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Review

An Insight into the Integration of Distributed Energy Resources and Energy Storage Systems with Smart Distribution Networks Using Demand-Side Management

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Abstract: Demand-side management (DSM) is a significant component of the smart grid. DSM without sufficient generation capabilities cannot be realized; taking that concern into account, the integration of distributed energy resources (solar, wind, waste-to-energy, EV, or storage systems) has brought effective transformation and challenges to the smart grid. In this review article, it is noted that to overcome these issues, it is crucial to analyze demand-side management from the generation point of view in considering various operational constraints and objectives and identifying multiple factors that affect better planning, scheduling, and management. In this paper, gaps in the research and possible prospects are discussed briefly to provide a proper insight into the current implementation of DSM using distributed energy resources and storage. With the expectation of an increase in the adoption of various types of distributed generation, it is estimated that DSM operations can offer a valuable opportunity for customers and utility aggregators to become active participants in the scheduling, dispatch, and market-oriented trading of energy. This review of DSM will help develop better energy management strategies and reduce system uncertainties, variations, and constraints.

Keywords: demand-side management (DSM); distributed generations (DGs); energy management systems (EMS); renewable energy sources (RES); optimization; waste to energy (W2E)

1. Introduction

The management of energy consumption is a critical challenge pertaining to the current load consumption schedule of the electrical power system. With the introduction of several efficient and intelligent devices for use by diverse customers and prosumers participating in a power flow network at the residential and industrial usage load levels, there is a necessity for standard and robust energy management architecture and implementation at the prosumer and the generation levels. The main focus is on load consumption management on the demand side, which can be accomplished by integrating various programs focused on efficiency and minimizing loss at both the appliance and the intelligent grid system level. The consumers and the energy-generating organizations participating at the energy market levels will gain significantly from such an adjustment in the load profile. Introducing standardization protocols for efficiency and consumption management approaches can help resolve severe concerns such as fossil fuel use, carbon emissions, energy costs, and other sustainability elements, to some extent. Integrating multiple communication and Internet of Things (IoT) protocols in renovating conventional grid systems into intelligent grids has enabled a bidirectional information exchange [1]. This data can be utilized for a variety of energy management strategies. On the demand side, by incorporating various digital sensing and communication protocols, smart device control, and connectivity between utilities and geographically distant grid organizations, appliances can leverage this information to strategically provide an optimal strategy for better operation and efficiency characteristics. Understanding the problems related to integrating different sources and technology can provide ideas to establish synchrony between generation and load.

The notion of demand-side management (DSM) is a solution to these significant challenges related to grid sustainability, security, reliability, and load profile management from the perspective of consumption and for providing strategies for load reduction. DSM is a collection of load management solutions that plan, integrate, and monitor preassigned routine operations on the basis of a consumer's consumption behavior [2]. The DSM architecture can conservatively dispatch available generation capacity, lowering emissions and peak load usage while allowing users to use their preferred energy type [3]. DSM was launched in 1970 [4] when the electrical sector offered the DSM model and architecture to manage time-of-use (ToU) and peak electricity consumption and to analyze consumer load usage profiles. DSM can establish synchrony between generation and load, taking on maximum cases of obstacles.

There are substantial incentives to employ distributed generation (DG) to reduce greenhouse gas emissions, improve power system efficiency and reliability, implement competitive energy policies, and delay transmission and distribution system upgrades. DGs are made up of renewable units such as wind turbines (WTs), photovoltaics (PV), fuel cells (FCs), and biomass, as well as non-renewable units such as micro-turbines (MTs), gas engines (GEs), diesel generators (DiGs), etc. By being near the clients, DGs avoid needing a transmission system. The integration and control of DGs, storage devices, and flexible loads can form a microgrid, a low voltage distribution network that can operate in isolated or grid-connected modes [5]. Due to a lack of sufficient energy generation sources, microgrids frequently struggle to meet demand. The intermittent nature of loads and renewable energy sources create this barrier [6]. As a result, to address this issue, an energy management system (EMS) is required. Using an EMS for a microgrid is a relatively new and trendy issue that has recently received much attention.

