin, as well as the battery analytical techniques that will evaluate the information and provide insight into the battery-grade level and aging [18,32]. To explore the advancement of information of data and connection technology, combining fossil fuels with clean power, and implementing energy management using the cloud, powered pivot, and gathered loads were used to enhance power economization in a smart society [24].

2. Smart Grids System

The growing energy demand has led researchers to establish a new energy management mechanism or find alternate energy resources [33]. For this purpose, the utility transforms its infrastructure into intelligent smart grids (SGs) by using bi-directional communication technologies to make wise decisions [34]. SGs mix electric power and bidirectional communication that supply the end-user with a high-performance and efficient mechanism by combining integration and communication technologies [35,36]. In this section, five of the major aspects will be discussed to show the best scope of these systems based on smart grid benefits, opportunities and components as depicted in Figure 2. These aspects are demand response (DR), power supply (PS), distributed energy resource (DER), microgrid trading (MT) and virtual power plants (VPPs) [37].

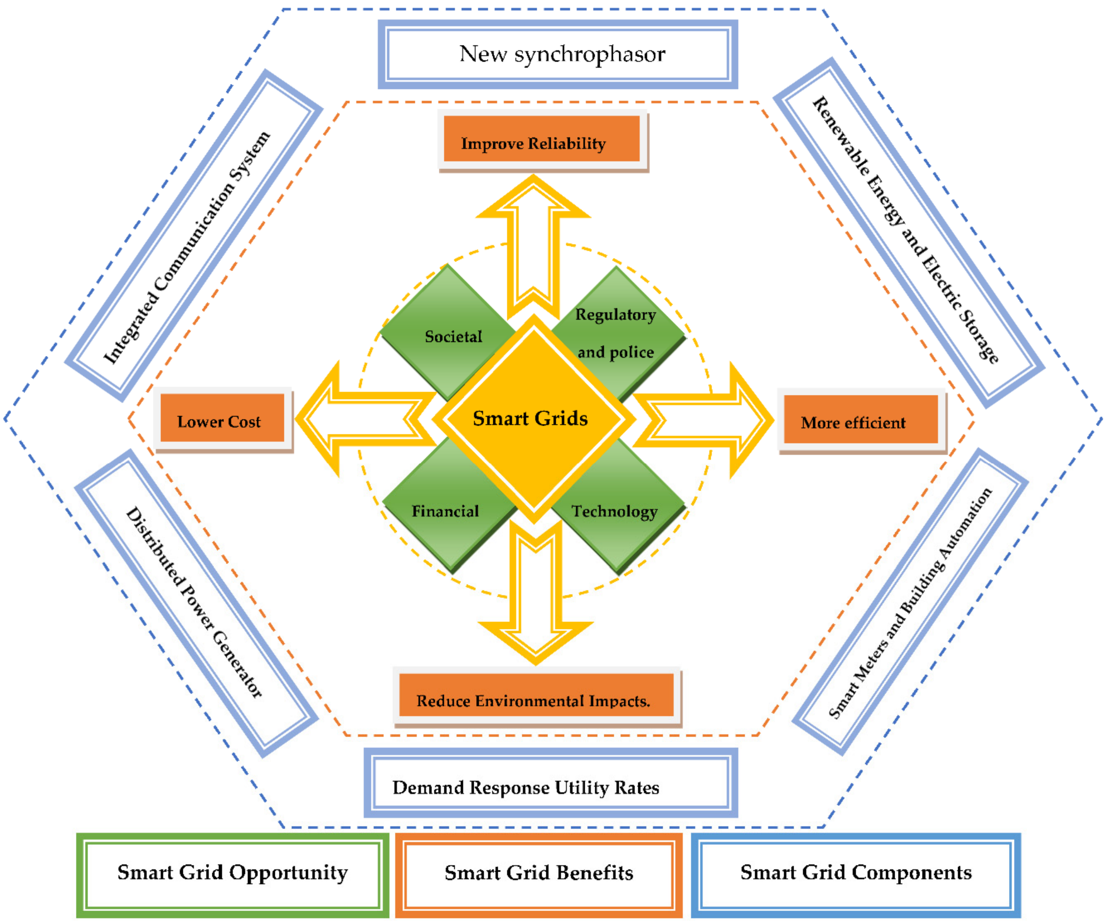

Figure 2. Smart grid opportunity, benefits, and components.

2.1. Demand Response (DR)

The world's most pressing concern today is energy. As a backup generator, fossil fuels are frequently employed, although their production of CO_2 affects life and the environment [38,39]. A novel technique called DR makes virtual generation better DR [40,41]. Users may program their gadgets using this approach. There are several issues with traditional smart-grid design (without the cloud) [42], which is the master-slave design that led to a risk of distributed denial of service (DDoS). However, any error may cause the entire system to fail [43]. There is a limit on how many clients may serve due to memory storage limitations, stability, and management [44]. Besides, information and data management challenges, which millions of intelligent meters necessitate for an effective method for handling massive amounts of data [45]. Cloud computing may provide a cost-effective alternative for data analytic and storage methods [46,47]. Recently, the high insertion of green power, the advancement and implementation of new technology such as electricity storage methods and electronics technologies, and the effective engagement of (DR) from the user aspect, the intelligent network is currently succumbing to a deep change [48]. Customers'/clients' power consuming routines are changed by DR due to the current power cost, benefit plans, and whenever the device dependability is threatened [49]. DR's elastic scheduling may be tailored to customers' economy and power use goals, that have been used over time to help business, manufacturing, and housing customers reduce their power consumption [50]. DR scheduling is classified depending on reward and cost. These two groups are intertwined, and many of their activities are customized to reach mutually beneficial objectives [51]. DR is the favored procedure of participation among clients and the electricity network in the electricity marketing development. In addition to minimizing the variance among maximum load and maximum valley, the load profile could be developed; these lead to making the device's cost cheaper, and to the system pressure being relieved to obtain more money to be invested in raising the load. DR lowers the price of their energy usage for energy users, impacting their pleasure [52]. The home load has the highest ability to profoundly alter the requirement peak load amid the weights that may successfully involve DR [53]. Users may be overseeing and administering personal electricity using DR services. Consumers are motivated to employ clean power and allocate energy-saving technologies to conserve electricity, lower personal power costs, and make money by selling their extra electricity to the system through DR programs [54,55]. It is essential to provide a reliable, accurate, cost-effective, and safe electricity energy. The above technological advances should be able to combine the behaviors of many participants, buyers, suppliers, and prosumers efficiently [56,57]. The demand response procedure's success in regulating supply, conservation, call for cooperation, and lowering energy costs is proven based on a prototype electrical system [58,59]. For instance, the energy information administration's last annual energy outlook study predicted that household power demand will rise in the next few years [60–62].

2.2. Power Supply

An electrical device transforms electricity (the proper voltage, current, and frequency) from a source to an electrical load [63]. This section describes the relationship between power and energy, and their management techniques; as seen in Equation (4) and (5). Both power and energy are defined in terms of the work that a system accomplishes. It is critical to understand the distinction between power and energy. A reduction in power consumption does not always imply a reduction in the amount of energy utilized. For example, reduce central processing units (CPU) performance by lowering voltage and frequency led to reduced power consumption. It may take longer to complete the program execution in this situation. The amount of energy consumed may not be reduced even with reducing power usage [64]. As explained in the next parts, energy consumption may decrease through implementing static power management (SPM), dynamic power management (DPM), or by combining the two solutions and services [65,66]. Furthermore, electricity consumption may be divided into three categories:

First: The energy consumed via parts of the system due to leaking electricity in the supplied technique is called SPM. It is unaffected by clock rates and does not rely on use situations dictated by the device type and architecture used in the service's CPU [67].

Second: Dynamic power consumption (DPC): This type of energy usage is caused by device action and is largely influenced by clock rates, I/O traffic, and the utilization situation. DPC is caused by two factors: changed capacity and short circuit current [68,69]. To identify basic terms: Charge can be defined as the quantity of electricity responsible for electric phenomena in Coulombs (C). Current is defined as the passage of electric signals through a network for each component during a given period, measured in amperes (A), which is expressed in Equation (1) [70]. Voltage is the amount of effort or energy necessary to move an electric charge, measured in volts (V) and expressed in Equation (2). Power is the system's rate of work, measured in watts (W), described in Equation (3). Compute power is the element current multiplied by the element voltage, expressed in Equation (4). Energy is the entire quantity of tasks finished during a period of time, measured in watt-hours (WH), described in Equation (5).

$$a = \frac{\Delta c}{\Delta t} \tag{1}$$

where a is ampere, Δc is change of current and Δt is change of time.

$$v = \frac{\Delta w}{\Delta c} \tag{2}$$

where v is Volt and Δw is change of watt and Δc is change of current.

$$p = \frac{\Delta w}{\Delta t} \tag{3}$$

where p is power, Δw is change of watt, Δt is change of time.

$$P = \frac{\Delta w}{\Delta t} = \frac{\Delta c}{\Delta t} * \frac{\Delta w}{\Delta c} = a * v \tag{4}$$

via derivation and substitution of variables, $P = a * v$

$$E = P * \Delta t \tag{5}$$

where E stands for energy, P for power, and Δt stands for alteration of time.

2.2.1. Battery Management

The battery management is worked from different perspectives, such as automatically controlling the SoG and the system that maintains battery aging and health. The rest of the research society considered the authority of the power consumption and reduced the costs of PS [71]. (GA) [72], particle swarm optimization (PSO) [73], fuzzy logic (FL) [74], metaheuristic optimization algorithms (MOA) [27], etc. have all been used to preserve battery life and control the charging process, which includes charging from 20% and stopping when it reaches 95%. These methods and algorithms use a mix of energy sources ranging from wind energy, fossil energy, solar energy, and RE [75,76]. However, the focus is to resolve the issues between battery control and energy supplies used during freightage (see Figure 3).

