Energy Conversion and Management: X 21 (2024) 100527

Contents lists available at ScienceDirect

Energy Conversion and Management: X

journal homepage: www.sciencedirect.com/journal/energy-conversion-and-management-x

Hybrid energy system integration and management for solar energy: A review

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ARTICLE INFO

Keywords:
Solar Energy Integration
Integrated Energy Management System
Solar Energy Forecasting
Demand Side Management
Supply Side Management
Time-of-Use
Direct Load Control

ABSTRACT

The conventional grid is increasingly integrating renewable energy sources like solar energy to lower carbon emissions and other greenhouse gases. While energy management systems support grid integration by balancing power supply with demand, they are usually either predictive or real-time and therefore unable to utilise the full array of supply and demand responses, limiting grid integration of renewable energy sources. This limitation is overcome by an integrated energy management system. This review examines various concepts related to the integrated energy management system such as the power system configurations it operates in, and the types of supply and demand side responses. These concepts and approaches are particularly relevant for power systems that rely heavily on solar energy and have constraints on energy supply and costs. Building on from there, a comprehensive overview of current research and progress regarding the development of integrated energy management system frameworks, that have both predictive and real-time energy management capabilities, is provided. The potential benefits of an energy management system that integrates solar power forecasting, demand-side management, and supply-side management are explored. Furthermore, design considerations are proposed for creating solar energy forecasting models. The findings from this review have the potential to inform ongoing studies on the design and implementation of integrated energy management system, and their effect on power systems.

Introduction

Currently, about 770 million people globally do not have access to electricity [1]. It is estimated that by 2035, global demand in energy will increase by a third [2]. The upward trend in global energy demand is currently being met mostly by fossil fuels like coal, oil and natural gas, which have as their by-products global warming and emission of greenhouse gases (GHG) [3,4]. In British Petroleum's Statistical Review of World Energy [5], fossil fuel accounted for 82 % of primary energy use in 2022, with coal and natural gas growing post-pandemic by 6 % and 5.3 % respectively. To curb the GHG emissions and meet the emission reduction targets set out in the Paris Agreement, the governments globally have increasingly turned to renewable energy sources (RES) to help satisfy demand. According to BP [5], RES contributed about 10.2 % to power generation, reaching double figures for the first time.

RES, like solar and wind, have been widely adapted and are increasingly being used to meet load demand. They have greater

Abbreviations: AMI, Advanced Metering Infrastructure; ANN, Artificial Neural Network; BESS, Battery Energy Storage Systems; CCHP, Combined Cooling, Heat and Power; CEMS, Centralized Energy Management System; CoE, Cost of Energy; CPP, Critical Peak Pricing; CRP, Cost-reflective Pricing; DG, Distributed Generation; DLC, Direct Load Control; DR, Demand Response; DSM, Demand Side Management; ED, Energy Dispatch; EMS, Energy Management System; EV, Electric Vehicle; GHG, Greenhouse Gases; HEMS, Home Energy Management System; IDR, Integrated Demand Response; IEMS, Integrated Energy Management System; IES, Integrated Energy System; IoT, Internet of Things; IRENA, International Renewable Agency; ISEMS, Intelligent Smart Energy Management System; LCoE, Levelized Cost of Energy; LSTM, Long Short-Term Memory; MG, Mini-Grid; NERC, Nigerian Electricity Regulatory Commission; NPV, Net Present Value; NWP, Numerical Weather Predictions; PEMS, Predictive Energy Management System; PV, Photovoltaic; REHS, Renewable Energy Home System; REMS, Real-time Energy Management System; RES, Renewable Energy Sources; RHMG, Renewable Hybrid Mini-grid; RMG, Renewable Mini-grid; RSHMG, Renewable Smart Hybrid Mini-grid; RTP, Real-time Pricing; SEF, Solar Energy Forecasting; SEMS, Smart Energy Management System; SHS, Solar Home System; SM, Smart Meters; SoC, State of Charge; SR, Supply Response; SSM, Supply Side Management; SVM, Support Vector Machine; TOU, Time-of-Use; UC, Unit Commitment; VRE, Variable Renewable Energy.

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https://doi.org/10.1016/j.ecmx.2024.100527
Received 18 August 2023; Received in revised form 31 December 2023; Accepted 6 January 2024
Available online 9 January 2024

penetration due to their availability and potential [6]. As a result, the global installed capacity for photovoltaic (PV) increased to 488 GW in 2018, while the wind turbine capacity reached 564 GW [7]. Solar and wind are classified as variable renewable energy (VRE) and are non-dispatchable due to their intermittent nature [2]. However, economies of scale and improved research and development of VRE technology has led to a decrease in price of VRE components. The combination of price reduction and desire to limit the environmental impacts of fossil fuels has seen a greater penetration of VRE in the grid [8].

Renewable energy technologies increasingly have both off-grid and on-grid applications, but the intermittent nature of certain RES poses a challenge to grid operators as energy supply does not always match the consumption. As RES penetration levels increase with the advancement of decentralised distributed generation (DG), adequate steps must be taken to make sure that system constraints like fluctuating supply, capital costs of DG and grid extensions, and rising load demand, does not compromise the stability of the grid. Grid integration is the process of creating practical, affordable ways to integrate VRE into the grid while preserving or enhancing system stability and reliability. [9].

Solar energy is gaining popularity because of its versatility in various industrial applications including power generation for residential and commercial use, solar drying of fruits for industrial food processing, powering automotives and aeroplanes and so on. Furthermore, governments and organizations are promoting the use of solar energy through various incentives and policies because of its relative safe-use, scalability, and favourable environmental impact compared to other sources. While the current installed capacity of wind energy might be higher than that of solar energy, the latter is projected to have an annual growth rate of 47.6 % compared to 18.9 % for the former [7]. In addition, it is projected that around 45 % of the world's energy consumption could be met by solar energy by the mid-21st century [10]. In their research, Yao et al. [7] concluded that both demand side and supply side integration costs are lower for solar energy than for wind. PV systems using battery banks are the most popular because they are easier to install and cost less in terms of capital investment than other renewable energy technologies [11]. According to the International Energy Agency's World Energy Outlook 2020 report, solar power was able to achieve the cheapest electricity rate in history. It was cheaper than coal and gas in most countries with price bids as low as 0.0104 US$/kWh [12]. Combined with increased efficiency of solar cells, and improved economies of scale leading to mass production of high-quality wafers [13], it is easy to see why solar remains a popular choice for power generation. Currently the energy intensity of silicon wafers production is about 6 kg CO_2e/kg of silicon metal [14], considerably less than other sources.

An energy management system (EMS) can be used to balance the supply and demand of a power system, which is a key requirement in integrating intermittent RES like solar energy. However, the emergence of big data, cloud computing, Internet of Things (IoT), advanced metering infrastructure (AMI) and other advances in communication has transformed the conventional grid into a smart grid [15,16]. The technology requirements of the smart grid have necessitated the evolution of the conventional EMS into an integrated energy management system (IEMS) [15]. While EMS can be predictive or in real-time, by definition, an IEMS leverages advancement in technology and communication, integrating predictive and real-time controls to initiate both supply and demand responses in balancing the load and power supply in the grid. While EMS may refer to a single power source, an IEMS has the ability to integrate multiple energy systems and initiate various control strategies.

A comparative assessment of various IEMS architectures, based on the interconnectedness of their individual components is crucial in understanding how they impact the power system, provide grid stability, and ways they can be improved. As can be seen in Table 1, the published reviews listed does not give an analysis of IEMS frameworks. For instance, Jafari et al. [17] focuses on the limitations and techno-economic requirements of energy storage systems (ESS). Farag et al. [18] highlights issues with solar integration but focuses more on dust particles. Formolli et al. [19] analyses existing integrated solar energy sites with a focus on recommendations that will improve future urban solar energy projects. Peng et al. [20] focuses on PV generation, ESS and solar thermal for heating. Rubio-Aliaga et al. [21] proposes a multifaceted approach considering economic energy and environment to solve groundwater pumping issues by using RES. In both studies by Ozoegwu et al. [22,23], the focus is more from a policy standpoint.

To address the research gap, which is the absence of a review on IEMS, this paper will review current IEMS frameworks/architectures,

Table 1
Recently Published Reviews Related to Solar Energy Management System and Integration.

Source	Publication Date	Scope
Khan et al. [24]	2022	• Summary of various optimization modeling techniques of a hybrid renewable energy system (HRES) Review of sizing, control and energy management strategies for HRES
Panda et al. [25]	2022	• Review of DSM in integrating DER and Energy Storage Systems (ESS)
Rayid et al. [26]	2022	• Prospects and challenges of renewable based mini-grid implementation in Bangladesh
Apeh et al. [27]	2022	• Review of the contributions of PV to national development
Khan et al. [28]	2022	• Review of optimization techniques for HRES couples with Hydrogen technologies
Alami et al. [29]	2022	• Review of challenges and solutions to PV technology proliferation
Lamnatou et al. [30]	2022	• Review of smart grids /smart technologies related to PV systems, storage, buildings, and the environment
Khosrojerdi et al. [31]	2022	• Integrating artificial intelligence in smart grid
Banu et al. [32]	2021	• A review on the advancements in methane cracking for hydrogen production
Klass et al. [33]	2021	• A review on four ammonia production methods
Ozoegwu et al. [23]	2021	• An overview of Nigeria's energy policy objectives and strategies
Stevovic et al. [34]	2021	• Using nature-inspired optimization for solar energy integration
Dashtpeyma et al. [35]	2021	• Development of a resilient solar-based EMS
Peng et al. [20]	2020	• State of the art of solar energy utilization in buildings
Shafiul Alam et al. [36]	2020	• Review of challenges and solutions to RES integration
Østergaard et al. [37]	2020	• Review of technologies and systems that use RES
Syafaruddin et al. [38]	2020	• Modeling and Simulation procedures, control strategy for hybrid power generation
Nižetić et al. [39]	2019	• Review of smart technology applications focused on efficiency improvement, sustainable and smart resource management
Azuatalam et al. [40]	2019	• Comparison of energy management strategies for small-scale PV-battery systems
Rubio-Aliaga et al. [21]	2019	• Multidimensional characterization to evaluate PV integration
Guo et al. [41]	2019	• Review green energy integration for wastewater treatment plants
Lauka et al. [42]	2018	• Development of a methodology to define solar energy potential for urban planning
Ozoegwu et al. [22]	2017	• A review of the past, current, and future status of solar integration in Nigeria.
Khoshkbar-Sadigh et al. [43]	2015	• Impact of large-scale PV penetration into the grid
Inman et al. [44]	2013	• A review of forecasting methodologies and their applications

identify gaps in current knowledge and propose areas for future research by:

- identifying and providing a comprehensive overview of the IEMS building blocks including energy forecasting, multi-energy generation, energy storage, demand side management and supply side management;
- comprehensively reviewing each building block of the IEMS based on their adaptation and grid deployment as described in current literature; and
- providing a side-by-side comparison of various IEMS architectures.

Following the introduction, Section 2 describes the methods and gives the bases for the various literature reviews that span section 3 to 8. Section 3 presents the power system that is most favourable for the IEMS to operate in. Section 4 provides an overview of the state-of-the art in solar energy forecasting and provides a comparison of various forecasting models. Next, Section 5 provides a literature review of demand side management and highlights the different types of demand responses. Section 6 gives an overview of supply-side management and its application in current literature. Section 7 explains how an EMS works, siting examples of its application in literature. Section 8 brings together the various concepts from Section 3 to Section 7 and shows how they combine into an IEMS. A detailed comparison of some existing IEMS frameworks is also presented. Finally, Section 9 is a discussion on the authors perspective of various IEMS frameworks including future research. This concluding section also highlights the key findings and contribution to the IEMS literature.