1.1. Motivation behind the Adoption of DSM

The necessities of the load–grid from the perspectives of synchronization, stability of operation, security and data protection from external attacks, reliability issues, and profit maximization requirements have prompted attention in various areas of DSM research. The following are motivations for the rising interest in the application of DSM techniques:

- To reduce consumer annoyance during the adoption of DSM by incorporating demand reduction bidding during peak hours, incentive DSM, and demand response (DR) programs.
- To create an interactive load management market, which is a prosumer-based market in which each customer plays a part in achieving low-cost energy usage.
- To match energy supplies and dispatch additional available sources within the current system and regulate the required demand.
- To enable proper demand and supply balance by either reducing or shifting energy use from critical loading periods to fewer off-peak times, factoring in economic standards and active control methods.
- To consider electricity generation and trading tariffs, environmental considerations, demand-based usage patterns, and prosumer convenience levels when creating optimal load dispatch and usage scheduling.
- To adapt to changes brought about by erratic consumption and a lack of understanding of the operational state of daily-use devices and machines [6].

- To conduct forecasting based on weather data assessing client comfort levels and convenience.
- To achieve the lowest possible electricity cost from an economic standpoint, maximizing energy consumption from geographically nearby renewable energy sources (RES) from an environmental perspective and preventing power quality issues.
- To raise consumer awareness of DSM's benefits, which can stimulate adoption or improve electricity usage patterns.
- To combine operational flexibility for an individual home with the flexibility of other residential customers in the neighborhood to achieve operational flexibility for a unique family.
- To improve grid efficiency and reliability by minimizing the peak-to-average ratio (PAR) by offloading optional loads during peak periods [7].

1.2. Benefits of DSM

DSM comes into play to solve such difficulties concerning the current situation on the load end and to enable greater flexibility and the robust scheduling of specific devices and gadgets at an autonomous stage through intelligent control mechanisms. DSM can provide several advantages, such as:

- To help minimize voltage fluctuations on a poor distribution feeder by providing grid support [6].
- To resist environmental concerns by lowering peak demand, which decreases the need for new traditional generating plants.
- To allow the principles of DSM to be successfully implemented, where it can benefit both customers and the utilities economically.
- To guarantee steady and sustainable power delivery within the system, thereby avoiding shortfalls.
- To provide cost savings in energy usage while also assisting in achieving positive environmental goals.
- To decrease load profiles by intelligently managing loads [7].

1.3. Issues and Challenges in Implementing DSM

The path to DSM integration is littered with several challenges and issues that must be solved for the program to be executed effectively and efficiently among the participating institutions. Some of the concerns and difficulties that will be discussed are as follows:

- Residential loads frequently contribute a major portion of load demand owing to seasonal and daily peak load consumption, causing the available grid system to be under-sized in handling peak energy usage.
- Pricing blocks that can be adapted according to consumption at multiple levels can be implemented smoothly.
- To use the best load scheduling approaches possible.
- Centralized controllers for both control choices and control actions are required to implement direct load controls (DLCs), interruptible tariffs, demand-bidding programs, and emergency programs. Because the client wants to save money on energy, and the utility wants to maximize profit from the available energy, the goal is to balance energy and save money.
- Consumer response to the price signals supplied by the utility and market tariffs, which modifies consumer behavior, fluctuates unexpectedly depending on their ability and willingness to adapt quickly, indifference to minor tariff adjustments, and pricing system awareness.
- To address the opposing objectives of consumer convenience and reduced-cost consumption, decrease load consumption for customers and increase revenues for utility companies with accessible energy generation sources, etc., while formulating energy regulations.

- Inadequate system-wide scalability measures to address the multi-vendor dilemma, upgrade, and expansion.
- Usage of robust system privacy measures to secure the vital information of participating customers.
- To address the neighbor effect, some consumers over-estimate other consumers' price rates, where any change affecting a consumer influences the choice and preference of nearby present customers.
- A generalized operational framework of DSM is necessary owing to the characteristics and objectives of DSM participants and loads operating in an independent system in order to provide the customers with more control over their energy consumption.
- The reduction in peak load requirements and the minimization of overall load usage tariffs for residential occupants while maintaining an acceptable degree of comfort and choice for the user.
- Integrated volatile power sources such as wind and solar impact grid stability and create issues.
- The difficulty of balancing supply and demand for electricity in the face of uncertain demand and uncontrollable sources.
- DR faces four significant operational issues: scalability, distribution of control, unpredictability, and aggregation.
- Supply and demand may become imbalanced at different locations along a changeable demand curve [6].
- The need to build a model of energy generation is essential due to the effects of traditional power generation and global climate change.
- Lower peak demand and overall load consumption costs while maintaining appropriate comfort and convenience for residents. Integrated unreliable power sources such as wind and solar impact system stability and create issues.