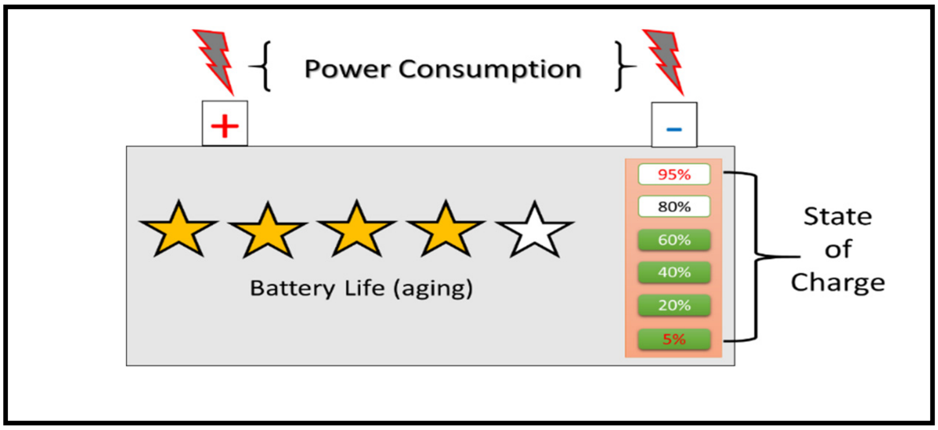

Figure 3. Power consumption control.

State of Charge (SoC)

A cell (SoC) depicts current capacity as a function of its rated capacity. The SoC's value ranges from 0 to 100 percent. The cell is fully loaded if the SoC is 100 percent, whereas an SoC of zero percent shows that the cell is entirely discharged [77]. In practical applications, the percentage or level that defines the start or end of the charging process is varied according to the charging system, whether it is manual or automatic. The beginning SoC is assigned as 0% and target charging SoC as 80% to compare improvements. In the same study, the optimal charging current series for 0–80% SoC with different setting time had charging times that ranged from 1 to 3 h, with a step of 0.5 h. Knowing the battery beginning SoC, the target SoC, and the charging time, it has been found that the current charging command can be easily calculated by the database-based method. Compared with the constant current charging strategy, the proposed method can effectively decrease the charging loss [72]. Furthermore, electrochemical techniques and post-mortem examination allowed the samples kept at 30%, 60%, and 100% SoC and 55 °C to be comprehensively examined. It was determined that the most severe capacity fading occurred when the batteries were kept at 55 degrees Celsius and 100% SoC [78]. In addition, higher stored SoC resulted in a more substantial rise in bulk resistance (R_b) and charge–transfer resistance (R_{ct}) of a full battery at 55 °C. Still, the discharge rate capability of the stored battery remained unchanged [73]. Furthermore, higher stored SoC resulted in a more substantial rise in bulk resistance (R_b) and charge–transfer resistance (R_{ct}) of a full battery at 55 °C. Still, the discharge rate capability of the stored battery remained unchanged [78]. However, the minimum SoC in the study never fell below 20% to avoid reducing battery life. Therefore, there was always 20% energy in the batteries in this study [73]. Factors such as charge, discharge rate, and charging/discharging hours played a significant role in correcting the load characteristic of the grid, and the islanded micro-grid was the optimal operation of energy systems [73]. The numerical simulations were used to evaluate the system's net savings for various SoC settings in the control strategy. Considering expanding data samples, the proposed approximate dynamic programming approach beat the classic dynamic programming approach [79]. The proposed approximate dynamic programming approach for microgrid power system optimization problems is a computationally efficient tool [80,81] (Figure 4).

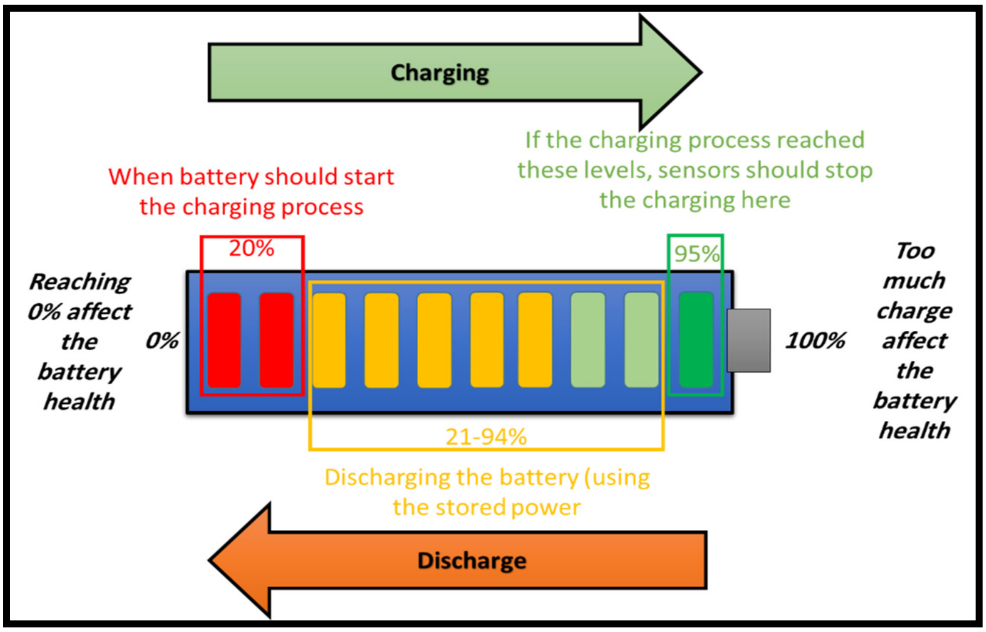

Figure 4. State of charge (SoC).

Battery Life

Determining battery aging is a crucial issue to predict the available charge in battery-operated systems [82]. According to the literature, the batteries were charged and discharged in 5 h to produce a 5 kilowatt (KW) average, while the battery life was anticipated to be around ten years [73]. In comparison to the standard charging method, the results showed that the multi-stage constant current charging technique could significantly reduce charging time by 56.8%, extend battery life by 21%, and enhance energy efficiency by roughly 0.4 percent of constant current and constant voltage [83]. Moreover, we used four cells for experiments to ensure the consistency of the results and to reduce the effect of the cell-to-cell variations [84]. The cells were new and uncycled and stored in a thermally managed storage chamber at 10 °C at 50% SoC before experiments to minimize their calendar aging [84]. In addition, different temperatures, charge–discharge rates, and the depth of discharge can give rise to the evolution of the dominant aging reactions that can offer guidance in selecting a reasonable factor range when designing accelerated aging tests [85]. However, the autoregressive recurrent Gaussian process regression (GPR), which considers current and historical voltage, current, and temperature measurements, as well as the prior SoC estimate, increased the estimation performance [86]. In addition, this battery management system (BMS) with FL controller method improved the battery's function and life [87].

Power Consumption

Reducing energy costs is another subject in battery management, as many researchers considered reducing power consumption in their studies. The electricity needed to operate the system is not produced by the deployed MG system [88]. Therefore, a sizing method based on the system's consumption profile and the site's weather conditions was introduced to upgrade the MG system to produce the total electricity needed by the load [89]. Moreover, they found that integration of a photovoltaic system leads to the reduced economic viability of the battery by reducing the revenues generated by the battery while performing peak shaving [89]. In addition, we proposed a scheme that creates three clusters of various objective functions to coordinate charging and discharging cycles; the first cluster uses time of use tariffs to reduce grid-integrated energy storage batteries (GIESBs) power charging costs. The second cluster uses per-unit generation from photovoltaics (PVs) and wind turbines (WTs) to reduce GIESBs charging power. The third cluster, however, reduces the GIE's discharge capacity [90].

2.2.2. Renewable Energy (RE)

Integrating RE with other power sources is considered to achieve many objectives: (1) reduce the carbon footprint; (2) reduce costs of power consumption [91]. This selection must assure user safety, efficiency, and cost savings for a given application. As a result, criteria such as power consumption, application deployment area, cable size, and line transmission losses are considered. This method was used to create a 48 V DC bus in a small-scale laboratory system with minimal power usage [91]. Furthermore, an electric bus management system (EBMS) considers variables that may have an impact on distribution network or bus efficiency, such as the power tariff. To counteract the negative effects of opportunity charging systems, RE-based charging stations can be installed. The number of possibilities for configuring connections to be lowered during the hours of 22:00–23:00 h, encourages discussion about linked DC motor load with wind and solar power-based hybrid power systems based on a simulated outcome [92]. A battery-based energy storage system is used to control the excess power generation to maximize the utilization of these energy sources based on the required load [93]. The switching transients of renewable sources and batteries do not affect DC motor speed (load), and hence constant output power as per requirement is available. The adaptability of artificial neural networks (ANNs) allows the system to be tested in a different scenario. The controller can be trained for any change in the signal. The training accuracy is 94% [94]. It will also require city utility authorities combining novel grid elements on the Internet of RE domain in order to actualize a sustainable, transformed smart city. In the future, power business, pure renewable electricity grid structural assets, and Internet of RE technology will become increasingly valued [95]. The primary motivation for this expected paradigm shift toward renewable power grids on the Internet is to manage electricity storage [96]. The cross-cutting nature of solely renewable electricity grid architecture on the Internet of RE platforms and intelligent city elements will help shape future environmentally friendly towns [94]. Energy management systems (EMS) for various RESs target small DC grids for remote rural communities with unstable load conditions [97].The technology can be used to electrify rural settlements with the greatest possible use of RESs and storage devices. The power dissipates to the consumer through maximum RE penetration and batteries throughout the day without any divergence in the system, according to simulation and experimental investigations of the DC micro-grid with the suggested EMS [97]. Micro-grid implementation is a viable method for improving supply quality while lowering sustainable energy implementation costs.

For a hybrid micro-grid (HMG), a control scheme presents a structure for ensuring continuous PS to consumers in fifteen different modes of operation. PV, fuel cells, wind, and battery storage with configurable characteristics that were all investigated. The supervisory controller sets the reference values for the generation subsystems using the state machine approach by following a predetermined path. The discrepancy between the generated and demanded power, as well as SoC, are considered by the fuzzy controller during charging and discharging battery banks. As a result, in order to obtain the best system configuration and component sizing by defining objective functions for energy cost and power loss probability, the multi-objective particle swarm optimization (MOPSO) methodology was utilized. The modeling findings show an increase in the price of electricity, which leads to a significant increase in the use of HMG based on renewable resources. As a result, harnessing renewable resources to create electric power in India's remote places is a viable option [98]. Based on the literature, algorithms of battery management, RE, and cloud computing are summarized in Tables 1 and 2.