Methods

In reviewing the existing literature on IEMS, it was determined that there are five major parts of an IEMS framework that supports solar energy integration: the power system the IEMS operates in, solar energy forecasting (SEF), demand side management (DSM), and supply side management (SSM). David et al. [45] largely substantiates this by conducting a bibliometric study using the Scopus database from 2000 and 2019 on PV solar energy management. From the analysis, ten potential study areas were established on future research trends including forecasting techniques and DSM, both of which are mentioned as future trends, load status studies, and efficient battery use which has applications in both SSM and DSM, and so on.

Solar energy forecasting

The capacity to reliably estimate generation while keeping some flexibility in demand control will be necessary for solar energy integration into the grid [46]. Effective grid integration and planning depend on improved generation predictions [47]. Energy forecasting is fundamental and crucial to practically every area of the economy, including residential, commercial, and industrial [48]. There are research methods that focus on predicting load consumption patterns or peak demand as a way of renewable energy integration [49–52]. However, for an energy system that uses solar energy as its primary source of power, the uncertainty in the system lies more in the variable nature of solar energy. In addition, many loads are invariably affected by weather parameters like solar radiation [53,54] which makes load consumption the dependent variable. Therefore, it is more effective for the stability of a solar-driven energy system and the dispatch of solar energy to the grid, to accurately predict solar energy supply than load consumption.

To support the theory above, Cai et al. [51] concludes that the prediction of energy consumption has to do with improving grid quality and allocation of power supply. Basmadijan et al. [46] on the other hand states that maintaining an equilibrium between power demand and supply solely rests with the supply side. For efficient MG sites that have PV generation units, a precise characterization of the solar energy available is crucial [55]. The argument is that supply is more easily controllable than demand because of the stochastic or unpredictable way consumers use energy [56]. For conventional grid sources, EMS is based on demand forecasting and supply planning. For RES, EMS is based on supply forecasting and demand planning. Therefore, the answer to the question of renewable energy integration is more suited to the prediction of renewable energy supply also known as solar energy forecasting (SEF).

By being able to accurately forecast solar resources, one can then predict what generation will be like and reduce uncertainty [3,47]. Accurate energy supply forecast informs what control measures can be taken to maintain energy supply–demand balance in the system. For instance, in periods of low energy supply, alternative or standby generators can be deployed to augment power generation. Operational control of both supply and demand in a power system is crucial to renewable energy integration and aids in the balance of power [3].

Energy management system

With the emergence of solar energy as an important source of energy supply, more thought must be given to increasing its usage in an efficient and sustainable way. One such solution is the use of an EMS to match demand and supply. An EMS is a tool that combines complex software and hardware to monitor, control and optimize energy use to reduce cost [52]. The EMS has a control system program that initiates a response depending on the energy supply forecasted. This response could either be a supply response (SR), demand response (DR) or a combination of both. Control systems are an important counter to the fluctuating and intermittent nature of RES like solar and wind energy [57]. An electric power control system uses control loop mechanisms to manage, regulate and direct the electrical components within a power system, and thus the power system itself [57]. Control systems use a feedback controller to modulate control. Parameters such as system frequency or voltage could be used as the process variables where a pre-determined control signal is generated once there is a difference between the value of the process variable and a reference value.

Supply side management

EMS using control systems is critical in implementing SR, DR or a combination of both, to ensure sufficient energy supply to satisfy demand [58]. SR is a subset of SSM. SSM refers to the efficient generation, transmission, and distribution of electricity to meet customer demand [59]. SSM is crucial in creating an energy reservoir to supplement inconsistent energy supply resulting from intermittency of some RES. There are several SSM techniques including integrating battery storage [60], optimizing and synchronizing alternative or back-up power [61], dispatching algorithm for multiple energy supply sources [62], ramping up and down of generation through automatic control and so on.

Demand side management

Conversely, DR is a subset of DSM. DSM is the process of using energy efficiently by managing customers' energy consumption [63], in addition to reducing energy costs and emissions [64]. In the resource-constrained areas of the grid, usually found in off-grid rural communities, storage batteries are often over-sized to increase the reliability of the power system. DSM can act as an energy buffer while reducing the capital and operating costs of the power system. Examples of DSM are energy storage using, energy efficiency in buildings [65], initiating DR and so on. DR focuses on short term adjustments made to load usage [60] and is broadly categorized into two: price-based DR and incentive-based DR. For efficient energy utilization, there is a need to integrate RE and other distribution energy resources with DSM [66]. Conversely, successful implementation of DSM can be achieved through energy forecasting [67]. In addition, efficient power scheduling should be done using RE forecasting and managing electricity tariffs through DSM [68]. A reliable EMS is vital to the success of DSM [69]. It is clear to see that SEF, SSM and DSM are strongly linked in an EMS.

In general, the review found that scientific journals mostly addressed optimising the system in terms of storage, energy dispatch/supply, consumption, and equipment sizing. Largely undiscussed was a comparative overview of the IEMS framework. To analyse IEMS frameworks, we conducted a comprehensive literature review for each sub-section of the framework, including the EMS. The aim was to identify and emphasize key concepts and design considerations for each parameter and their interconnectedness within the IEMS. Fig. 1 illustrates the approach used in the study.

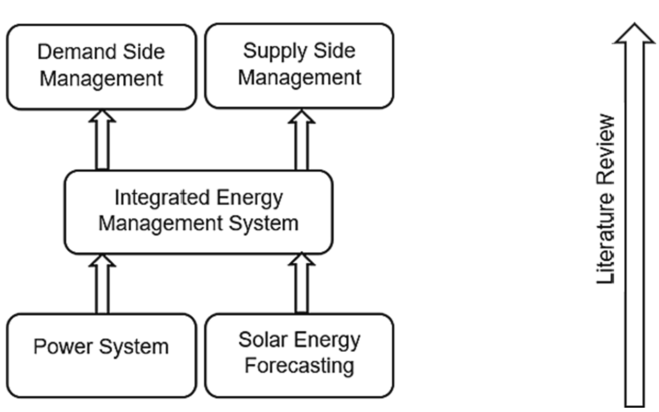

Fig. 1. Review approach for IEMS Framework.

Renewable smart hybrid mini-grids: The future of renewable energy integration

A smart MG is a collection of controllable and physically proximate distributed generator(s) and load resources, where there are multiple sources of AC power and at least one of these is based on a renewable energy technology such as wind or solar energy [4]. With the advent of smart grids, these resources can be better controlled to deliver efficient and reliable power despite their intermittent nature [46]. Due to their modular and distributed nature, smart grids are a viable and sustainable way to provide power in developing countries [70].The renewable smart hybrid MG is ideal for dispatching an EMS because it requires smart communication of multiple load and supply sources at the same time. There are different classifications and iterations of the smart grid or MG namely the renewable energy home system (REHS), renewable hybrid mini-grid (RHMG) and the renewable smart hybrid mini-grid) (RSHMG). Fig. 2 shows the three different configurations. An examination of their different characteristics and their importance to the deployment of an EMS is further explained.

Distributed generation: Mini-grid & renewable energy home systems

The conventional method of providing new electricity connections mainly from traditional sources like fossil fuels is not sustainable, as the environmental costs and rising fuel prices make grid extension expensive and less attractive [4,71]. For the problem of universal electricity access, the idea of a central utility gradually extending the grid is being overshadowed by a more robust solution using decentralized DG. While the former causes transmission losses [72], the latter provides the use of locally available energy sources. This eliminates transmission costs and reduces power losses [4] as well as increases the flexibility and reliability of the overall system.

DG, particularly using RES, has proven to be a viable answer in terms of cost and flexibility [3]. DG shows a greater capacity of renewable integration without compromising the grid [73]. DG renewable configurations differ with respect to capacity. At one end of the spectrum are MGs and integrated solar farms, while at the other end are smaller renewable energy home systems (REHS) like rooftop solar arrays. The increase in solar energy penetration has also largely increased due to the fact that RES now have small-scale and large-scale applications [74] with users ranging from small residential customers to large utility operators. This is not independent of the fact that RE is relatively affordable and can be accessed by a wide spectrum of customers [2]. Fig. 3 gives an overview of the DG classifications.

The Nigerian Electricity Regulatory Commission (NERC) defines MGs as systems with integrated generation and distribution networks that have installed capacities below 1 MW [75]. This can be with or without storage [76]. NERC also goes further to classify MGs as being either isolated (no connections to any network) or interconnected to the main grid [75]. A study by the International Renewable Agency (IRENA) gives a more general definition of MGs as simply an integrated structure of energy sources and loads that may or may not include functions of generation, storage control, management, measurement, conversion and consumption [77]. MGs are increasingly popular because of technology flexibility and an efficiency in integrating large scale DGs [78].

REHS are gaining popularity due to lower installation and operational costs [11]. Like the name implies, these are systems that use one or more RES as its primary or back-up source. They can either be standalone or grid-connected. An example of a REHS is the solar home system (SHS). The SHS is comprised of solar panel(s), a charge controller, battery, an inverter and a load. At the very basic level, the inverter is not included, and the load is DC in nature. REHS can range from several watts to several thousand watts. They usually represent the low end of the DG spectrum.

REHS and MGs are quite similar in the sense that they both operate a decentralized grid. In fact, MGs may be viewed as a bigger version of the REHS in terms of energy production capacity. Ekpe and Umoh [70] infer that a solar home system (SHS), which is an example of a REHS, can be easily scaled up to a MG. There are, however, some other differences. REHS tend to provide a lower tier of service than MGs [77]. Though central utilities on an average provide a higher tier of power supply to multiple customers than both, they have to consider power losses due to distance and its equivalent costs. MGs on the other hand can provide the quality of service a central utility provides while being closer to the customer. In fact, MGs are a replica of the much larger central power systems albeit on a smaller scale [79]. REHS are tailored to a particular customer's load profile [76] while MGs can reasonably be designed and optimized to match the aggregate load profiles of the customers it supplies [80].

Renewable mini-grids and hybrids

A MG based on some-form of renewable energy is referred to as a renewable mini-grid (RMG) [77]. RMGs are viable alternatives in supplying areas with no connection to the grid (off-grid), areas with inefficient or erratic energy supply, or areas where grid extension is not cost effective [3,77]. These MGs can serve as a backup to the main grid or at other times help supply power during peak demands [63], thereby reducing the burden on centralised utility networks.

RMGs can also be paired with generation from non-renewable sources like diesel generators to form a renewable hybrid mini-grid (RHMG) [63,70,77]. RHMG are a cost-effective way of improving power system reliability through renewable energy integration [81,82]. Typical configurations of the RHMG have the renewable component as the primary source while diesel and/or batteries serve as backup [83]. RHMGs are able to combine the advantages of each generation source. For instance, a solar-diesel MG takes advantage of the stable power supplied by a diesel generator versus the intermittent nature of solar energy, while solar as a renewable energy source isn't affected by varying fuel prices. As compared to single-source power systems, RHMG supply greater load for longer and are more efficient and cost-effective [84]. Falk et al. [85] also attributes faster and more flexible energy

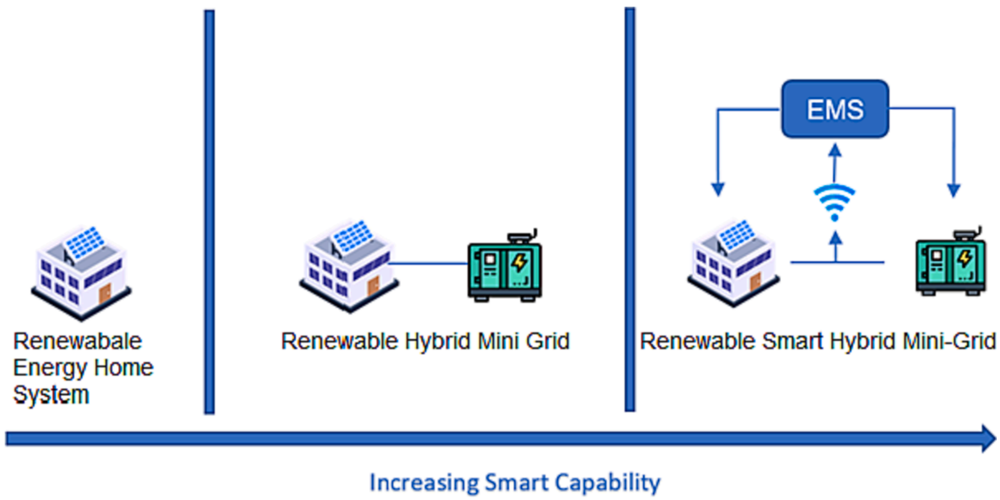

Fig. 2. Power System Configurations for EMS Deployment.