1.4. Suggested Solutions in DSM Implementation

The following suggested solutions are viable for implementation and for driving grid integration programs in a more effective and coordinated way to deal with the above concerns and obstacles faced during the implementation of various policies concerning DSM using DGs systems:

- An adequately designed pricing structure will result in a flexible electricity system, allowing residential customers and utilities to achieve their goals.
- Time-of-day (ToD) pricing can incentivize large-scale residential and commercial users to conserve energy.
- The load profile forecast mechanism can serve as a transitive feedback signal, and the tariff associated with it can serve as a transitive incentive signal.
- A stochastic and multi-objective optimization technique for the optimal scheduling of various domestic appliances utilizing model predictive control (MPC) optimization.
- The transitive energy concept is a viable coordination paradigm for maximizing the importance placed on prosumers and operators at the utility level and their overall participation in the market structure.
- From the perspective of trading entities present in the market and their involvement and market-based signaling, extensive changes in government laws consider both energy providers and customers.
- A variety of sophisticated methodologies can factor in individual residential prosumer overhead and comfort levels, optimize individual consumption schedules, and offer positive DSM impacts [7].
- To allow the electricity markets to generate higher revenues, an incentive-based program can change conventional consumers into new era prosumers by modifying their behavior and habits of use [8].
- For the improved functioning of DR ideas in residential utilities, measurement and verification protocols and an automated procedure are required [9].

- Complete service-oriented topology and structure is a necessity to allow for provisions of appropriate infrastructure oriented toward dynamic integration techniques and for a more flexible operation to bring out the best in the power system scenario [10].
- DSM contributors can consume or generate energy in a coordinated operational state as cooperative agents or virtual power plant models, which can simulate the performance of an aggregated virtual single power source indirectly incorporated into the power system [11].
- The introduction of generation systems such as solar photovoltaics (SPV) and energy storage system combinations for usage during peak hours.

1.5. Outline of This Paper

This paper is presented to address the issues and solutions of DSM using a methodological and critical survey-based exploration of the implementation of DSM using DERs. Efforts are made to put forth the following points concisely: Firstly, to assess and study the suggested optimization techniques and implementations of DSM in the present literature. This will allow the researchers with the necessary exposure to arrive at more practical and better optimization techniques to establish a proper energy management system (EMS). In addition, energy management modeling studies are examined in terms of uncertainty modeling techniques, objective functions, constraints, and optimization techniques. Lastly, EMS-related papers are reviewed and analyzed correctly to help the researcher find out the problems and the solutions.

The remaining part of this review article is designed as follows: Section 2 represents the detailed review methodology used to formulate this paper, Section 3 states the brief introduction to DSM and DR, Section 4 briefly states the various DGs possible in an intelligent grid network, Section 5 represents the DSM with different types of cleaner energy, Section 6 briefly illustrates the energy management system and some standards related to DG integration, Section 7 explains some issues related to different types of DGs being integrated with DSM techniques, Section 8 represents the various optimization techniques ascribed to DSM with objective and objective functions, Section 9 deals with the different research gaps and critical analyses, and the future scope and conclusion are analyzed in Sections 10 and 11, respectively.

2. Review Methodology

Any research project's primary focus is on three key elements: the purpose, study technique, and outcome, as well as future implementation prospects. An approach based on an analytic-based search technique was undertaken on numerous scientific and interpretive sources such as Google Scholar, ResearchGate, IEEE Explorer, and Scopus to gain a detailed and complete overview of existing research publications. Combinations of thematic words, such as "Demand-side management distributed energy resources", "Demand response", "Energy management using distributed energy sources", "Optimization", "Scheduling", "Distributed energy sources integration in microgrids", and so on, were used to filter out the critical articles using search engines. Specific search engine parameters were employed to find relevant, on-point, particular research papers for the review study. Exact keywords, peer-reviewed publications published in English mainly in the last ten years, and open-access articles were the deciding factors.

Based on the research articles, an eight-point prospect was developed:

- DSM techniques in general, with sub-strategies investigated from a modification standpoint.
- Incentivized and price-based programs, as well as demand response strategies.
- The customer rationale for employing distributed generation to implement DSM.
- Researching the architecture and topology of the EMS system, as well as comparing it to alternative DSM methodologies.
- The scope of limitations and constraints associated with implementing DSM using DER architecture with present issues.

- Published research methods and optimization approaches.
- Analysis and conclusions from the study of the approaches employed in the optimization challenges stated.
- Action plan for the future.

As shown in Figure 1, 31 review papers, 40 case studies, 15 news articles, 107 technical papers, and 10 research reports were reviewed and placed in this paper.