Table 1. Summary of the literature algorithms of battery management, renewable energy, and cloud computing.

Category	Algorithm & Tools	Battery Categories	Ref.
Battery Management	Constant current/Constant voltage (CC/CV)	Several types of batteries, Lithium-ion Battery	[99,100]
	Arbitrage optimization algorithm	Non-Available (NA)	[22,27,101,102]
	CubeSat battery algorithm (CubeSat)		
	Maximum efficiency tracking (MEET)		
	MOA		
	First access first charge (FAFC) scheduling	Lithium-ion Battery	
	Flat feeder profile		[72,103,104]
	(GA)		
	JAYA algorithm		
	Pontryagin's minimum principle (PMP)		
	PSO	Electric vehicles batteries, Lithium-ion Battery	[28,73,75]
	Orthogonal least squares algorithm	Lithium-ion Battery	[86]
	MATLAB algorithm	Variety of batteries	[105]
	Liquid cold plate control equation	LiFePO4 battery	[106]
	Stochastic algorithm	Electric vehicles batteries	[107]
Renewable energy	(GA)	NA	[108,109]
	Markov decision process (MDP)		
	Levenberg–Marquardt algorithm (LMA)	Several of batteries	[110]
	Gaussian algorithm		
	Forgetting factor algorithm		
	Trust-region reflective		
Cloud Computing	BMS-Master and BMS-Slave	Lithium-ion and lead-acid batteries	[18]
	The home energy management system (HEMS)	Electric vehicles batteries	[111,112]
	Branch and bound algorithm	NA	
	Smart home energy management system (SHEMS)		[113,114]
	Energy-performance trade-off multi resource cloud task scheduling algorithm (ETMCTSA)		

Table 2. Assessment and analysis of the literature studies for battery management (BM), renewable energy (RE), and cloud computing (CC).

Tools/Algorithm	Achievement	Implementation			Ref.
		BM Dc-Device	RE	CC	
Constant current (CC)/constant voltage (CV)	Reduce the number of battery chargers to Improvements battery charging and management.	✓	×	×	[99]
GA	Propose a new charging algorithm to reducing the charge energy and loss.	✓	×	×	[72]
MEET algorithm	Three types of battery energy storage systems (BESSs) were used to improve the system's availability and energy efficiency.	✓	×	×	[102]
Orthogonal least squares algorithm	Provide a feature stemming from (GPR) for deduces the unknown SoC value's probability allocation	✓	×	×	[86]
Scheduling algorithm	The numerical analysis illustrates adaptive resonant beam charging (ARBC) led to 61% battery charging energy and 53–60% supplied power.	✓	×	×	[22]
GA	used optimum charging methods are reduced charge times, performance improved, and extended battery life	✓	×	×	[83]
MATLAB algorithm	The sorting and cumulative voltage summation (SCVS) was shown to perform the best through the solar energy option of charging the battery.	✓	×	×	[105]
PSO developed based on standard IEEE 69-Buses network	A hybrid approach uses to manage the electric vehicle charging station (EVCS) to peak shaving and the most efficient charging/discharging of EVs applied to a standard network (IEEE 69 buses).	✓	×	×	[73]
PSO	Scheduling controllers can reduce the power consumption and costs of grids.	✓	×	×	[28]
Arbitrage optimization algorithm	A battery energy storage system (BESS) capable of discharging for 1.5–2 h at maximum power and provides quick response and energy arbitrage.	✓	×	×	[115]
CubeSat battery algorithm	Choosing electric power system (EPS) architectural converters for solar panels and unregulated dc-bus have the maximum efficiency.	✓	×	×	[101]
MOA	A double-layer metaheuristic optimizer provides a novel stochastic technique for optimizing solar hosting capacity in distribution networks.	✓	×	×	[27]
Stochastic algorithm	Propose a simple statistical model to breaking a battery energy storage system up into minor segments that lead to significant increases.	✓	×	×	[107]
JAYA algorithm	Compact and optimized SOC estimating model for statistical error values such as SOC error used to validate the model's performance.	✓	×	×	[104]
NA	Reduce the amount of data sent by extracting features voltage descriptive.	✓	×	×	[116]
NA	Clean electric power using information and communication technology (ICT), the user can monitor the load, battery, and panel current.	✓	✓	×	[117]
GA	The household load control system that included (RESs) led to lowered cost of electricity from (228 to 51) USD and the peak-to-average ratio (PAR) from 2.68 to 1.12.	×	✓	×	[108]
LMA, Gaussian algorithm and Trust-Region Reflective Algorithm (TRRA)	Established microgrid system for testing and simulation, focusing on dimensioning and control techniques, the residue discovered less than 5%.	✓	✓	×	[110]

Table 2. *Cont.*

Tools/Algorithm	Achievement	Implementation			Ref.
		BM Dc-Device	RE	CC	
(SHEMS)	The smart monitoring and control system preserves and manipulates data from the PV, wind energy conversion system (WECS), and batteries.	✓	✓	×	[113]
Branch and bound algorithm	Propose an energy-efficient approach that can operate in an online fashion ANN-based approach outperforms all benchmarks.	×	×	✓	[111]
BMS-Master and BMS-Slave	Propose a cloud control strategy to enhance the analytical electrical energy and information storage in the cloud using lithium-ion and lead-acid batteries.	✓	×	✓	[18]
NA	Propose a closed-loop program for an effective management strategy for lithium-ion batteries by concurrently changing factors.	✓	×	✓	[118]
ETMCTSA	Propose the energy-efficient hybrid (EEH) scheme for increasing electrical energy consumption efficiency using a single strategy to minimize energy usage in terms of power use effectiveness (PUE) and data center energy productivity (DCEP).	×	×	✓	[114]
NA	Design embedded network platform using smart sensor gadgets with telecommunication functions and molecular channel systems to maintain battery health.	×	×	✓	[119]
Optimization algorithm of the HEMS	The combine between a smart thermostat and (HEMSs) a 53.2 percent decrease in daily costs is obtained (TOU)	×	×	✓	[112]

2.3. Distributed Energy Resource

DER are energy generating and storage systems that supply power where required. DER systems, which produce less than 10 megawatts (MWs) of power, may generally be scaled to fit your specific needs and can be installed on-site. Therefore, one single source is limited and can probably be costly, whereas to achieve efficient energy storage, a combination of all technologies is required. Power conversion systems for storage purposes must also be considered [120]. This is required to increase their control and dependability, as well as to ensure that storage systems are properly integrated into power networks [121]. A next-generation SG without energy storage is similar to a computer without a hard drive—severely limited [122]. A suitable EMS is required to obtain the optimum performance for clusters of distributed energy resources (DERs). The multi-agent systems (MASs) paradigm, as utilized and described, may be used to organize distributed control methods [123]. Some of the benefits of employing MASs for successful, intelligent grid operation in the energy market are discussed in [124,125]. The MAS application reduces the overall cost of power system production, integrated microgrids, comprised dispersed resources, and lumped loads [126]. To maximize the hybrid RE production system's economic performance and energy quality, a hybrid immune-system-based PSO was presented and applied to reduce fuel cost in the generating process [126].

Conversely, the distribution system operator (DSO) can dispatch at least a portion of the DERs; implementation of a coordinated integration of the various DERs recommends a centralized method. The best operating strategy of the DER system is generally analyzed by using a multi-objective linear programming methodology in centralized control methods [127]. The combination of the energy costs with the reduction of environmental effects suggest reducing operational costs, including energy losses, curtailed energy, reactive support, and shed energy [128,129]. Additionally implemented is a two-stage short-term scheduling process. The first task is to create a day-ahead scheduler to optimize

DER production for the next day. In the second step, an intra-day scheduler that modifies scheduling every 15 min is also proposed, which considers the distribution network's operation needs and restrictions, as shown in Figure 5 [130].

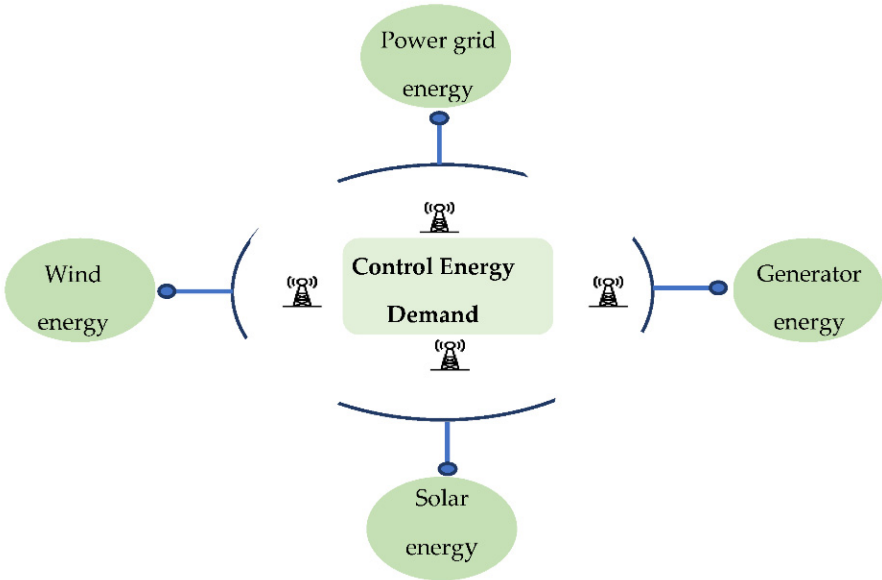

Figure 5. Schematic illustrating concepts of distributed energy resources.