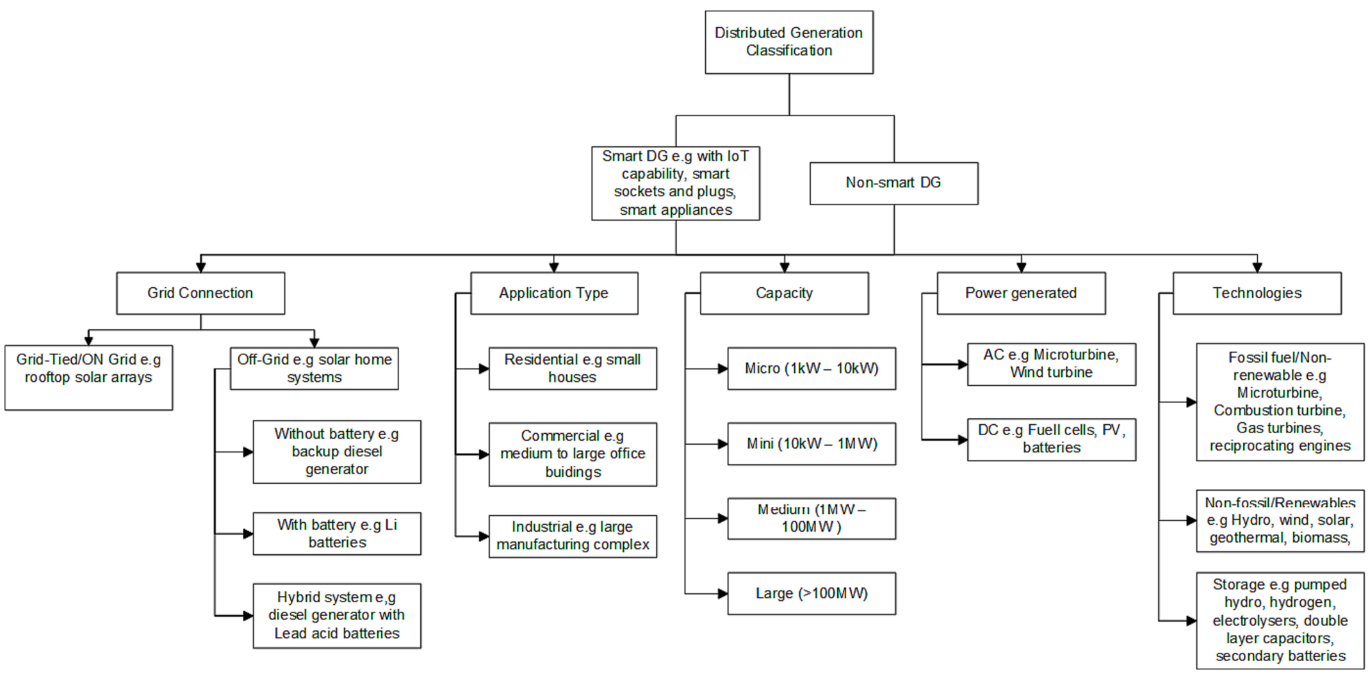

Fig. 3. Classification of Distributed Generation Systems.

supply as advantages of RHMGs especially when incorporated with some form of storage. RMGs are viable in providing reliable, affordable and environmentally friendly supply of energy [63,77,80].

Grid-tied versus off-grid

IRENA groups MGs based on their connection to the grid and the type of service provided. Connections are categorized as autonomous (isolated) or interconnected (grid-tied) while the type of service is either lower tier or higher tier [77]. However, Szewczuk [86] makes the case for an interconnected system over an isolated system by highlighting the lower cost per connection due to the fact that power from the grid can sometimes substitute storage and help with system balancing. In addition, since grid-tied MGs are part of the main grid, they can be configured to help with the utility's short-term problem of on-grid congestion and peaking loads [63], and its long-term problem of grid extension. Furthermore, Robert et al. [79] sites the semi-autonomous design of the interconnected MG as the reason it contributes to the overall reliability and resilience of the system. Isolated or off-grid MGs can only help with the latter problem and require complex energy balancing mechanisms if the primary source is RE. There is, therefore, a stronger case to look at an interconnected system that addresses both on-grid congestion and grid extension. Typical configurations of the RHMG are operating:

- as the primary power provider with the main grid as a back-up;
- as a back-up to the main grid; and/or
- a system to shave up peak demands and supply critical loads [77].

The EMS should be robust enough to be deployed either for on-grid or off-grid power systems. The EMS's function for an on-grid application will be to reduce the strain on the grid by optimising the operations of any energy storages, co-ordinate power dispatch and reducing peak load demands. In an off-grid application, the EMS's main function will be to maintain the integrity of the grid by matching supply to demand, since there is no back-up as the main grid is absent. EMS can also be applied to frequency and voltage control of the grid.

Renewable smart hybrid mini-grid

Deployment of interconnected MGs has been limited and the technology is still emerging [77]. The ability for various equipment and components in the power system to interact and communicate with each other, interpret and respond to external and internal inputs in order to preserve the stability of the system makes the grid "smart". The objective of the smart grid is to upgrade the existing power system to one that is safe, adaptable, resilient, expandable, and sustainable [87,88]. Adding intelligence or smarts to a system yields better results for all stakeholders involved, for example optimally switching power sources and load shedding [3]. To increase grid penetration, RMGs or RHMGs "require technology advancements in design and planning phases" [77]. According to IRENA [77], these technological advancements include intelligent controls that can interpret high level algorithms, integrate accurate RES predictions with adequate battery control. Moreno-Garcia et al and Judge e al. [89,90] identify these technologies as AMI, smart meters (SM), sophisticated communication and information architectures or advance control and automation techniques. The incorporation of these technologies transforms the RHMG into a renewable smart hybrid mini-grid (RSHMG) [63]. Palahalli et al. [91] describes smart grids as the interaction between power and communication devices to control power flow within the grid network. These communication devices must be reliable [70] so that the flow of information between monitoring and control devices results in the accurate response. Smart grids must be able to integrate all components of the system, from supplier to the end-user, and possess real time monitoring and control [89]. The emphasis on smart grid is because the central technology used in implementing DR programs or cost-reflective pricing (CRP) is the SM [92]. SM is part of the AMI that integrates measurement, communication, control and monitoring between the supply and demand side of the system [90,93].

Smart grids have also given rise to smart homes. Smart homes with residential power generators are also capable of monitoring and controlling customer appliances and loads [65].

Solar energy forecasting

The push for integrated renewable energy generation is seen as a key step in reducing the dependency on depleting fossil fuels used in power generation. However, the intermittent nature of RES, like wind and solar energy, means that a higher penetration of these sources in the traditional grid would lead to reliability and quality issues [13,79,89,94]. Therefore, a reliable way to forecast energy resource availability is crucial in making sure energy demand always matches supply. Accurate resource forecasting reduces the need for storage and other reserves [79] and helps the energy sector to minimize power fluctuations while maintaining the overall reliability of the system [66]. The results of a study by Kromer et al. [95] show that by incorporating forecasting and day-ahead shaping of customer's load, need for storage was reduced by 10 %-20 % and levelized cost of energy (LCoE) by about 10 %.

SEF is the process of predicting future solar irradiance or solar power generated from historical and/or present meteorological observations [96]. There are many SEF methods and techniques usually derived from considerations like data input, forecasting architecture used to map the input data, the forecasting methodology, the forecasting time frame/scale and the predicted outcome [97]. In considering the data type, this could be historical, real-time, or forecast data. The data source describes the origin of the data for example if data comes from an on-site weather station as opposed to a local weather station. Table 2 shows a review of some studies based on data source and types.

Table 2 shows the possibility of different permutations of data types and sources that have not been explored. There is clearly room for further research and contribution to this area as highlighted by David et al. [45] in Section 1. While some studies may choose to use one data (univariate) type, Table 2 reveals that majority rely on two data sets: the historical PV generation and a meteorological data type. Even fewer studies make use of more than two data sources. A more in-depth analysis of current literature, and an expansion of the concepts

Table 2
Review of Research Studies on Data Source and Types.

Research Study	Historical Observed Weather Data from Weather Station	Forecast Weather Data	Historical Observed Weather Data On-Site	Historical Observed Energy Meter Data
Sarp et al. 2021 [98]			✓	✓
Aprillia et al. 2020 [99]			✓	✓
Cannizzaro et al. 2021 [100]			✓	✓
Gu et al. 2021 [101]			✓	✓
Nguyen et al. 2021 [102]			✓	✓
Pan et al. 2021 [103]			✓	✓
Ngoc-Lan Huynh et al. 2021 [104]	✓			✓
Pedregal et al. 2021 [105]	✓			✓
Ahmad et al. 2021 [106]	✓			✓
Korkmaz 2021 [107]	✓			✓
Li et al. 2019 [108]	✓			✓
Najibi et al. 2021 [109]	✓			✓
Rodríguez et al. 2018 [110]	✓			✓
Thukral 2020 [111]	✓			✓
Wang et al. 2018 [112]	✓			✓
Yakoubi et al. 2021 [113]	✓			✓
Zang et al. 2018 [114]	✓			✓
Chen et al. 2020 [115]	✓			✓
Anaadumba et al. 2021 [116]				✓
Kushwaha et al. 2019 [117]				✓
Iyengar et al. 2014 [118]		✓		✓
Andrade et al. 2017 [119]		✓		✓
Leva et al. 2017 [120]		✓		✓
Persson et al. 2017 [121]		✓		✓
Abedinia et al. 2017 [122]	✓	✓		✓
Carrera et al. 2020 [123]	✓	✓		✓
Kim et al. 2019 [124]	✓	✓		✓
Kyliashkina et al. 2019 [125]	✓	✓		✓

highlighted in Table 2, can be seen in Table 3.

In Table 3, the second column describes the type of power system used in the forecast. As can be inferred from Section 2, each power system is unique and has characteristics that will influence how the solar energy is forecasted. In the data source column, data used in the studies were historical and forecast weather data as well as power or energy meter readings from the PV plant. Some studies use more weather data parameters than others in selecting the predictors to train the forecasting model. These predictors have a direct impact on the predicted outcome. This is important because the more relevant data used in training, the more accurate the model is [110]. In summary, the more weather parameters considered, the higher the possibility of getting better predictors.

The proximity of the weather data to the power system is another factor to consider when assessing a forecasting approach. Although weather data from a local weather station may be accurate, it is possible that they don't fully reflect the site's local characteristics. By having a weather station on-site, this weather information can be further refined [2]. Local weather conditions that affect the weather but are not represented in data from local or regional weather stations can be captured by the on-site weather station. Therefore, the presence of an on-site weather station is important and is included in column 5 of the table.

According to the temporal scale, solar forecasting is divided into ultra-short-term (1 min to 1 ahead), short-term (1 h to 1 week ahead), medium-term (weeks, months, and quarters) and long-term forecasting (1 year to several years ahead) [134].

The forecasting architecture describes how the forecasting methodology maps the input data to the predicted outcome. Solar forecasting methods are divided into physical, statistical, and hybrid models [135]. Physical methods are divided into Satellite-Imaging models, Sky Images and Numerical Weather Predictions (NWP) [136]. NWP uses meteorological weather data like pressure, temperature, humidity and so on, to predict either the solar radiation or PV generated. NWP output data are the most widely used for 24-hour or day-ahead forecasts [137,138]. Statistical methods like Artificial Neural Networks (ANN) and Support Vector Machines (SVM), are data-driven and rely on historical data to make predictions. Both the physical and statistical models can be combined to form hybrid models that provide a higher forecasting accuracy.

Demand side management

Power system management can be categorized into demand side management (DSM) and supply side management (SSM) [139]. Increase in energy demand and prices necessitates energy optimization at both the supply and demand side [65]. SSM and DSM are both critical in the planning phase for the integration of intermittent RE [140] and are useful in reducing peak loads and increasing network capacity [139]. Energy planning must consider the effects of both DSM and SSM in designing energy systems that are reliable, financially viable and environmentally responsible [59]. The ultimate goal of integrating both DSM and SSM is to meet customers demand needs in a reliable and cost-effective way.

DSM and SSM can be uniquely viewed with regards to ramping up or down the demand or supply respectively. In terms of DSM, the goal is to reduce consumer demand to a manageable level at which load demands can be effectively supplied by the system. On the other hand, DSM can be used to increase demand by activating shiftable demand load and storage during times of surplus energy production.

As described by Szewczuk [86], smart grids make use of smart technologies that focus on concepts like "*dynamic demand management, automated battery control, low-cost solar forecasting, intelligent refrigeration, optimal grid planning and automated fault detection and diagnosis*". Kakran et al. [63] include components like DG, demand side responses and other smart devices for example smart meters. The purpose is for increased grid reliability, significant savings, and improved power quality [71].

DSM is the process of using energy efficiently by managing customers' energy consumption [63], thereby reducing the load demand and maximizing the capacity of the power system. It refers to monitoring and control processes that reduces the energy demand at the customer's side of the meter [141]. Despite the advantages of the RSHMG, the intermittent nature of renewable energy sources like solar energy can lead to periods of reduced electricity generation. Also, non-existent or constrained storage, along with fluctuating peak demand, can often reduce the reliability and efficiency of the system [142]. While energy storage can help mitigate some of these problems, its relatively high cost hampers its deployment [67,143]. At these times, DSM can be a useful tool to reduce demand peaks [93] and more evenly spread demand so that it better matches with supply [142,144]. DSM is also listed as a key resource that can help maintain stability in the grid when supply and demand do not match up [13]. With no control over the supply, the aim is to modify the load to fit the supply pattern [64]. In summary, DSM integrates load shifting and energy efficiency to balance supply with demand [145]. Harper lists price incentives and distributed intelligent load controllers as examples of DSM techniques and DSM technologies, respectively. DSM implementation can potentially reduce the total investment costs of MGs [67]. For example, remote or off-grid battery system storage can be reduced as DSM can account for times of high peak. In an analysis of a SHS by Mehra et al. [146], by grouping the load into critical and non-critical (shiftable) loads, the capital cost of the system was reduced by 26 %. In terms of cost to the investor/operator, DSM can move demand to periods of excess generation, thereby eliminating or limiting the need for energy storage [143]. For consumers, DSM means cheaper electricity through effective and optimal load scheduling based on current electricity prices. The implicit benefits of reducing peak demand include mitigating against electrical system emergencies, deferring the cost of building additional transmission and distribution networks, and reducing blackouts [59].

DSM is also critical to stand-alone systems since backup power cannot be called from the grid [126]. This is even more pronounced if a RES is used as the primary source. The DSM architecture [141] is shown in Fig. 4.

Demand response

DR is a process whereby the energy demand of a customer is reduced by directly or indirectly shutting off or reducing the consumption of some of the customer's appliances [141]. In effect, customer loads are shifted from peak hours to off-peak hours [90,147] or from periods of high generation to lower generation [13]. Parrish et al. [148] provided a broader definition of DR to include the flexibility to increase as well as decrease energy demand to respond to surplus energy or reduced demand peaks, respectively. When the energy supply is low, non-essential loads can be turned off and later re-scheduled to periods of higher generation. During peak load periods, a utility can shave off load by incentivizing customers to turn off equipment and shift loads to off-peak periods. The incentive must be structured so that it provides participating customers with payments exceeding their operational value for short durations a few times a year. Customers can either pay higher tariffs during peak periods or move non-essential load to off periods and still get a discount.

The flexibility of DR is well suited to meet the fluctuating supply levels of variable RES [8] and is an emerging tool at very high penetrations of VRE [9]. It is also important to note that DR focuses on short-term adjustments made to load usage [60] as a way of balancing the energy in the system rather than a more permanent long-term fix as suggested by many SR methods. DR is often referred to as a bottom-up approach, where the flexibility of the Customer's demand cancels out the variability of RES, making the system more reliable and stable [149]. DR can be categorized into two [141] as shown in Fig. 5.

Typically loads in the DR program are categorized into interruptible, schedulable, and non-schedulable loads. Interruptible loads are loads

Table 3
A summary of Studies on Solar Energy Forecasting.

Research	Power System	Data Source	No. of Weather Data Parameters O - Observed F - Forecast	On site Weather Station	Forecasting Methodology	Forecasting Architecture	Prediction time	Predicted Outcome
[123]	93 MW hybrid PV-wind	* Forecast weather * Historical weather * PV data* Sun elevation	f – 7O – 16	No	* Deep feedforward network (DFN)* Recurrent neural network (RNN)* Hybrid network (HN)	* Forecast → DFN * Observed → RNN* DFN + RNN → HN = solar energy	24-hour-ahead	Solar power generation
[126]	74 kW DC Microgrid	* Historical weather * Real time weather in 30 min intervals * Time * PV Data* Wind Data	O – 5Real time – 3	Yes	Support Vector Machine (SVM)	* Historical + real time → SVM = solar irradiation * Solar irradiation → solar cell equation = solar energy * Historical → SVM = wind speed * Wind speed → wind energy generator equation = wind energy	24-hour-ahead	* Solar power generation* Wind power generation
[65]	* 2.3 kW Wind Turbine * 3.3 kW Solar System* 22kWh battery storage	* Observed weather * PV Data* Wind Data	O – 4	Yes	* Wavelet Transform (WT) – 3-level Wavelet decomposition* Artificial Neural Network- multilayer feed forward back propagation (FFBP) network	* Wind speed → wind curve = wind power generation via wind curve * Solar radiation → Isc, Voc formula = solar power generation	5-min-ahead	* Solar power generation* Wind power generation
[62]	Hybrid Microgrid * 25 kW Solar System * 15 kW Wind Turbine * 300 kW Diesel * 30 kW Fuel Cell * 30 kW Battery * 30 kW Grid* 30 kW Water Micro Turbine	* Forecast weather * PV Data* Wind Data	f – 2	No	* Probability Density Functions (PDF) - Solar* Rayleigh distribution - Wind	* Forecast → PDF = solar irradiation * Solar irradiation → solar power output formula = solar generation * Forecast → Rayleigh = wind speed * Wind speed → wind generation formula = wind power	24-hour-ahead	* Wind Speed* Solar irradiation
[127]	* Solar PV system* Micro-hydro turbine power system	* Current - Imp* Voltage -Vmp	N/a	No	Artificial Neural network: Feed-forward with Levenberg - Marquardt back propagation	Imp + Vmp → feed-forward = solar generation	24-hour-ahead	Solar power generation
[128]	640 W PV system	* Forecast weather * Historical weather* PV Data	N/a	No	Random Forest: Non-linear multiparameter regressor	Forecast + historical → Random Forest = solar generation	24-hour-ahead	Solar power generation
[66]	N/a	* Historical weather* PV data	O – 5	No	Particle Swarm Optimization (PSO) based Support Vector Machine (SVM) regression model	Historical → PSO with SVM = solar irradiation	24-hour-ahead	Solar irradiation
[11]	14.52 kW PV	* Load demand data	N/a	No	Residual Dilated Causal Convolutional Network (Res-DCCN), Naïve, Support Vector Machine (SVM), Artificial Neural Network (ANN)	PV data → Res-DCCN-A = Solar generation forecast Load data → Res-DCCN-B = Load demand forecast Losses from Res-DCCN-A + Losses from Res-DCCN-B = Dual modal loss → Adam Optimizer	1-hour-ahead	Solar power generation
[129]	N/a	* Wind data* Load demand data	N/a	No	Probability Density Function (PDF) based on kernel method using Monte Carlo Simulation	Historical → PDF using Kernel function and density estimator → Monte Carlo simulations = Solar irradiation + wind speed	N/a	* Wind Speed* Solar irradiation
[13]	5 kW PV	* Historical weather* PV data	O – 4	No	Wavelet decomposition-Generalized Neural Network (GNN) based online forecasting model	N/a	15-min-ahead	Solar irradiation

(continued on next page)

Table 3 (*continued*)

Research	Power System	Data Source	No. of Weather Data Parameters O - Observed F - Forecast	On site Weather Station	Forecasting Methodology	Forecasting Architecture	Prediction time	Predicted Outcome
[130]	N/a	* Historical weather* PV data	O – 4	No	K-nearest neighbour (KNN)	*Historical data → Similar analysis using KNN *Weighed average of similar days = solar generation forecast	24-hour-ahead	Solar power generation
[131]	434 kW PV	* Historical weather* PV data	O – 1	N/a	Modified Support Vector Machine (SVM) with Gauss Newton Method nonlinear least squares	Historical solar insolation → Modified SVM = solar generation	24-hour-ahead	Solar power generation
[132]	*1.4 kW PV* Grid Connected	* Historical weather* PV power	O – 2	Yes	* Principal Component Analysis (PCA)* Full Recurrent Neural Network (FRNN)	*Historical data → PCA *Historical data → FRNN	N/a	Solar power generation, current and voltage
[133]	N/a	Historical weather	O – 11	No	* Random Forest (RF) * Artificial Neural Network (ANN)* XGBoost	*Historical data → PCA + feature *cleaned data → RF,ANN,XGBoost	N/a	Solar irradiation

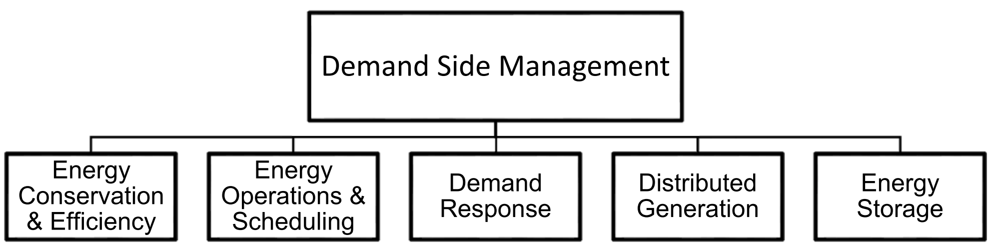

Fig. 4. Demand Side Management (DSM) Architecture.