2.4. Microgrid Trading

Microgrids are small-scale power networks that provide a more flexible and reliable energy distribution in limited geographic regions [131]. For fulfilling local demands, they generally use DERs such as distributed generating units and energy storage facilities. As a result, they can minimize dependency on the traditional centralized power grid (also known as a microgrid or primary grid in power system literature) that generally relies on massive central station generation [132]. Besides, the environmental benefits of using locally accessible RESs such as solar panels, fuel cells, or WTs also have economic benefits because if DERs and loads are physically close together, microgrids can minimize transmission and distribution losses [133–135]. A microgrid system was used to maintain the energy arbitrage, balance, reserve frequency regulation and transmission-level for voltage control, investment deferral, grid capacity support at the distribution level, time-of-use (TOU) cost management, etc. [136–138]. Furthermore, it considered as a detection device from the connected grid and operate autonomously in island mode if technical or economic situations demand, which is considered as local energy in the surrounding area [139]. Power delivery from a distance is inefficient because part of the electricity—as much as 8% to 15%—evaporates in route. A microgrid solves this inefficiency by generating power close to the people it serves; the generators are either nearby or within [140,141]. A microgrid system warrants research attention for several reasons: first, it is local, making electricity close to the people you serve; generators are near or within the building or on the roof in solar panels. The tiny network addresses inefficiencies in significant networks, which lose energy during transmission from producing units to transmission and distribution lines across vast distances. Second, it is independent and can be disconnected from the primary grid and run on its own. When the electrical system goes down due to a storm or other disaster, they must deliver power to their consumers. Third, the generators, batteries, and surrounding building energy systems are all controlled by microgrid intelligence. In addition, the controller coordinates a variety of resources in order to meet the energy goals of the microgrid's consumers, which can be searching for the cheapest energy, the cleanest energy, the most reliable electricity, or something else entirely. The controller accomplishes these objectives by raising or decreasing any of the microgrid's resources or combinations of those resources for optimum impact, as shown in Figure 6 [142].

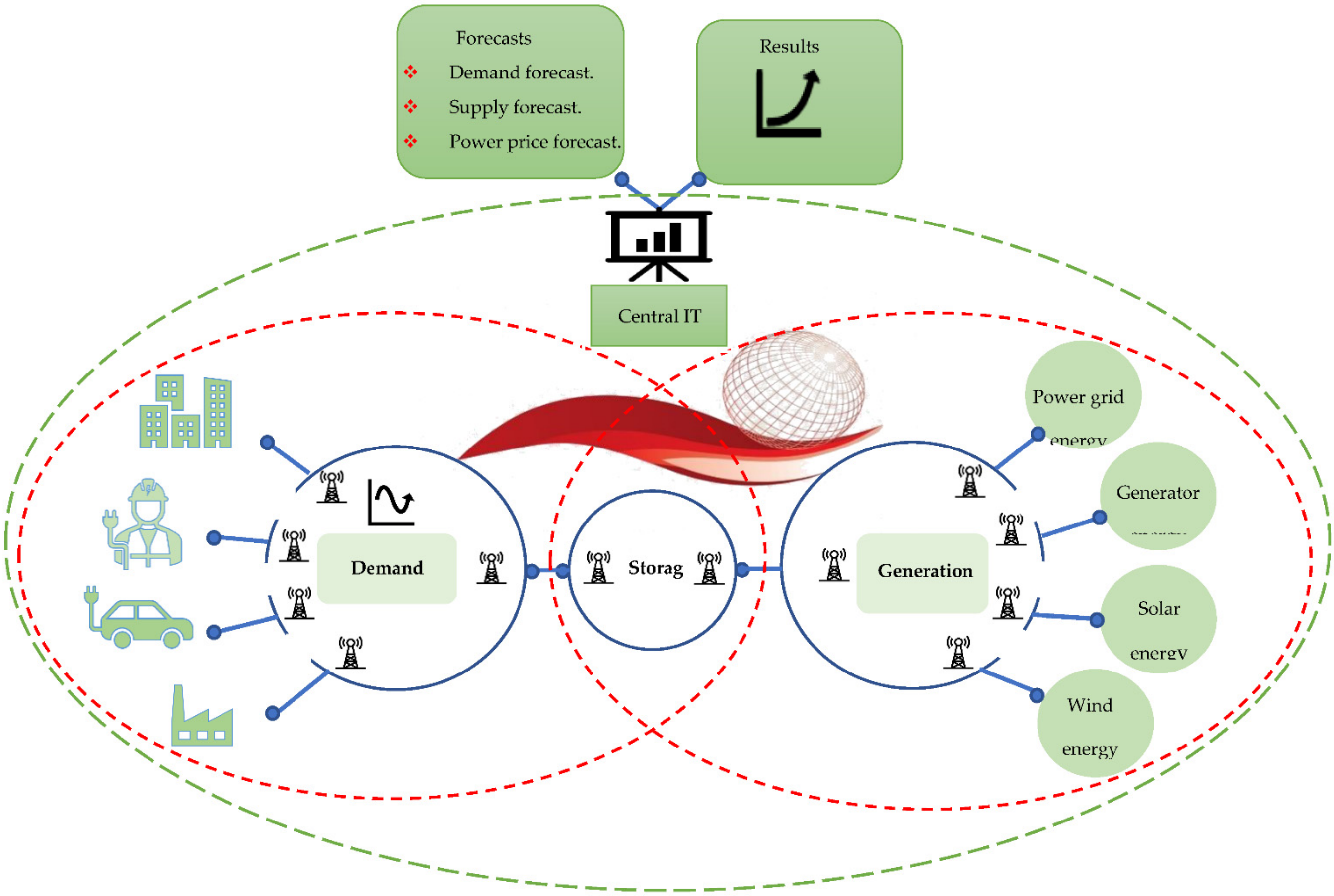

Figure 6. Schematic illustrating concepts of distributed energy resources.

2.5. Virtual Power Plants (VPPs)

Electrical energy has a significant impact on people's lives all around the world. As the demand for electricity grew, the power infrastructure and the global environment were placed under additional strain [143,144]. Buildings are a substantial producer of greenhouse gases (GHGs) [145,146]. An effective EMS is required to address the fast increase in demand [147]. Furthermore, several nations have committed to submitting an annual GHG emission reduction plan under the Paris agreement, making the use of (RESs) essential [148,149]. Due to the network's new topology RESs, traditional EMSs are no longer effective. In order to aggregate and accommodate RESs while considering geographic distribution and uncertainties, an optimal scheduling algorithm must be developed [150,151]. The VPP concept is one of the most promising and practical energy management solutions, allowing for unique features by integrating embedded technology and communication networks into the energy system. Despite the fact that Awerbuch and Preston proposed VPP in 1997, there is still no clear description for the VPP [152]. From a variety of perspectives, VPPs have been proposed in the literature. At the same time, the usual inclination is to aggregate DERs for energy management purposes [146]. Many research has concentrated on business and marketing factors [153]. Other publications, however, have emphasized technological viewpoints such as Internet of energy (IoE) [154], EMS [155], combination of RESs [156], an independent microgrid [110], or a data and connection system [117]. A trading platform used by DERs to make wholesale market contracts is known as VPP. VPP is a DER aggregator that considers the impact of the network on their output [157]. VPP is a control system for DERs, flexible loads, and storage that is defined as an information and communication system. According to the investigation, a VPP is a collection of DERs, controllable loads, and storage units combined to operate as a single power plant, with an

EMS at its core [158]. VPP is defined as an aggregation of several DERs distributed at the distribution network's medium voltage (MV) level [159].

In general, several solutions have been presented in recent years to overcome the aforementioned difficulties. The VPP concept is one of the most promising energy management concepts, allowing for unique features through the integration of embedded technologies and communication networks into the energy system. VPP uses a bidirectional energy flow to provide real-time monitoring and energy efficiency. As a result, they were able to exchange their excess electrical energy on the market without the involvement of a third party [160]. Prosumers, conversely, who install any small-scale RES, or storage (batteries) can trade because the scheduling algorithm maximizes their surplus energy. Customers without RES or storage can also contribute by moving loads, trimming peaks, and filling valleys, among other things. Lastly, through enhancing operating planning, VPP may conform with power administration rules [161,162], as well as the five main areas that best illustrate the scope of the intelligent grids system, such as DR, PS, DER, MT and VPPs, as shown in Table 3.

Table 3. Main scope of the smart grids system.

Main Scope	Description
Demand Response	A novel technique makes virtual generation better. Users may program their gadgets for interaction with the power grid to improve load profile, and user power usage costs should be reduced without compromising their pleasure.
Power supply	An electrical device transforms electric current from a source to the proper voltage, current, and frequency to power an electrical load.
Distributed Energy Resource	Systems for producing and storing energy for efficient storage and production that distributes electricity where it is needed.
Microgrid Trading	Small-scale power networks provide more flexible and reliable energy distribution in limited geographic regions for fulfilling local demands. As a result, it can minimize dependency on the centralized power grid by detaching and operate autonomously to reduce transmission, distribution losses, energy arbitrage, balance.
Virtual Power Plants	It is the most important future solution that can be applied in energy management, and integrating systems and networks into the energy system is a system of telecommunication and information that controls DERs, loads that are adaptable, and storage.

3. Cloud Computing

Cloud computing is an useful computing paradigm that provides on-demand access to facilities and shared resources over the Internet [163]. Infrastructure as a service (IaaS), platform as a service (PaaS), and service as a service (SaaS) are three notable services it offers, while storage, virtualization, computing and networking are supported [164,165]. Implementing cloud computing applications is a top priority, especially in today's environment, for things such as providing appropriate financing for social services and purchasing programs. Grids are geographically distributed platforms for computation. They provide high computational power and merge extremely heterogeneous physical resources into a single virtual resource [166,167]. Grid computing is a set of resources; the primary resource is the central processing unit (CPU), which is mainly used to perform massive and complicated calculations. Cloud computing technology is used by the majority of existing information technology (IT)-based enterprises. Cloud computing is a rapidly evolving technology, and companies are constantly adding new services to their cloud environments to stay competitive and fulfill customers' expanding demands [168]. Furthermore, many different organizations are moving their IT-based systems to cloud-based models [169]. Customers can use cloud computing resources in the form of virtual machines (VMs) that are deployed and run-in data centers. The data centers are composed of several physical servers, each with its own set of resources [114]. The cloud computing ecosystem for energy management is described in Figure 7.