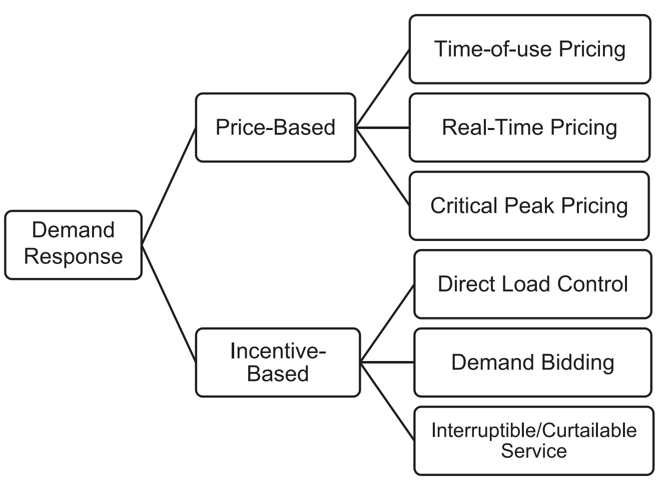

Fig. 5. Demand Response Architecture.

that can be turned off for short periods without too much discomfort to the consumer [65] for example, water heaters. Examples of schedulable loads are those that can be controlled by a thermostat, such as air conditioners and space heaters, as well as those that don't necessarily need to run at a certain time, including dishwashers, clothes washers, and dryers. [8]. Minhas et al. [126] classified these loads as "*controllable or flexible load demands*" examples of which are refrigerators and charging electric vehicles. Non-schedulable or non-controllable loads are sometimes referred to as base loads [126]. These loads are of utmost priority to the customer, for example, light sources and power sockets. Some other literature may use different nomenclature like shiftable and uncontrollable loads for schedulable and non-schedulable, respectively [150]. It is important to note that while some loads like water heaters may fall under both interruptible and schedulable loads, other loads like washing machines, electric cookers and dishwashers should not be interrupted during operations. Therefore, schedulable tends to refer to these types of loads.

An alternative to the direct participation of users, sometimes referred to as customer control, is the process of demand response automation using existing control systems [79]. The latter is also known as direct load control, which may use pre-agreed load profiles or dynamic real-time profiling according to hour-ahead forecasts to shut down and restart certain customer load appliances.

DR programs are also linked to customer perception and satisfaction. The ability of customers to reduce costs by scheduling their load based on preference is a key motivation for customer participation in DR programs. DR also create "virtual" power that can be called upon to reduce the load. By optimizing DR, system operators can build smaller MGs and reduce capital and operating costs.

Price-based demand response program

Refers to changes in power usage by customers in response to changes in electricity prices in the form of tariffs. These changes would occur if the corresponding tariff associated with different periods is significant enough. In other words, customers are more likely to change their consumption habits if they are required to pay for more during peak hours as opposed to off-peak hours [59]. Price-Based DR programs can be categorized into Time-of-Use (TOU) pricing, Critical Peak Pricing and Real-Time Pricing [141].

Time-of-use pricing

TOU pricing is based on the time interval for which the electricity is used [93]. Typically, a day is divided into three intervals: peak interval, mid-peak interval and off-peak intervals [93] with some literature referring to the mid-peak as the “shoulder” interval [68,151]. The charges for operating loads during peak periods are usually significantly higher than at other time intervals, in many cases double or quadrupled [145]. In this way, the consumer is encouraged to either reduce peak period loads or shift them completely. Using less energy during peak periods and more during off-peak simulates the effect of peak shaving and valley filling, leading to a more balanced energy system [150]. For example, flexible loads, such as preheating electric hot water heaters or charging electric cars, are shifted to times of high solar energy production where the cost is likely to be cheaper than the traditional grid electricity. Other time frames can be time of day (day versus night), day of the week (weekday versus weekends) or even time in the season (summer vs winter) [152].

TOU can be further broken down into static or dynamic. A static TOU tariff offers a minimum of two different rates for fixed periods in the day. For example, an operator can charge higher rates for weekday evenings and a lower rate for mornings. The dynamic TOU tariff offers different rates for different hours of the day, usually with input from real-time load/supply forecasting. It is also important to note that both TOU rates can either be automated or involve direct customer participation.

TOU is considered one of the main pricing strategies used in the power market, along with RTP and multistep electricity pricing [49]. It has wide applications in the electricity markets because it has many advantages [13].

Critical peak pricing

Critical peak pricing (CPP) are tariffs based on the peak hours of the day. Peaks are sometimes determined by the real-time energy market, or if a contingency or an event such as equipment breakdown, or high temperatures, occurs [153,154]. The aim is to reduce the short-term peak in consumption. Peak hours logically will have a significantly higher energy cost than off-peak periods to incentivize customers to operate their loads during the latter [155].

Real-time pricing

Real-time pricing (RTP) tariffs are charged over very small intervals to reflect the true nature of fluctuating energy prices. In other words, this tariffs frequently correspond to wholesale market prices [156]. RTP, also called dynamic pricing, mirrors a utility’s production cost in real time [157]. To capture such granular data requires relatively expensive data monitoring and collection technology, high rate of data collection and efficient data processing techniques. This makes implementation of RTP expensive than other tariffs.

Incentive-based demand response program

Incentive-based DR programmes are usually established by the utility or operator where the customer is given added financial incentive to reduce their load during peak periods [93] or during periods when the utility/operator determines that not reducing demand will lead to a system collapse.

Direct load control

Direct Load Control (DLC) is the process whereby the demand response operator remotely shuts down or reduces a customer’s load or appliance [93,158,159]. The choice of customer loads are loads that can bare such short-term interruptions [159] with little inconvenience to the customer. The decision to shut down certain loads is usually taken by the system operator to preserve the stability of the grid (sometimes called load shedding) or by the customer to reduce operational costs. A number of studies have evaluated DLC. Parrish et al. [160] used DLC to shed unnecessary loads by using undervoltage and underfrequency relays to monitor customer loads. This method was shown to have up to 97 % power supply reliability.

Some DLC programs use load controllers or load relays [159] that may be centralized [151] to achieve instant load control. Customers are offered discounted rates or incentivized payments to participate in such programs. Acute circumstances that threaten the integrity of the grid tend to be the reasons for activating DLC [161]. This means that the customers may not be pre-notified, nor consent sought due to the urgency of the situation.

Demand bidding

Demand bidding or demand side bidding is a concept that enables consumers to participate directly or indirectly in electricity trading, with favourable tariffs or cash incentives often tied to some demand management. In other words, operators can offer customers cash incentive to achieve a daily load reduction target [162]. Since most customers are not experts in the nuances of the electricity markets, they may choose to trade indirectly through electricity retailers or municipalities who act as intermediaries between the market and the customers [163]. These intermediaries submit bids on behalf of the customers and, through their expertise can negotiate cheaper rates based on their knowledge of electricity prices [164].

Interruptible/curtailable program

In a summary, interruptible or curtailable programs are those that use financial incentives to encourage load-shedding responses [165]. They take advantage of a customer’s interruptible loads by switching them off or keeping them on pause, during peak or emergency events to maintain the required reserve capacity and preserve the stability of the system [165]. This is achieved when the system operator looking to obtain reserves, signs an agreement with the customer to interrupt their load based on some agreed pre-conditions. In return, the customer is offered a payment based on the reserve capacity realized or the energy delivered from that capacity. Just like in the case of DLC, the customer receives no prior notice because the emergencies or events are often without warning [162].

A comparison of the various DR programs is listed in Table 4.

Supply side management

SSM refers to the efficient generation, transmission, and distribution of electricity to meet customer demand [59]. Efficiency in this context describes supplying reliable and quality power at an optimized price with reduced impact to the environment. SSM must also satisfy demand without unnecessary infrastructure investments [139]. SSM also refers to optimizing supply from various sources to respond to base and peak demands [58].

To match demand with supply, alternative generation must be factored into system planning when the primary source is insufficient. System operators often have primary protocol which involves a response by synchronous generator(s) to a shortage in supply by providing additional power to match consumption. This response is almost always instantaneous. Alternative energy can be supplied from rechargeable batteries, power generators, and other RES sources. Bear in mind that battery storage can be either a SSM or DSM response depending on the state of charge (SoC) of the battery. In other words, If the load requirement is not being met, batteries can act as back-up and supply the load. On the other hand, if excess power is being generated, batteries can behave like a load and absorb power to recharge.

By increasing the energy supply, SSM ensures system reliability by providing power to customers whenever demand increases for example initiating battery storages, ramping up generator production etc. Conversely, supply is reduced to prevent wastage of excess supply generated, and to reduce emissions and operations costs [166].

Table 4
Comparison of demand response programs.

Incentive-based demand response program			
Components	**Direct**		**Indirect**
	Direct Load Control	Interruptible Service	Demand Bidding
Incentives	* Discounted electricity rates * Incentivized payments	Payment based on reserve capacity realized	Revenue from predefined prices and quantity
Initiating party	* System operator * Customers	System operator	Customers
Advanced warning	* No prior notice* Pre-notified (if initiated by customer)	No prior notice	Pre-notified
Non-compliance penalty fees	Yes	Yes	No
Price-based demand response program			
Components	Time-of Use Pricing	Real-Time Pricing	Critical Peak pricing
Tariff category	* Peak * Off-peak	Standard	* Peak * Off-peak
Planning strategy	Set in advance	Real-time	Set in advance
Tariff time-scale	Several hours or days	15 min to hourly	No. of peak days in a year
Tariff Type	* Static (fixed)* Dynamic (varies)	Dynamic	* Static * Dynamic
Seasonality	Optional	No	Yes
Drivers	Customers' load pattern	Wholesale market price	* Real-time energy market * Contingency or event

Back-up power and supply side management: Batteries and generator dispatch

The availability of back-up power is critical to SSM especially when RES are used as the primary generators. To ensure power stability in both off-grid and on-grid PV-connected systems, the hybrid PV system and the battery system are deployed [167].

The hybrid power system utilises electrical energy input into a MG from conventional sources like coal, gas, petrol or diesel. Other energy inputs may include RES and nuclear [70]. Typically, in areas where grid extension is not economically feasible, stand-alone RES and diesel generators have been deployed to meet load demand [82]. Communities served may be rural or insular, and DGs are commonplace in the local energy system [168].

There are many studies [70,82,169–171] that include generators as part of the MG configurations. In a case study of an RSHMG, Ekpe and Umoh [70] propose including a generator array as a back-up to the PV array and the grid as a measure to improve the grid's reliability due to the erratic nature of power supply from the central grid. This shows that a generator is a viable energy source in maintaining grid reliability. Tsai et al. [170] perform a techno-economic analysis of stand-alone diesel system, stand-alone PV/storage system, PV/diesel hybrid system (RHMG), PV/diesel/storage hybrid system for the Pratas island in Taiwan. The results of the analysis revealed that the PV/diesel hybrid system configuration had the lowest cost of energy (CoE) at 0.3569 $/kWh. Murugaperumal et al. [171] validated the design and techno-economic feasibility of an RHMG that uses a diesel generator. The research concludes that the combination of these sources increases system reliability. Pujari and Rudramoorthy [82] proposed using a diesel generator to supply customers under peak load conditions when RES is limited. In an analysis of six different hybrid combinations of PV, battery, wind turbine, and a diesel generator supplying a load demand of 332.97 kWh/d, the RHMG system of PV, diesel generator, battery had the lowest net present cost (NPC) and CoE. Although crucial for system stability and dependability, diesel generators are sometimes viewed and modelled as "a black box" that raises operating costs and has a negative impact on the environment due to their excessive fuel consumption [172].

Battery Energy Storage Systems (BESS) can store energy from a variety of sources and discharge it as needed. Rather than wasting electricity, BESS enables excess generation to be stored when demand is low and used later at a more critical time. The flexibility created from this approach leads to a reduction in cost for the user. In addition, BESS can be charged during off-peak periods to take advantage of reduced utility pricing while supplying its energy as an alternative during peak periods. Both scenarios are widely used by electric vehicles in a vehicle-to-grid model. For example, Zeynali et al. [173] uses a two-stage stochastic programming in a smart home application to lower an average household's cost of purchasing electricity. In this case, a home energy management system coordinates a BESS and the vehicle-to-home capabilities of an electric vehicle. In another example, Song et al. [174] use a multi-objective approach to reduce running costs and improve user comforts by adjusting home energy management scheduling, photovoltaic integration, and battery energy storage integration. By using RTP tariffs in the scheduling, cost reductions of about 40 % were realised.

BESS is also used in combination with other sources to reduce the overall CO_2 and electricity costs of the system. For instance, Kusakaka et al. [175] uses a BESS to reduce the fuel consumption of a diesel-powered RTG crane, thereby reducing the operations costs by up to 40 %. BESS tend to have higher up-front costs than other hybrid alternatives and lose the ability to hold a charge as time goes on. This cost and reliability flaw makes BESS the weakest link in the PV system [176–178]. In mature energy price markets with high BESS penetration, the benefits of owning a BESS come from the price difference between times of energy scarcity (or high demand) and times of abundant inexpensive energy [179]. Therefore, the higher the adoption rate, the smaller the price difference which will make buying a BESS less appealing. To mitigate against cost and reliability issues, an EMS is often used to optimally charge and discharge the battery. The EMS will prevent excessive charging, discharging and heat, to prolong the BESS life while charging when electricity rates are low and discharging when they are high.

Flexible power supply generation

Flexibility in power supply is the ability of the system to ramp up or down power generation in response to load demand. It can be done manually or automatically, as part of a strategy or a response to an isolated event. Dispatchable generators, load-following generators, and peaking power plants are all synonymous with flexibility and can shed power generation as part of SSM. Gas turbines, modern coal plants, controllable fuel-based generators, BESS, pumped hydro storage are examples of dispatchable generation units that can be switched on or off depending on load requirements, occurrence of an event, or an economic dispatch strategy [180,181].

While solar and wind are widely viewed as non-dispatchable energy sources because they are not meant to be switched off, they can be curtailed when their penetration levels create an instability in grid. In general, curtailment refers to using less wind or solar energy than is possibly available at a given time [182]. Other causes of curtailment are grid congestion and energy supply overproduction [183]. The key concept is that any power source that can be controlled by increasing or decreasing its output in response to demand at a given time fulfils the criteria for SSM.

Energy management system

Home Energy Management System (HEMS), Integrated Energy Management System (IEMS), Smart Energy Management System (SEMS) or Centralized Energy Management System (CEMS) are synonymous with EMS and are classified as systems that optimize SSM and DSM techniques to facilitate the production and use of reliable and cost-effective energy. Historically, EMS referred to management of energy and improvement of energy efficiency. EMS are a set of computer tools that monitor, regulate, and improve the generation, transmission, and distribution of power [69]. The EMS accepts conditions and constraints from either the supply and demand side (or suppliers and consumers) and optimally schedules the consumers load within those constraints [166]. According to Ma et al. [72], the EMS handles monitoring, communication and bi-directional interaction between the source and the load. Historical grids were mainly supplied by single sources with radial distribution configurations. The grid has since evolved with advancements in technology and communication. For smart grid applications, Zhao et al. [49] emphasizes that EMS uses tools like SM, sensors, and other detection devices to achieve five main objectives: minimizing costs, load curve optimization, reduction of CO_2 emissions, maximizing renewable energy outputs, and improved user comfort. These objectives are classified under the three broad frameworks of economy (cost savings), environment, and human comfort.

EMS is broadly classified into two categories: predictive energy management system (PEMS) and real-time energy management system (REMS) [147]. PEMS involves using historical data to generate a load forecast, an energy supply forecast, or a combination of both, to make sure supply optimally matches with demand. However, because forecasting is not a 100 % science, real time scheduling of the load needs to be integrated to adjust the prediction errors. As the name suggests, REMS uses real-time algorithms to adjust the control of the load or supply based on the SSM or DSM parameters.

Energy management system control

The EMS can be sometimes called the control system [65]. EMS control is mainly classified into three categories: centralized controllers, decentralized schemes and distributed control strategies, with the centralized controllers more widely proposed for systems that require integrating forecasting with SR and DR [72]. The EMS with a centralized controller works by having a direct connection with each distributed energy resource in the system. The forecasting input into the EMS controller can be in the form of supply forecast, load forecast or a combination of both. It is also able to monitor and process information, store data and initiate the required SR and/or DR responses based on pre-determined objectives or constraints.

Deka et al. [58] uses a single-phase digital PIC microcontroller to regulate the power flow to individual customers. The software was developed in C- language and compiled by MikroC compiler. The controller is programmed with a pre-determined load limit that if exceeded by the customer, results in power being cut-off to that customer. When this is adjusted below the pre-set value, power is restored back to the user. The research points out that the controller was selected because of its "performance, power efficiency and design flexibility" [58].

Shakeri et al. [147] explores a HEMS that uses smart plugs and a local controller. The local controller is the brain of the system. It uses electricity price, customer's preference and the batteries' SoC to determine if load should be supplied by the utility, battery or postponed to a later timeslot with lower or off-peak electricity prices. Smart plugs are the interface between the local controller and load and can measure and monitor power consumption of connected electrical appliances. They communicate this information to the local controller and receive feedback on what appropriate control action to implement.

While the above method is effective for power supply that is constant, customers enrolled in a system using this technology will encounter blackouts if they exceed the power threshold. The intermittent nature of solar energy suggests supply will always fluctuate and therefore a more robust approach is required. What this research proposes is for the control system to adjust the supply by calling on standby or alternative generation to meet the required demand. The key difference is that the microcontroller makes decides based on both the real-time supply and demand, and not just the demand.

The EMS highlighted in [128] optimizes the system based on energy storage in batteries, customer's load consumption and cost-reflected energy purchases. It has as its input the estimated PV energy forecast, the demand forecast and the maximum contracted power. The aim is to optimally decide next day energy usage by minimizing energy cost and efficiently using the batteries. The EMS algorithm prioritizes consumption of the PV, supply of demand above contracted power, and then charging the battery based on excess PV or electricity purchased at low cost.

Smart meters

Smart meters (SM) are an important element in converting an EMS into a smart EMS, playing an integral part in the communication platform of a smart grid [69]. SM are measurement devices that continuously track and log power consumption in real-time at pre-determined intervals [184]. For the consumer, SM are the most important tools in designing a good DSM program [185]. On a very basic level, this is achieved by providing the customer with their consumption information to influence how they manage it. For the service producer or supplier, the ability to remotely access or control SM reduces operational costs, determines revenue, and improves security in energy supply. In addition, the accuracy of supply and demand forecasts depends on the SM [186].

SM performs other tasks including managing electricity and scheduling appliance usage [187], reducing energy theft, increasing energy efficiency [188], automated data collection [189], and fraud detection [190] to name a few. Smart meters enable a two-way communication between customers and producers and offer flexibility in demand side control. This bi-directional communication is the most important feature of SM [191].

Integrated energy management system

EMS and IEMS are sometimes used interchangeably [192,193]. Jabbour et al. [194] also switch between the two acronyms but qualify the term "integrated" as an approach that addresses a multi-objective optimisation problem for energy saving, user comfort and maximising energy from renewable energy sources. However, it is important to properly differentiate them based on function and scope. EMS's definition historically came from the management of a single energy supply source, Wang et al. [195] defines an IEMS as a platform that integrates energy dispatch and control for multiple energy sources. The aim of the IEMS is to achieve reliable and economical operation of integrated energy systems (IES) while meeting the system constraints and realizing optimal scheduling. The authors site the constraints of dealing with multi-energy systems as the reason IEMS, with the development of *Energy Internet* and the use of big data, is a necessity. According to Zhang et al. [196], the enhancement of building performance by existing EMS strategies was done in two silos: building simulation and control management. This led to longer operating times and inaccuracies. The proposed IEMS corrects this by integrating the physics of the building, renewable energy systems, energy storage, energy distribution systems, heating and cooling technologies, allowing the flexibility of control strategies based on the users' objectives. This suggests that the IEMS can manage multiple energy sources and control strategies. Yi et al. [197] firstly define IES as a system that is made up of numerous subsystems involved in the generation, distribution, and storage of various energy sources. IES integrates multiple energy and power sources using advance energy conversion technologies to efficiently improve energy use, increase system flexibility and reduce carbon emissions [198,199]. Just like EMS, IES is sometimes used interchangeably with IEMS. Reviewing the literature, IES is often defined as an optimization problem with set function objectives. For example, Guo and Xiang [200] propose an interactive Integrated Energy System Planning (IESP) platform that aggregates various energy sources (electricity, gas, heat) and takes as its input investment decisions, load profiles, meteorological data, and techno-economic parameters converting int a mixed integer linear programming problem. The objective is the optimal component size of each energy source, optimised total annual cost and carbon emissions. Huang et al. [201] propose the park integrated energy system (PIES), which is a stochastic optimal scheduling method that aims to achieve low-carbon but economically optimal results while considering generation-side and customer-side uncertainties and their impacts on the system. These uncertainties are comprised of factors such as the variable nature of RES and fluctuations in multi-energy load demands influenced by weather and seasonality, geographic location and so on. Like Huang et al. [201], Feng et al. [202] consider the optimization of the IES considering RES and energy demand uncertainties using the information gap decision theory method. He et al.[203] solve the annual cost of planning for an IES as the objective of its optimization problem by considering electric vehicles swapping stations and carbon capture power systems while using natural gas, heating networks, PV and wind energy on the supply side. The focus of these models is on energy conversion within constraints and not on the IEMS components highlighted in Section 2.

Another category of IES to consider are energy system modelling software. Software like PLEXOS use multi-objective decision optimization particularly to solve unit commitment (UC) and energy dispatch (ED) problems. For example, Papadopoulos [204] highlights a case study of a multi-objective problem maximising the profits of an operator's generation portfolio, minimizing total system costs, and minimizing total generated emissions. These objectives are characterised by Pareto optimality, where the solutions to the objective problem are Pareto solutions in which the improvement of an objective does not diminish another. Here again the objectives and constraints relate to the energy conversion and use. In a review of 75 energy and modelling software, Ringkjøb et al. [205] classifies them based on technological and economic parameters, general logic, and spatiotemporal resolution. General logic is further broken down into purpose (power system analysis, operation decision such as ED and UC, investment modelling), approach (top-down or bottom-up) and methodology (simulation or optimisation). Most software are black boxes and not openly sourced, with no description of their architecture or methodologies. While some software are classified under supply/demand modelling approaches, this is related to energy markets and not management of supply and demand within the IEMS. Finally, the authors mention that only a few models like EMPS and E2M2 account for uncertainty of VRE sources. The authors highlight "demand side" as an area of future model development suggesting the focus has been more on the supply side. A literature survey suggested that two of the most applied software in 100 % RE systems are LUT Energy System Transition model and EnergyPLAN [206]. These models develop optimised solutions while performing interconnected multi-node, full-hourly, multi-sector energy modelling analysis [207]. LUT Energy System Transition model integrates power, heat, transport, and other industry processes into an IES, using linear optimisation to match total annual energy generation to demand on an hourly basis. While synthesised power load data is one of the model's key inputs, DSM is not considered a key input. EnergyPLAN is a deterministic model that focuses on designing national or regional energy planning strategies. Just like LUT model, EnergyPLAN is ideal for intermittent RES because it produces hourly simulations but does not take DSM inputs, taking actual demand instead. Other more recent energy modelling tools like H2RES use linear optimisation to minimise the discounted yearly operation and system costs while providing long-term capacity investment and dispatching optimisation [208].