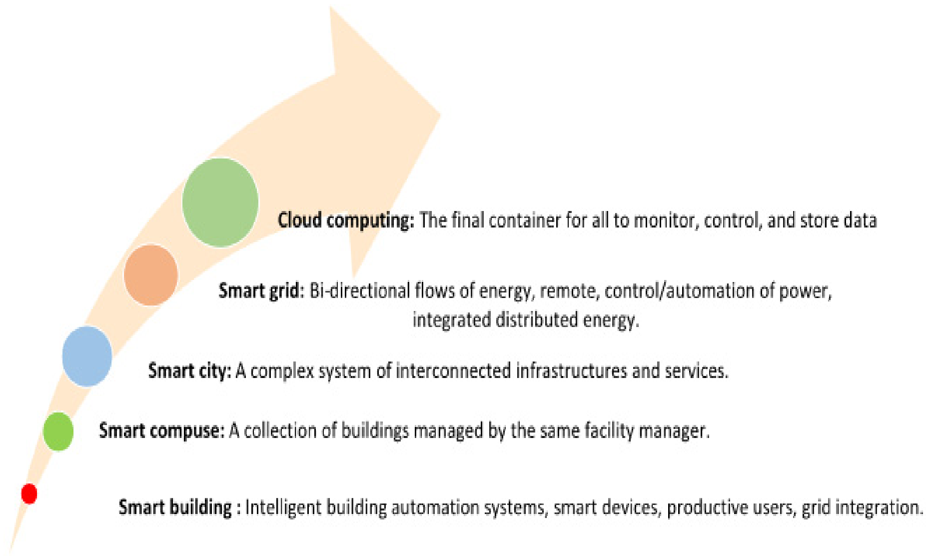

Figure 7. The cloud computing ecosystem for energy management.

3.1. Cloud Computing and Storage of Data

The IaaS model of cloud computing provides consumers with storage services. People have begun to save their data on clouds due to the large storage capacity [170,171]. Through virtualization, the issues around the storage of user data IoT applications can be solved by providing storage, processing, and networking resources [172]. In mission development, two-measure CPU usage and storage capacity are the best typical capabilities of the cloud to reduce local storage overheads [173]. These parameters' significance may minimize computation cost, communication, CPU usage reduction, and battery and data redundancy elimination in terms of storage and computing by performing task scheduling. Research on storage techniques has gained momentum due to the significant advantages of quick storage services in the cloud. Still, these techniques have specific challenges because there is a higher demand for quick access and secure storage. Cisco predicts, that by 2021, cloud computing systems will account for around 94 percent of all computing. Furthermore, by 2025, the size of data created and altered is expected to reach 175 zettabytes, according to International Data Corporation (IDC) [174]. The aforementioned necessitates cloud suppliers to establishing and simplifying additional services [114,169].

3.2. Cloud Computing and Software Services

Cloud computing using virtualization technology offers end-users computational resources, on-demand resources, flexibility, dependability, dynamism, scalability, and better availability wherever and at any time, which are examples of different services [175]. Elasticity is one of the keys characteristics of cloud computing, which refers to the system's capacity to respond to changes in workload [176]. Cloud services are now employed in most applications via the internet, which has become the contemporary economy's backbone. As a result, resource scheduling has become a hot topic in the cloud because ineffective scheduling techniques can lead to a variety of issues, including long computation times, reduced profit, poorer throughput, higher cost, and inappropriate resource usage, which are all examples of an uneven workload at resources (over-utilization or under-utilization) [177]. Resource usage in cloud computing is directly related to power consumption when resources are not used properly (over-utilization or under-utilization) due to high processing demand from end users and no service delays from the cloud. Integrating energy-sensitive servers has become a popular topic in the cloud world [178]. Therefore, future research is required to address the challenges and meet end-user demand within a reasonable timeframe. Reducing power consumption by switching underused hosts to sleep or hibernation without violating service level agreements (SLAs), which are digital contracts between end users and cloud services, ensures quality of service while resources are ready. Therefore, several energy-conscious server integration methods have been proposed in the last decade [179]. Either of the two scenarios is intended to achieve server consolidation. Most of the suggested scheduling methods must strive toward greater resource utilization and energy efficiency. However, most available algorithms are still in their infancy due to constraints [180]. Most algorithms focus on a single parameter (energy) and ignore other factors such as cost, reaction time, elasticity during run time, etc. [181].

3.3. Cloud Computing and Energy Savings

Local or green power sources are considered an excellent method to conserve energy at a data center by locating it near where the electricity is generated to reduce transmission losses [182]. Shutdown, hibernation, and sending in various low-power stages are examples of cloud computing approaches. At the same time, cloud computer energy consumption should be managed to optimize energy consumption for a specific computing task. When it comes to reducing energy usage per unit of work, cloud computing is a more energy-efficient option [183]. According to studies, employing the cloud might result in a 38 percent reduction in global data center energy expenditures by 2020, but a 31 percent reduction in data center power usage (from 201.8 terawatt-hours (TWh) in 2010 to 139.8 (TWh) in 2020). According to another report [183], cloud computing might help businesses save billions of dollars on their energy expenses. This equates to a reduction in carbon emissions of millions of metric tons each year [184].

3.4. Cloud Computers as VPPs

A VPP is a network of multiple tiny power stations (a cluster of dispersed generation facilities, such as microchips, WTs, small hydro, backup gensets, etc.) that operate as if they are one power unit [185]. There is a necessity to check the cloud computing entity linked to the power network in multiple locations, frequently given by several suppliers, connected to different distributors, and operating in multiple countries at the same time [186]. Energy consumption can be managed with specialist software designed for cloud computers and based on the VPP concept; generators are seen as resources and flexible users in the same way that cloud computers are [187]. Furthermore, the cloud computer is a potentially adaptable consumer. The cloud computer software already aggregates and controls its consumption; therefore, it performs the function of a VPP [187]. Existing cloud systems as consumers and energy systems as producers are separate systems that typically operate in parallel with little cooperation during one-way PS. To attain higher overall performance, such parallel networks require more complicated interaction [188]. The load provided by cloud computer centers provides a reliable picture of consumption demand. This energy storage device is an effective way for owners to reduce electric power prices while also reducing demand on the power grid [189]. The SG should be sensitive to the electricity system's present load. The computational cost of methods to minimize power consumption is determined by the required delay and the amount of load to be reduced. These application execution and scheduling models will need to account for cloud resource availability [190,191]. This strategy could include launching more VMs as demand for power rises, or expanding cumulative bandwidth capacity to handle a higher sampling rate of streaming data [185].

4. Big Data

With the increased use of numerous digital devices that generate heterogeneous, structured, or unstructured data in recent years, the volume of data has exploded, culminating in what is now known as huge data [192]. Traditional database systems have proven inefficient when it comes to storing, processing, and analyzing large amounts of data [193]. As a result, handling big data is a critical component of business and management rivalry. Nonetheless, it has posed a new challenge for both science and industry in terms of information and communication technologies, driving the development of data-centric architectures and operational models [194,195].

Since normal tools and methods are not built to manage such huge data quantities, the emergence of big data has highlighted a serious management dilemma [196]. At the same time, conventional infrastructures are unable to meet the distributed computational needs of managing vast amounts and types of data. This is owing to the increasing number and complexity of data sets, as well as their volatility, which makes processing and analysis difficult to perform using standard data management approaches and technology [197]. Current infrastructure struggles to keep up with massive amounts of data, yet it is a difficult task [198]. The current methods and technology for handling big data management issues place a premium on volume, variety, and pace [199].

Moreover, big data comprise complex data that are massively produced and managed in geographically dispersed repositories [200]. To handle enormous data difficulties, innovative management strategies and technologies are motivated by this complexity [201]. Although there have been several studies on giant data management, none have been thoroughly investigated. Giant data mechanisms are summarized in Figure 8.

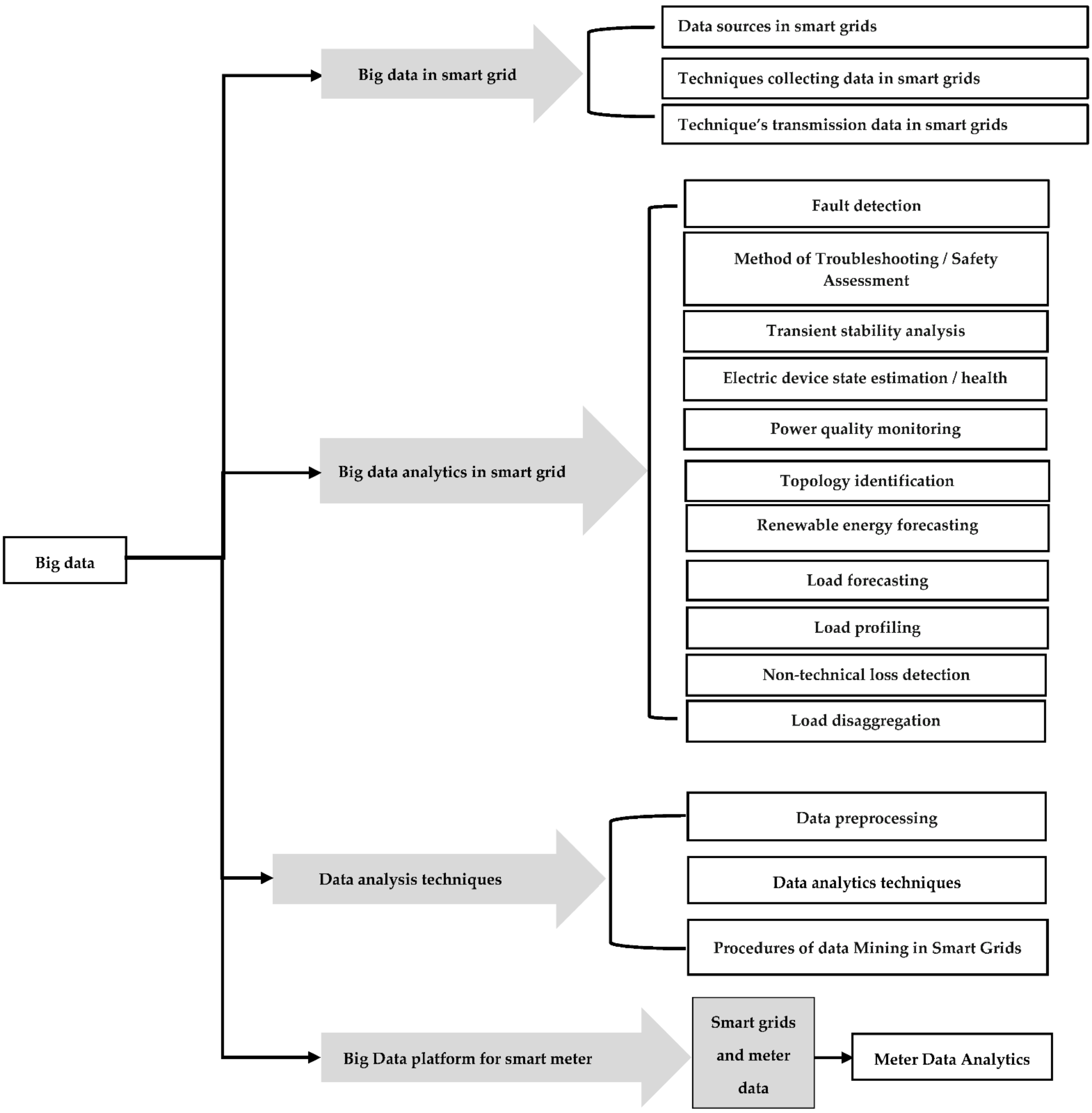

Figure 8. Big data mechanisms.