Yi et al. [197] describe IEMS as a subcategory of IES, where the "management" term deals with controlling energy distribution under different price conditions. Ren et al. [209] idea of an IEMS is the combination of smart power consumption and IoT into a single framework. Through IoT, various utility data collection nodes including utility type, consumption cost, predicted consumption pattens and so on are transmitted to their respective databases in the designated centralized data server through a wireless network. This is more efficient than the old EMS method of transmitting smart meter data to centralized storage through GPRS communication. From the above definitions of IEMS, we can broadly infer two things. That IEMS is an integration of multiple energy systems and multiple control strategies leveraging on technology like IoT. Multiple energy systems may refer to varied energy sources like hydro, biomass, solar storage, spinning or stand-by reserve plants and so on while multiple control strategies could involve supply and demand optimisation algorithms, forecasting, and dispatch models. EMS may relate to just one energy system and can be either a PEMS or REMS, while IEMS can implement PEMS through RES forecasting and make adjustments in real-time (REMS). Finally, the concept of integrated demand response (IDR) put forward by Huang et al. [210] is introduced due to changes in technology and the energy market. The authors subscribe that the traditional DR and it's single strategy of power system scheduling and control is not sufficient for future grid networks which have developed into multi-energy systems with varied forms of energy consumption, storage, and technologies like combined cooling, heat and power (CCHP). In essence, just like DR has given way to IDR in the context of multi-energy systems and control, IEMS must succeed the EMS in today's complex power networks. On the strength of this, we define IEMS as a system that manages multi-source or multi-energy systems by leveraging on advancement in technology and communication to integrate both PEMS and REMS controls, and initiate supply and demand responses with the aim of balancing the load and power supply in the grid.

Several studies [58–60,166,211,212] have been identified that combine SSM and DSM, or SR and DR, into an EMS to balance supply and demand in a system. In their approach, Deka et al. [58] consider both SSM and DSM strategies supported by an IEMS for data centres. The study chooses to explore the various scenarios of demand side flexibility rather than the actual response. It also explores the operational considerations of consolidation, shifting, migration and frequency scaling in participating in DR programs.

In Karunanithi et al [59], three DSM scenarios were analysed: energy conservation, peak load shifting and a simultaneous combination of both. On the other hand, the three SSM strategies considered are reduction of T&D losses, increasing the efficiency of all thermal power plants and the simultaneous combination of both.

Monyei and Adewumi [166] use carbon capture and sequestration technology as SSM techniques to reduce operations and emissions cost. On the DR side, RTP and TOU are used to reduce the consumer's electricity bill.

Luo et al. [211] looks at the integration of SSM and DSM in multi-energy systems in buildings. The research focuses on its SSM by using a tri-generation of using the prime mover set of solid oxide fuel cell-gas turbine with cool storage, heat storage and electricity storage managed by an optimization algorithm. Utility electricity was used as the back-up. For DSM, electric cars and other dispatchable appliances were scheduled using predictive modelling with inputs from weather data and other building information. This predictive modelling is part of the demand optimization algorithm. In essence, both supply and demand algorithms would simultaneously predict supply and demand patterns in a day respectively and make sure they coincide.

Ghiasi et al. [212] uses adaptive fuzzy control to regulate supply from the combination of PV, fuel cells, plug-in electric vehicle, the grid, and battery energy storage as the supply sources. DSM strategies use game theory to schedule controllable loads during off-peak periods. Another research that includes the integration of an electric vehicle (EV) was conducted by Aoun et al. [60]. The researchers consider the use of an intelligent EMS, EV integration with smart charging and discharging and load scheduling of appliances as part of the demand response. On the supply side, the integration of a PV system with and without storage was analysed. The sources of energy to the were PV, diesel generator, utility grid and power from the EV batteries.

On another note, there are EMSs that combine energy supply forecasting with either DSM [62,126] or SSM. Very few have investigated all three and their integration into an EMS. In research for the mining industry, Ortiz et al. [213] focuses on using PV and BESS as the primary source of SSM using a mining case study while having the grid as a backup. DSM technique included managing the hardness of rocks fed to the semiautogenous grinding mill by sending hard rocks (which are harder to grind) into the mill when energy costs are low and sending soft rocks when costs are high. In addition, solar radiation forecast analysis is done over 13 years of data by combining a trend analysis and a forecast model to determine probabilities for different day types, and hence the marginal probabilities.

Su et al. [129] includes both RE and load forecasting along with an integrated supply–demand side management response. The study uses the Non-dominated Sorting Genetic Algorithm-II (NSGA-II), to solve the multi-objective optimization that includes minimizing energy consumption, maintaining a gas network buffer, improving profits by scheduling loads with best electricity prices, and reducing operational power consumption. The supply side was simulated through an energy network simulation module that included energy sources from PV, wind, the utility grid, and a natural gas network. SSM included an energy conversion model of gas-fired power generation for times of low supply, and a power to gas system for times of excess power production. The DSM framework is developed based on dynamic pricing.

In research by Pascual et al. [61], an energy management strategy incorporates both battery and thermal storage along with DSM and forecasting techniques. The research analyses a combined thermo-electrical microgrid with wind, PV, solar concentrators and Utility as the primary sources and hot water storage and battery storages as the backup. The SSM relied on the EMS to call up power from battery bank and utility when RE production is low. The DMS's unique strategy is to absorb excess power to the electric heater during peak production, thereby converting the excess power to thermal storage.

Pawar et al. [66] uses an Intelligent Smart Energy Management System (ISEMS) made up of three stages: PV data collection and generation, forecasting model integrated with smart energy management gateway and smart sockets to turn on and off appliances, and an internet-of things (IoT) environment for users to view energy details and manage appliance priorities. The ISEMS manages the system by checking if current demand exceeds a pre-defined maximum demand. If this condition is met, the ISEMS decisive algorithm will turn-off appliances to reduce the demand based on a priority order determined by the user. The ISEMS will also notify the user through the IoT environment when loads are being used during peak periods so that the user can change/update priority requests.

In a study by Shivam et al. [11], a PEMS is deployed using a three-level hierarchical control method which are monitoring and prediction, multi-objective optimization and control of PV-battery hybrid system. A PEMS controller is connected directly to the PV and battery bank, and connected to the grid via a smart meter, drawing from all three sources to satisfy the load based on its algorithm. The PEMS monitors and collects PV, load and SOC data, separating them into day or night by logic control. The output is then fed into the machine learning forecasting framework resulting in PV and load forecasts. Multi-objective optimization is used on the predicted values to find the SOC limit for the battery bank based on maximum battery SOC limit, cost of electricity and maximum allowable CO_2 emissions. The load demand is then satisfied using PV energy, battery bank or the grid. If excess energy is generated that surpasses the battery bank's scheduled maximum SOC limit, then it is sold to the utility grid. Table 5 shows a summary of IEMS related studies.

In addition to the power system in which the IEMS is deployed, Table 5 also classifies power supply into primary and back-up to highlight what type of system configuration is being used. In column 5, the IEMS control system describes the algorithm by which the IEMS selects both a SSM and DSM response.

The forecasting methodology applies to the algorithm used to arrive at the forecasted outcome. PV power forecasted is broadly divided into three broad categories: direct, indirect and hybrid models [218]. The direct method does not require any internal data from the PV system and determines the PV power directly by relying more on historical data. The indirect model forecasts solar radiation first, and then uses analytical power equations to determine the PV generated based on the power plant's technical parameters. The hybrid model is simply a combination of the direct and indirect models. Finally, the last two columns give the SSM and DSM responses used in the IEMS. Due to the different types and approaches of SEF, SSM and DSM, it is obvious to see that there are many possible combinations. The studies choice of which method to use depends on constraints and objectives unique to each location or case study.

IEMS perspective and future research

The outcome of Table 4 shows that there is potential for different combinations of SSM and DSM, with SEF within an IEMS. Other potential research areas can arise by simply varying any of the parameters in Table 5. As stated before, although the choice of SEF, SSM and DSM are determined by constraints and objectives, there is potential to investigate the different combinations and how they affect the power system. For example, does DLC work better by itself than a combination of DLC and TOU? This can lead to other research questions like what are the savings and costs of each type of SSM or DSM, and how does this affect the customer or system operator? A possible research methodology would be to analyse consumption and costs of each SSM or DSM response added to the system against a baseline with no SSM or DSM responses.

IEMS is not limited to PV, and research can be extended to other predictable RES like wind and tidal energy. Other research areas could include integrating artificial intelligence (AI) within an IEMS to support the decision making of a system operator. The ability of AI to sort through different objectives and constraints, while determining the best possible control strategy will be crucial in IEMS adoption across all levels of the grid. From a policy standpoint, it would be important to know the barriers that exist in sharing, accessing, and controlling user load preferences in determining what DSM strategy to implement. With the IEMS's need to access all or most of the system's databases, much thought needs to be given to system security and the protection of both the user and system operator. Finally, in the event of an IEMS fault or collapse, what back-up measures can be set-up to keep the fault from extending to the grid.

To buttress the point of the significance of different DR combinations, Papadimitriou et al. [219] examines DR programs used in several energy hubs studies, and compares them based on factors like cost, dependability, and adaptability. The authors found out that different DR programs were used to achieve different objectives like minimizing costs and/or power interruptions. DR programs have advantages in different settings and iterations must be carried out to determine which DR option gives the best outcome for a particular objective. For instance, while incentive-based DR programs like DLC showed great prospects in reducing power peaks in the energy hubs, they tend to increase the annual cost for the consumer. In terms of performance, TOU pricing is the most popular time-differentiated electrical tariff to reduce load demand and achieve efficient levels of electricity [220–223], it does not always produce the best results. For instance, in a study by Nourollahi et al. [224]., RTP reduces the operation cost of a conventional AC microgrid and a hybrid AC-DC microgrid by 8.1 %and 53.89 % respectively compared to TOU (7.1 % and 42 %). In another review of optimal charging and scheduling of EVs [225], RTP showed the most promise over TOU, CPP, and peak time rebates. In a study by Cui et al. [226].,

Table 5
A summary of Studies on Integrated Energy Management Systems.

Research	Power System	Primary	Backup	EMS - Control System	Prediction Time	Solar Energy Forecasting Methodology	Forecast Outcome	PV Power prediction	SSM	DSM
[126]	74 kW DC Microgrid	Wind-PV	Utility	EMS with adaptive nonlinear control theory	24-hour-ahead	Support Vector Machine (SVM)	* Wind Speed* Solar irradiation	* Solar cell power equation* Wind generator power equation		Direct Load Control (DLC)with Sliding Mode Control (SMC)
[56]	* 3.75 kW PV * 6.4kWh Battery	PV	Battery	HEMS	24-hour-ahead	N/a	Solar power generated	N/a	Rule-based control strategy to manage energy sharing	Optimisation based strategy: DLC & RTP, DLC & TOU
[62]	Hybrid Microgrid * 25 kW PV * 15 kW Wind Turbine * 300 kW Diesel * 30 kW Fuel Cell * 30 kW Battery * 30 kW Grid* 30 kW Water Micro Turbine	Water, Wind, PV, Fuel cell, Battery, Diesel generator	* Utility* Battery	N/a	24-hour-ahead	* Probability Density Functions (PDF) - Solar* Rayleigh distribution - Wind	* Wind Speed* Solar irradiation	* Rayleigh model for wind power* Solar power output formula	Power Dispatch algorithm with control	Incentive-based DR
[65]	Hybrid Microgrid * 2.3 kW Wind Turbine * 3.3 kW PV* 22kWh Battery	Wind-PV	* Utility* Battery	HEMS algorithm	5-min-ahead	* Wavelet Transform (WT)* Artificial Neural Network	* Wind Speed* Solar irradiation	* Power curve of wind turbine (kw vs m/s2)* Solar formula to determine Isc and Voc. P = Isc x Voc	Control algorithm: if load > net power (including storage), accept from grid and vice versa	TOU
[128]	640 W PV	PV	* Utility* Battery	EMS using 3 inputs.	24-hour-ahead	Random Forest: Non-linear multiparameter regressor	Solar power generated	N/a	Control algorithm:load consumption, if demand > max contracted power, supply from storage	
[214]	6.6 kV distribution network	Grid	PV	HEMS	24-hour-ahead	Just-in-time modelling scheme	Solar power generated	N/a	Controller and voltage regulator	TOU, DLC
[66]	N/a	PV	Utility	Intelligent Smart Energy Management System (ISEMS) with 3 stages	N/a	Particle Swarm Optimization (PSO) based Support Vector Machine (SVM) regression model	Solar irradiation	N/a		TOU for schedulable or chargeable loads
[11]	14.52 kW PV	PV	* Utility* Battery	PEMS	1-hour-ahead	*Residual Dilated Causal Convolutional Network (Res-DCCN),*Naïve, *Support Vector Machine (SVM), *Artificial Neural Network (ANN)	Solar power generated	N/a	Control algorithm: if demand > PV, use battery bank. If demand > PV + battery bank, buy from Grid.	Dynamic pricing
[129]	* Wind farm * PV * Natural gas network*Utility	* Wind farm * PV * Natural gas network*Utility	Gas to power	N/a	N/a	Probability Density Function (PDF) based on kernel method using Monte Carlo Simulation	* Wind Speed* Solar irradiation	* Wind power production formula * Real power production of PV and the combined efficiency of PV formulas	The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) with power to gas	Dynamic pricing

(*continued on next page*)

Table 5 (*continued*)

Research	Power System	Primary	Backup	EMS - Control System	Prediction Time	Solar Energy Forecasting Methodology	Forecast Outcome	PV Power prediction	SSM	DSM
[61]	Electro-thermal Microgrid * 6 kW Wind farm * 6 kW PV * Utility * 2 kW solar thermal collectors * 27 kWh Battery* 800L Hot water tank	* Wind farm * PV * Utility* solar thermal collectors	* Utility * Battery * Thermal	EMS using a Central Moving Approach (CMA)	24-hour-ahead	Weather forecasting with NWP model	* Wind Speed* Solar irradiation	* Estimated output power PV equation* Estimated output power Wind equation	Use power from batteries or grid to supplement RE production	Control strategy to increase power to electric heater during peak production, thereby converting excess power to thermal storage
[13]	5 kW Micro Grid	5 kW PV	Pumped hydro storage (PHS)	EMS algorithm	15-min-ahead	Wavelet decomposition-Generalized Neural Network (GNN) based online forecasting model	Solar irradiation	PV power output estimation formula	Control algorithm: if demand > PV, use PHS. If demand > PV + PHS, buy from Grid.	TOU
[147]	* 800 W PV * Utility* 4.8 kWh Battery Storage	Utility	* 800 W PV* 4.8 kWh Battery	HEMS algorithm	Intra day	N/a	N/a	N/a	Control algorithm: check electricity price. If cheap, operate on utility, if not check battery SOC. If load < SOC, use battery. If not operate on utility or postpone	TOU
[215]	Microgrid * 2.3 kW Wind Turbine * 3.3 kW PV * Utility* 22kWh battery storage	* 3.3 kW PV	* Micro gas turbine (MGT)* Electric Vehicle (Mobile Storage) * Battery	HEMS using mixed integer linear programming (MILP)	24-hour-ahead	Enhanced Differential Evolution based Artificial Neural Network (EDE-ANN)	N/a	N/a	N/a	N/a
[216]	* 5 Kw PV* 5 kW Battery	PV	* Utility* Battery	HEMS algorithm	24-hour-ahead (PEMS) 5-min-ahead (REMS)	Robust Self-Attention Multi-Horizon (RSAM)	Solar irradiation	N/a	Schedular algorithm	RTP, TOU, CPP
[217]	*40 W PV* 48 V 5Ah Li-ion Battery	PV	Battery	Simple Electric Utility Platform (SEUP)	1-hour-ahead	Long Short-Term Memory (LSTM)	Solar power generated	N/a	Use power from batteries to supplement RE production	DLC
[143]	* 1.5 MW PV* 0.5 MW/1MWh Battery	PV	Battery	SunDial	Multi-hour ahead	N/a	Solar power generated		Use power from batteries to supplement RE production	DR
[67]	* 1 kW PV * 1 kW Wind Turbine* Battery	Wind-PV	Battery	N/a	Ultra-short, short, medium, and long	Random Forest	* Wind Speed* Solar irradiation	*PV power module equation *Wind power module equation	Use power from batteries to supplement RE production	DR

due to the high billing instability and risk of price fluctuations, DLC in cooperative gaming was favoured over RTP in participating in a balance power market.

Looking at another angle, the absence or presence of PV as either a primary or secondary source affects the way the IEMS operates. In a study by Rastegar et al. [227], PV/utility with TOU improves a base case without DR by 65 %, while Utility and TOU without PV improves the base case by 61 %.

Different SRs and DRs can be classified either as predictive or real-time responses. For instance, the static TOU is used for longer time frames and is set in advance (predictive) while RTP is determined close to real-time load consumption [228]. By initiating predictive and real-time responses, the IEMS can be both a PEMS and REMS. A valid question emerges as to which of the EMS schemes is better and is it advantageous to have both. To answer that question is to look at both independently. The ability to forecast energy supply or load demand accurately is a crucial part of PEMS, leading to better customer preparation and participation, informed decision-making as well as efficient power system operations and reduced costs [229]. For instance, a forecast of low energy supply gives the PEMS or customer plenty of time to put effective contingency plans in place. But forecasting methods are not 100 % accurate due to the stochastic nature of load and PV generation [230]. The result of this is that PV and wind energy forecast errors increase absolute levels of real-time energy imbalance and day-ahead or intra-day spot prices [231]. To mitigate against this, a real-time control component of the EMS must be included to adjust the responses of the load and supply. Therefore, the integration of PEMS and REMS, also referred in some literature as an IEMS, is crucial in maintaining the supply–demand energy balance in the system while minimizing errors. In a study by Hafiz et al. [230], Long Short-term Memory (LSTM) - based deep learning neural network is used to forecast load and PV generation profiles. The deviations from the forecasted profiles are corrected by integrating an offline multistage stochastic optimization model with dual dynamic programming and a real-time based controller.

In another study, Jiang et al. [232] refers to the IEMS as a “double-layered coordinated control approach” and calls PEMS the “schedule layer” while the REMS is the “dispatch layer”. The schedule layer takes as its input forecasted energy, load data, and market prices and schedules the load sequence. It also creates a power reserve for each time-step to compensate for any forecasting errors. The dispatch layer follows the load sequence set by the schedule layer by optimising power flow and voltage limits, while activating the reserved power to correct the forecasting errors. In another study by Nge et al. [233], the authors use the REMS to compensate for PV forecasting errors by using method of Lagrange multipliers to form an optimal dispatch function to adjust battery power based on market prices. In yet another study, Elkazaz et al. [234] uses a hierarchical two-layer EMS. The first layer is a model predictive control layer which optimizes energy usage by efficiently scheduling home appliances. The second is a real-time controller layer which minimizes energy wastage due to forecast errors by optimally dispatching the BESS. The second layer achieves this by prioritizing self-consumption from the BESS when the load is greater than supply. Conversely, if the supply is greater than the load, the BESS is charged first before excess supply is exported to the grid. In the same study, the findings demonstrate that, for the same battery capacity, the two-layer EMS produced PV self-consumption of up to 91.1 % annually, as opposed to a single layer system, which only produced 78.8 %. When compared to a single-layer EMS, the two-layer system reduced household payments by up to 27.8 % annually. This suggests the two-layer is better than one. With that established, future research lies in investigating the effects in terms of consumption and costs of different SR and DR combinations used in the predictive and real-time layers of the IEMS.

Finally, the methods highlighted in this paper can be compared to other solar integration methods used in applications like UC, ED modelling, and solar energy optimization models. For example, Fang et al. [235] propose a multi-objective UC model that considers the operational risks of load shedding and wind curtailment, to integrate solar energy and optimally allocate power for peak-shaving in a hybrid wind and concentrating solar power plant. Robin and Kory [236] explore the resilience of a microgrid by proposing a stochastic mixed integer model for day-ahead UC that optimises transmission switching, emergency PV generation and power sharing between interconnected grids. Dispatch of multi-energy power systems, like the one proposed by Wang et al. [237], define system objectives like cost and energy absorption as part of an optimization problem to maximise VREs. A similar optimisation problem can be seen in vehicle-to-grid charging and peer-to-peer energy networks. Grid balancing as described by Aktar et al. [238] is difficult because of the stochastic nature of VRES and load demands. Grid imbalance can be reduced by using electric vehicles as mobile storage units. The authors propose a mixed integer linear optimization algorithm that determines the optimum number and specification of electric vehicles needed to maximise operational and economic benefits. The aim of all these methods is to sustainably increase the use of solar energy in the grid.

Conclusion

Today’s complex power network of multi-energy systems, multi-objectives, diverse load requirements and advancement in technology and communication means that the traditional energy management system (EMS) is not sufficient and must give way to an integrated approach. This paper puts forward the concept of an integrated energy management system (IEMS) as a system that manages multiple energy sources by leveraging on advancement in technology and communication to integrate both predictive and real-time controls, and initiate supply and demand responses to balance the load and power supply in the grid. There is a strong interconnection between solar energy forecasting (SEF), demand side management (DSM) and supply side management (SSM) when deployed in an IEMS according to Table 4. From just the simultaneous combination of SSM and DSM, the study by Karunanithi et al. [59] shows up to 18 % increase in system reliability. A decentralized solar energy based mini-grid can be a vehicle for solar integration by using an IEMS to match the load to supply. IEMS that manages today’s smart grid must be able to interact with both the supply and demand sides of the power system. This paper started with a review of the state of the art of IEMS and following conclusions can be drawn:

- Uncertainty in the power system can be reduced if integrated renewable energy sources (RES) can be predicted. For mini-grids that use solar energy as the primary supply source, it is beneficial to predict the supply than load consumption since the former dictates how the latter is used. In addition, load consumption is harder to predict due to the unpredictable nature of energy use by consumers.
- Advances in grid technology and communication, a diverse energy mix, and increased interconnections, mean the new EMSs must be able to interact with both the supply and demand sides of the grid. The grid has become smarter so EMSs must also become smarter.
- For efficient energy scheduling and utilization, SEF and an EMS should be integrated with demand side management (DSM).
- Renewable smart hybrid mini-grids (RSHMG) possess the requisite technology and infrastructure for solar energy integration. They also provide viable alternatives for grid-extension.
- The IEMS structure or framework has several possible permutations because of the different types of SEF approaches, SSM and DSM responses. The choice of which method to use is often dictated by constraints and objectives unique to the case study or location.
- Battery energy management system (BESS) is considered an essential part of future hybrid energy systems. However, there are potential issues related to capital and operating expenses, safety risks, and environmental impact, largely due to its capacity size. The use of an IEMS can help minimize these issues by reducing the required capacity, optimizing the charging and discharging processes to

maximize efficiency, and preventing overcharging, over-discharging, and overheating of the BESS.

- IEMS can both prevent an energy mismatch between supply and consumption, and in real-time adjust the consumption to the supply in the case of an unforeseen imbalance in the system.

CRediT authorship contribution statement

Tolulope Falope: . **Liyun Lao:** . **Dawid Hanak:** Writing – review & editing. **Da Huo:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgement

Mr T. Falope, one of the authors, expresses gratitude to the Petroleum Technology Development Fund (PTDF) [PTDF/ED/OSS/PHD/TOF/1945/20] for their support to this research.

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