4.1. Big Data in Smart Grid

An intelligent grid architecture model includes a framework from three dimensions that combines layers, zones, and in the realms of generation, transmission, distribution, DER, and customer premises, there are several domains to evaluate a SG [202]. An energy network with an embedded information layer generates a large amount of data in the grid, such as measurement techniques and monitoring instructions, which must be collected, transmitted, stored, and analyzed quickly and comprehensively [203]. The data analysis platform also presented several opportunities and difficulties [202,204]. The massive data characteristics in SG in many studies are consistent with the widespread 5 V vast data paradigm as shown in the Table 4 [205,206].

Table 4. Main features of big data in smart grids as revealed.

Features of Big Data	Description
Volume	Smart meters and advanced sensor technologies are becoming more widely used in the SG generates a tremendous quantity of data. As a result, standard database technology can't store or interpret data sets that are too big.
Velocity	The rate at which new data are created and moved while the demand for real-time data sharing is growing and posing a new issue.
Variety	Words, digital images, detector data, and video are examples of unstructured data that may be integrated with typical structured data utilizing big data technology.
Veracity	The messiness and trustworthiness of the data. The effective management of the electricity system is based on data analysis and state estimate. Therefore, the data transfer faults or devices and a large amount of big data lead to problems in the data analysis results, as well as measurement mistakes.
Virtual	The capability to draw out important data from massive amounts of data while maintaining a clear sense of its worth. Big data makes obtaining valuable information harder.

4.1.1. Data Sources in Smart Grids

SGs, similar to intelligent energy and information system, have a variety of data sources. Data is collected from sub-stations, distribution switch stations, and power meters [207]. In addition, nonelectrical data such as trade, economic data, etc. are included in the information source. For power plant scheduling, subsystem functioning, essential power equipment maintenance, marketing business behavior, data collecting and analysis are considered critical [208]. Measurement, business, and outer data are the three types of data sources described above [209]. Most power system operating characteristics are assessed using installed sensors and smart meters that offer data on the system's present and historical condition [210]. Social activity such as carnivals and weather conditions are examples of data from outside sources that cannot be monitored by smart meters, yet still affect the work and design of the electricity system. The data for business mainly consist of trading techniques and customer demand [211].

4.1.2. Techniques Collecting Data in Smart Grids

The intelligent grid collects and sends data from intelligent meters, providing energy information to all companies and customers [212]. The amount of intelligent meter readings for residential customers is anticipated to increase from 24 million per year to 220 million per day for a prominent utility provider [210]. In high voltage (HV)/MV transformers for voltage control, the present magnitude data is required for the automated on-load tap changer [213]. A standard intelligent meter measures voltage at the node, current at the feeder, load conditions, reactive power flow, and energies over time, complete concord alteration, and load up demand and among other things [214].

4.1.3. Techniques Transmission Data in Smart Grids

The smart grid's foundation communication is divided into home space networks, district space networks, and wide-space networks [215,216]. The most common forms of communication methods for intelligent meters are wired and wireless infrastructures [217]. The technique of wireless connectivity allows acquiring measurement data from intelligent meters at low prices and simple interfaces while the data center may encounter a magnetic challenge [218].

4.2. Data Analysis Techniques

Data analysis is the most crucial stage of the hug system for data processing that provides the foundation for uncovering useful information and assisting in decision making [219]. Data analytics, often known as data mining, is a computer process that uses techniques such as database, statistician, design detection, and expert system to uncover the possible relationships between variables [220]. However, the resulting data sets may have varied performance in terms of noise, repetition, and uniformity due to the many sources [221].

4.2.1. Data Preprocessing

Data integration strategies seek to effectively combine data from several sources into a single picture [222,223]. Densification of data preprocessing techniques to eliminate highly linked variables and minimize dataset size due to some algorithms for analysis of the data can be sensitive to imbalanced data [220]. A logarithm helps correct the distribution form of data with severe weakness if the original dataset only contains the highest and minimum temperature values [219]. Additional features such as temperature differential might be computed through the preprocessing stage if the source dataset only has the most significant and lowest temperature values. These characteristics are frequently beneficial in improving the accuracy of data analytic findings [221].

4.2.2. Data Analytics Techniques

The model for data analytics may be developed based on the provided data to identify the relationship between aspects and the associated types or values using supervised learning techniques. When analyzing an unnamed data approach, it is typically designed to identify the different classes across all objects [224].

4.2.3. Procedures of Data Mining in Smart Grids

The fundamental purpose of data analytics in the SG is to extract useful information from historical data and compare it with real-time data to guide operation and maintenance [225]. Data management strategies are used to organize and store the massive amounts of data gathered through intelligent meters and sensors. Following that, a mathematical model may be created using data mining techniques and clean data [226]. The status may be assessed in the generated model using real-time data, which gives potential strategies for guiding actual activities and resolving any issues [227,228].

4.3. Big Data Analytics in Smart Grid

4.3.1. Fault Detection

The SG is considered the driving force in the distribution arrangement system to reduce carbon release and create environmental sustainability [229]. Using distributed generation units in current power distribution networks enables the optimal use of widely available RESs such as wind and solar energy [224]. Furthermore, the microgrid's proximity to the generator power delivery dependability is improved, and power transmission loss is reduced. The ability to operate in island mode also protects the load from harm caused by power system issues such as voltage fluctuation, frequency deviation, etc. [229]. However, RE has an intermittent nature, which adds to the grid's unpredictability. When a large quantity of temperature or energy damages microgrids, the typical sized generators are unable to identify and fix the problem in a timely manner due to their low load capacity, posing a serious threat [230]. Most standard approaches, which focus on detecting overcurrent and negative sequence currents in large-scale centralized power systems, appeared ineffective in microgrids [231].

4.3.2. Method of Troubleshooting/Safety Assessment

Distribution automation (DA) focuses on the distribution level's functioning and system reliability. A successful DA can locate and isolate distribution system issues, resulting in faster restoration times and more customer satisfaction [232]. A growing amount of operational data is being collected via supervisory control and data acquisition (SCADA) or sophisticated metering infrastructure for status monitoring and problem diagnosis advanced metering infrastructure (AMI) [231]. A significant amount of data may be captured through AMI and communication foundations due to the advancement of green information and communications technology (ICT) technologies in energy systems [233]. A data-driven model of failure phenomena based on a hybridization of evolutionary learning and clustering methodologies is the input of a one-class, power system operational data, weather data, and relay protection device log data [234]. For accurate online identification of dangerous occurrences in the power system, the extreme learning machine (ELM) algorithm is used in an intelligent early warning system. The learning speed of ELM training is significantly quicker than traditional algorithms since the weights are arbitrarily generated and then calculated by matrix computing lacking iterative parameter modification [235]. The data-driven framework's ideal balance between earning precision and warning acuity is also explored. Using a ranking system, it extracted electrical features from high-impedance fault current and voltage data and generated an effective feature set (EFS) [236]. Thus, a statistical classifier for defect detection may be made using a limited number of signal channels. It also shows how to minimize many phasor measurement units (PMU) of data while keeping the important information for power system failure detection [237].

4.3.3. Transient Stability Analysis (TSA)

Transient stability is a key issue that is closely linked to the power system's safe operation. However, rising electricity consumption, rising RE penetration, and a deregulated market all drive the power grid to operate at or near its safe operational limitations [238]. According to the SG concept, massive data gathering by AMI contributes to the situation evaluation of energy systems, while assisting with energy administration, functioning of a system, and decision making [239]. As a result, effective recapitulation algorithms are necessary for identifying meaningful patterns and uncovering important information from the duplicate evaluation in the power system [240,241].

In addition to green energy sources deployed via the SG, wind farms are being implemented to utilize abundant and emission-free natural resources and the extensive installation of wind energy in the grid by addressing possible deterioration and instability caused by the extensive installation of wind power into the electricity network [242]. Energy fluctuation is the swing of the energy stream on the transport line caused by concurrent machine rotor angles advancing or regressing to each other, which produces high interruptions. High-pressure dropping, engine activation, and clearing short-circuit problems are all possible causes [243]. However, using a decision tree (DT)-based technique for defect detection and categorization within the half-cycle time during power swing [244], the DT-algorithm was used with 21 possible characteristics derived from phasor measurement unit (PMU) data following the Kalman filter procedure for smart relaying in the power system [245]. The DT and graded aggregate created a probability frame for the dynamic performance of energy systems following a disturbance [246]. The unbalanced groupings that may break synchronism could be identified effectively. Although the PMU and wide area monitoring system (WAMS) give clarity information for designers to uncover patterns of stable and unstable operation, the low likelihood of events occurring in the power grid has resulted in a significant issue of class disparity [247]. It is difficult to discern the characteristics of uncommon instability from significant synchro phasor observations using traditional data analytics [248]. A systematic one-sidedness learning appliance for short online voltage evaluation is being developed to fully utilize enormous electricity grid data [237]. To show the power system parameters and external data such as meteorological information, the random matrix theory was combined with a high-order data-driven model [249,250]. The eigenvalue-based analysis method has been shown to be effective for analyzing online transient states [251]. Based on parallel computing and K-nearest neighbors learning methods, a live monitor of instantaneous electromechanical dynamics in transmission systems is given [252]. The suggested framework is used to handle the massive amount of PMU data from the power grid and extract information showing time-varying power generation and consumption [253,254]. For an online assessment evaluation of the (TSA) problem, the core vector machine (CVM) model is trained offline using 24 characteristics taken from the raw data [234]. A statistical nonparametric regression methodology based on the critical clearing time was used to examine the temporary stability boundary of large-scale power systems in order to assess if a steady-state condition can recover after a particular fault [255].

4.3.4. Electric Device State Estimation/Health Monitoring

Power transformers are critical components for electrical energy conversion, and their failure can result in catastrophic blackouts in the power system. As a result, research into the life-cycle administration of power transformers founded on precise estimates has sparked considerable interest in a more stable and dependable power system [256]. Three traditional methods for association rule mining, including apriori, aprioriTid, and aprioriHybrid, are presented to obtain data about system processes and climatic circumstances into state estimate examinations [257]. For possible failure prediction, rule mining approaches are coupled with a probabilistic graphical model. Building automation systems (BAS) are developed and implemented in most commercial buildings to regulate the heating, ventilation, and air conditioning (HVAC) system to repair optimum heat and humidity for the inhabitants [258]. FL was used to offer a unique health monitoring system for detecting abnormal operating conditions [259]. In a power system, the number of aged assets grows, and various failure models based on variables such as aging time or circumstances have been developed. As a result, lifetime data such as service age, maintenance, and health index were used to create a failure rate model for general electric power equipment [260]. The stratified proportional hazards model (PHM) for processing and classifying lifetime data into multi-type frequent occurrences was created to make the most effective use of this data [261]. This PHM technique may be used to predict possible risk issues and health conditions [262].

4.3.5. Power Quality Monitoring

Electric PQ is the magnitude, frequency, and waveform of voltage and current in power systems, and it is closely linked to the power grid's safe functioning and consumer satisfaction [263]. In the electrical grid, nonlinear, power electronics-based loads, generators, harmonic distortions, and unstable situations are becoming more common [264]. In some residential areas, traditional electromechanical analog meters still work, and data analytics-based PQ analysis cannot be used effectively [264].

4.3.6. Topology Identification

Using information layers in the SG to address the problems posed by RESs in supplying the network is a viable solution [265]. SGs are becoming more sensitive and perceptible by improving sensors and gadgets that measure, monitor, communicate, and regulate them [266]. Because of the unpredictability of RES and the uncertainty of the load, a comprehensive decision based on a large quantity of data collection and analysis is required [267]. The SCADA and WAMS systems provide intelligent grid voltage and power data at sampling rates that are close to real-time [268]. The network model is built using both graph theoretical and probabilistic optimal DC power flow technologies that are low in carbon, which is being pushed by the government using warmth pumps, photovoltaics, electric cars, and other intelligent appliances in little voltage (LV) sharing networks to create a greener society [269,270]. As a result, there is increasing interest in visualizing LV networks using restricted metering and data collecting equipment [271]. A cost-effective option is network load profiling, based on identifying typical load profiles of LV systems. A three-stage network load profiling technique described by clustering, classification, and scaling seeks to analyze the current LV networks' capacities to accommodate the technologies that are low in carbon [272].

4.3.7. Renewable Energy Forecasting

Wind and solar energies are expected to be the essential sources of energy for the power grid, due to the plentiful and environmentally beneficial generation of energy [273]. Conversely, randomness and intermittent features are constant roadblocks to the constant largescale use of RES. The precise and reliable RES predicting technique has been the hot point worldwide to cope with such massive difficulties and to enhance dispatch planning, maintenance scheduling, and regulation [274]. The meteorological data is utilized to categorize the days into distinct groups. Then, a neural network is qualified to obtain wind energy forecasting data [275,276]. PV diffusion is forecasted using a data-driven approach. The suggested regular neural network (RNN) model is designed for ultra-short-term solar power forecast by deconstructing time-series information using distinct wavelet transform [277,278].

4.3.8. Load Forecasting

The actual short-term load projecting such as the RES estimation is the foundation for energy administration, system process, and market analysis [279]. Improving forecasting accuracy may result in several advantages and cost savings, as stated in [280]. The dynamic and highly efficient electricity of marketplace is constructed on accurate forecasts of energy consumption as customers frequently use smart networks to avoid neural network installation issues with a unique level of integration that overcomes load profile instability and uncertainty [281,282]. As part of the newest deep understanding approaches for residential load forecasting, a recurrent neural network-based framework with long short-term memory is used [283]. A hidden-mode Markov decision model is developed to predict user behavior in real time [284] and to analyze the latest phase of leveraging societal mass media via cell phone applications to increase consumer interaction and load forecasting [285]. In addition, the developing trends and obstacles examine the influence of social activities on prosumers' creation and consumption habits and the whole effect on final load and network usage [286].

4.3.9. Load Profiling

Load profiling refers to the process of describing the usual behavior of electric consumption [287]. In general, demand–load forecast management and capital planning in the time domain are expressed as an effective method of energy management [288,289]. The rationale for the best DR mechanism is to break down household energy consumption into three portions: stable, controlled and deferred loads [290]. DR is used to encourage consumers to modify their usage or feed-in patterns with a stimulant of charges or ecological data [291,292]. A good consideration of the unchangeable energy used by clients is the foundation for DR, that could relieve the distribution system's burden in terms of temperature and voltage constraints [293]. Knowing the charging load type of electric vehicles (EVs) is limited to be a critical phase for the constancy of power grids as they become more widespread [294]. To extract the charge–load model of an (EV) by measuring the actual power, Bayesian maximum probability is utilized to check the pliability of the collective EV charging demand [295]. Increasing the acceptance of smart meters placed according to the home standard, emphasizes the problem of enormous load profile data, which poses problems to measurement data transfer and storage, along with important data extraction out of the vast records [294–296].

4.3.10. Load Disaggregation

Non-intrusive load monitoring (NILM) is a type of load that separates general load profiles at the home standard from the power usage of specific machines [297]. NILM, out of just one smart meter, placed in the house is effortless to accept by clients than direct appliance monitoring framework [298]. The various types of residential electric machines possess varying possibilities for participation in the DR program, leading to a better understanding of their customers' behavior and a more energy-efficient approach [299,300]. NILM early approaches were mostly centered on detecting an edge in power transmission to indicate whether a recognized device is on or off [301,302].

4.3.11. Nontechnical Lack Detection

Non-technical lack (NTL) most often results in electrical rubbery or accounting mistakes of power system companies [303,304]. Non-cooperative game models for nontechnical lack examination of micro-distribution systems applied to AMI [305]. A report by Northeast Group, Limited Liability Company (LLC), shows annual losses due to power theft that were more than USD 89.3 billion worldwide [303]. Furthermore, large-scale electricity theft has the potential to generate dangerous power system imbalances. As a result, many researchers are interested in developing a practical outline to identify the NTL in a composite energy system, which is an approach constructed on the DT and backed by suggest vector machine (SVM) [292]. DT is programmed with various parameters such as heavy appliances, the number of people in the house, and climate circumstances to calculate the predicted rate of power used for the client at any given moment. The computed consumption is then sent to an SVM classifier that has previously been trained on the gathered data set to assess if the customer's conduct is regular or fraudulent. Fraud recognition is triggered, as a difference is found between power provided by the energy system and gathered data out of the smart meters. Therefore, the fuzzy clustering technique is used to find abnormalities in consumption patterns [292].

4.4. Big Data Platform for Intelligent Meter

4.4.1. Smart Grids and Meter Data

SGs are classified into three parts, which are the information infrastructure (data stream in the smart grid's cyber portion), computer networks (exchange control signals and measurement data) [306], and power infrastructure (energy distribution in the physical component of smart grids), which includes intelligent meters and energy devices such as towers, generator and adapters [307]. IT components include modeling, analysis, profitable transactions, information exchange, and management [308]. Big data management and analytics are the key problems in the SG [202]. Smart metering is causing a huge growth in the volume of data available. For example, in the United Kingdom, approximately 100 million data points are gathered biannual for energy companies to register for the 27 million residential power users. Power suppliers will be essential to absorb, store, and fully analyze 4500–9000 times more data when smart metering is perfectly installed and operating at a 30-min sample rate. The capacity to cope with massive data problems in the future will be critical for several essential intelligent grid applications, including situation awareness, state estimate, event discovery, load forecasting, and claim response administration [309].

4.4.2. The Analytics of Meter Data

The techniques of mining data are used to analyze the meter data of a variety of applications. These may support energy managers in uncovering knowledge and obtaining insights from large data [310]. The majority of the research is proven via utilizing comparatively modest data collections, such as claim or carry out forecasts [311], customer segmentation, pattern categorization, recommendations of power tariff, power consumption of equipment in particular homes, and demand-side management [312]. One of the most recent huge data sets published was over one million data points—still far from the predicted future [313,314].

5. Challenges

This section highlights three energy issues that remain unresolved in cloud computing applications for smart grids: energy distribution, energy mix and battery charging. Therefore, there is a challenge of migrating SG to cloud computing for energy management, information management, and cloud applications [315]. First, open issues for energy management, similar to clouds, have a variety of heterogeneous applications. The microgrids lead to challenging transmission of data between the cloud and the microgrids with/without real-time data. Therefore, it is urgent to install a virtual power stream controller to optimize the energy that can operate in any realistic and efficient mode for the smart grid. However, to reduce a claim from micro-grids during summit hours, it a necessary to mix and share energy storage with a cloud [316]. Second, problems for managing information, despite cloud computing being effective at managing smart-meter data, still have several obstacles to overcome [317]. Solving data-sharing issues is an excellent idea for combining public and private clouds for cost-effective communication in smart grids. In addition, the integration of mobile multi-agents in cloud computing may achieve an effective intelligent network process, which is still a problem due to heterogeneous communication architecture. It must be able to accommodate diverse energy sources while also allowing for large-scale interactive collaboration via cloud services and a reduction in cloud app delays. As in billing, users need dependable and cost-effective services. A single protocol failure may bring the entire intelligent grid system down [318]. Third, long-term evolution (LTE) allows for better coverage and lower latency, which presents challenges to existing cloud computing platforms. Platforms that address some of the long-term evolution problems related to quality of service (QoS) improve with the radio access network, network of mobile core, and datum center to supported virtualized infrastructural resources. Coordination and synchronized function are encouraged facilities for monitoring, preprocessing, dissemination, storage, analysis, and alerting metrics supported between different clouds, which is a unified and suitable interface. The world's most pressing concern is energy. As a backup generator, fossil fuels are frequently employed, although their production of CO_2 affects life and the environment [39]. A novel technique called DR makes virtual generation better. Users may program their gadgets using this approach. There are several issues with a traditional smart-grid design (without the cloud), which is the master–slave design that leads to a risk of DDoS [41,42]. Any error may cause the entire system to fail. There is a limit on how many clients can be served due to memory storage limitations, stability, and management. Furthermore, information and data management challenges include millions of intelligent meters necessitating effective handling of massive data. Cloud computing may provide a cost-effective alternative for data analytic and storage methods, as shown in Table 5 [319].

Table 5. Main features of big data in smart grids.

Category	Challenges
Smart grid	• Heterogeneous • Energy storage systems are insufficient. • Not combining energy storage with the cloud and sharing it • Big data management and analytics
Cloud computing	• Data-sharing issues • Lack of integration of multiple mobile agents with the cloud • Dependability not sufficient • Insufficient platform Implementation for offering long-term evolution • Unsynchronized function • Risk of DDoS • Any error leads the system to fail • Insufficient methods data analytic and storage methods
Big data	• Memory storage limitations • Stability • Management • Insufficient methods for handling massive amounts of data • Information and data management challenges

6. The Framework of the Charge Controller System

Overall, after the long review illustrated in this paper, the proposed framework contains an EMS stored on the cloud computing service. This system serves three different goals. The first is to monitor and combine different energy sources in order to obtain the best optimized system. The second goal is to control the switches in the energy hub, and the third goal is to manage the charging and discharging process. The system will yield many benefits:

a. Reduce the carbon footprint by including RESs such as solar plants (photovoltaic), WTs, and other RESs;
b. Enhance the demand power by monitoring and controlling the power balance at the same time;
c. Introduce an intelligent system and cloud computing to the power management field, and make the system manageable.

It is difficult to carry out an actual optimization charge controller on an intelligent power system via cloud computing, as it is based on numerous nonlinear parameters and contains many genuine bonds and limitations. Furthermore, because many actual characteristics are stochastic, handling a power system as a plant (dynamic systems) is problematic. Therefore, there are two suggestions: the first is to plan the optimization algorithm for the charge controller based on the real parameters; the next is to implement this proposed algorithm as a practical system that offers optimal interventional treatment solutions for all protection requirements. Therefore, this study focuses on presenting a final chart of the model that will consider three aspects: power demand management, RE, and cloud computing, which will be the main contribution of the future study conducted in Figure 9.

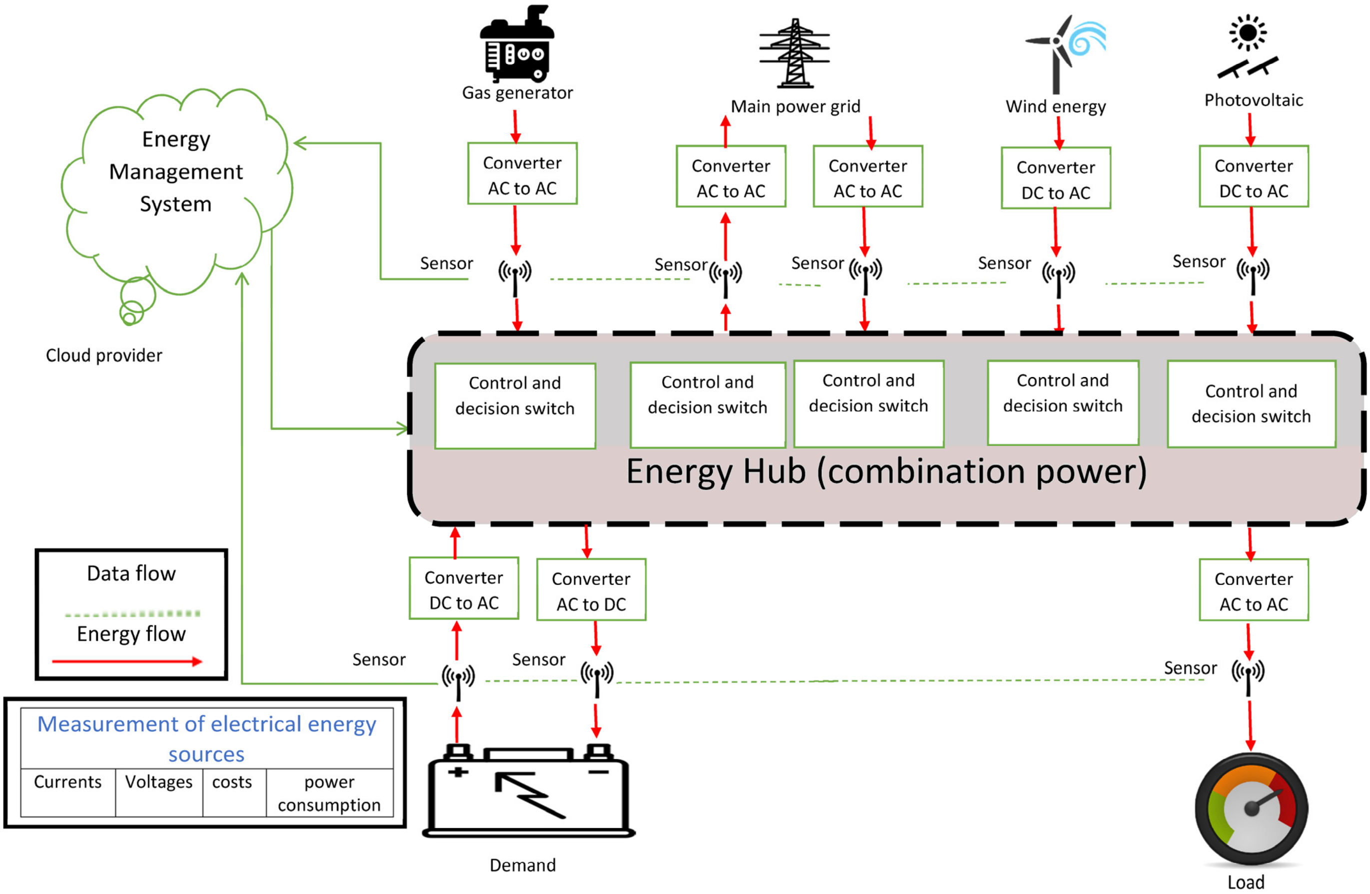

Figure 9. The framework system model for energy sustainability.

7. Conclusions

The study summarized the recently published literature that focuses on methods to reduce power consumption and costs. Furthermore, the recent literature discussed using cloud computing to store EMSs and managing them intelligently. Furthermore, it discussed how a well-maintained system of power mixing (power used to charge the batteries) can lead to better environmental results by reducing the carbon footprint. Furthermore, it discussed the recent literature that used cloud computing to store EMSs and manage them intelligently. As a result of this extensive literature review, the researcher proposed a final chart of the model that will consider three aspects: battery management, RE, and cloud computing, which will be the main contribution of the future study conducted by the researcher.

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Abbreviations

In this review, the following abbreviations are used:

Abbreviations	The Details
VPPs	Virtual Power Plants
DC	Direct Current
CDE	Carbon Dioxide Emissions
RE	Renewable Energy
USDOE	United States Department of Energy
SG	Smart Grid
SGs	Smart Grids
SES	Smart Energy Systems
AI	Artificial Intelligence
DR	Demand Response
PS	Power Supply
DER	Distributed Energy Resource
MT	Microgrid Trading
DDoS	Distributed Denial of Service
CPU's	Central Processing Units
SPM	Static Power Management
DPM	Dynamic Power Management
DPC	Dynamic Power Consumption
C	Coulomb
A	Amperes
V	Volts
W	Watts
WH	Watt-Hours
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
FL	Fuzzy Logic
MOA	Metaheuristic Optimization Algorithms
SoC	State of Charge
KW	kilowatt
GPR	Gaussian Process Regression
GIESBs	Grid-Integrated Energy Storage Batteries
PVs	Photo Voltic's
WTs	Wind Turbines
EBMS	Electric Bus Management System
ANNs	Artificial Neural Networks
EMS	Energy Management System
HMG	Hybrid Micro-Grid
MOPSO	Multi-Objective Particle Swarm Optimization
PMP	Pontryagin's Minimum Principle
MEET	Maximum Efficiency Tracking
FAFC	First Access First Charge
MDP	Markov Decision Process
HEMS	Home energy management system
SHEMS	Smart Home Energy Management System
BMS	Battery Management system
MWs	Mega Watts

ETMCTSA	Energy-Performance Trade-off Multi-Resource Cloud Task Scheduling Algorithm
IT	Information Technology
VMs	Virtual Machines
TWh	Tera Watt-hours
HV	High Voltage
MV	Medium Voltage
SCADA	Supervisory Control and Data Acquisition
AMI	Advanced Metering Infrastructure
ELM	Extreme Learning Machine
SCVS	Sorting and Cumulative Voltage Summation
EVCS	Electric Vehicle Charging Station
EPS	Electric Power System
EFS	Effective Feature Set
PMU	Phasor Measurement Units
WAMS	Wide Area Monitoring System
TSA	Transient Stability Analysis
CVM	Core Vector Machine
BAS	Building Automation Systems
HVAC	Heating, Ventilation, and Air Conditioning
PHM	Proportional Hazards Model
PQ	Power Quality
LV	Little Voltage
RNN	Regular Neural Network
NILM	Non-Intrusive Load Monitoring
NTL	Non-Technical Lack
LLC	Limited Liability Company
SVM	Suggest Vector Machine
DT	Decision Tree
SaaS	Service as a Service
ICT	Information and Communication Technology
PAR	Peak-to-Average Ratio
WECS	Wind Energy Conversion System
DCEP	Data Center Energy Productivity
TOU	Time-Of-Use
MASs	Multi-Agent Systems
GHGs	Green House Gases
IoE	Internet of Energy
IaaS	Infrastructure as a Service
PaaS	Platform as a Service
LMA	Levenberg–Marquardt Algorithm
TRRA	Trust-Region Reflective Algorithm
PUE	Power Use Effectiveness
RESs	Renewable Energy Sources
EFS	Effective Feature Set
BESSs	Battery energy storage systems
EEH	Energy-Efficient Hybrid
ARBC	Adaptive Resonant Beam Charging

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