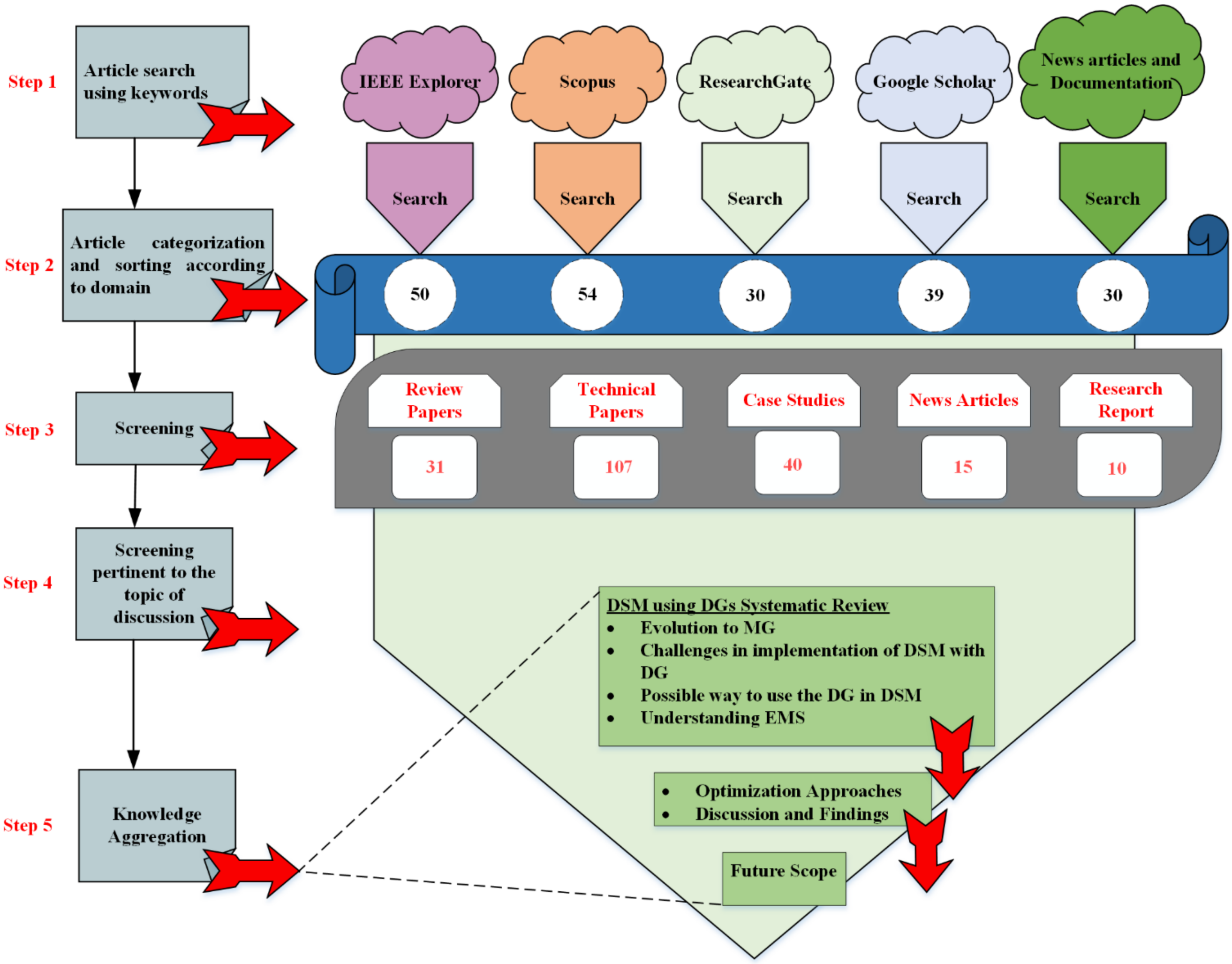

Figure 1. Review methodology for this paper.

3. Demand-Side Management

Demand-side management is an essential part of an intelligent grid architecture because it allows consumers to adjust their load consumption patterns, making it a critical feature of an energy management system in power delivery networks [11,12]. "The planning, implementation, and monitoring of those daily activities designed to influence customer use of electricity in ways that will produce desired changes in the utility's load shape, i.e., time pattern and magnitude of a utility's load," according to the Electric Power Research Institute (EPRI) [13]. Instead of relying on additional generation to meet demand, DSM prioritizes the integration of power-saving techniques, the implementation of variable or dynamic unit pricing, and the adoption of DR-based programs to minimize peak load, managing the DGs to establish a proper power balance, as shown in Figure 2.

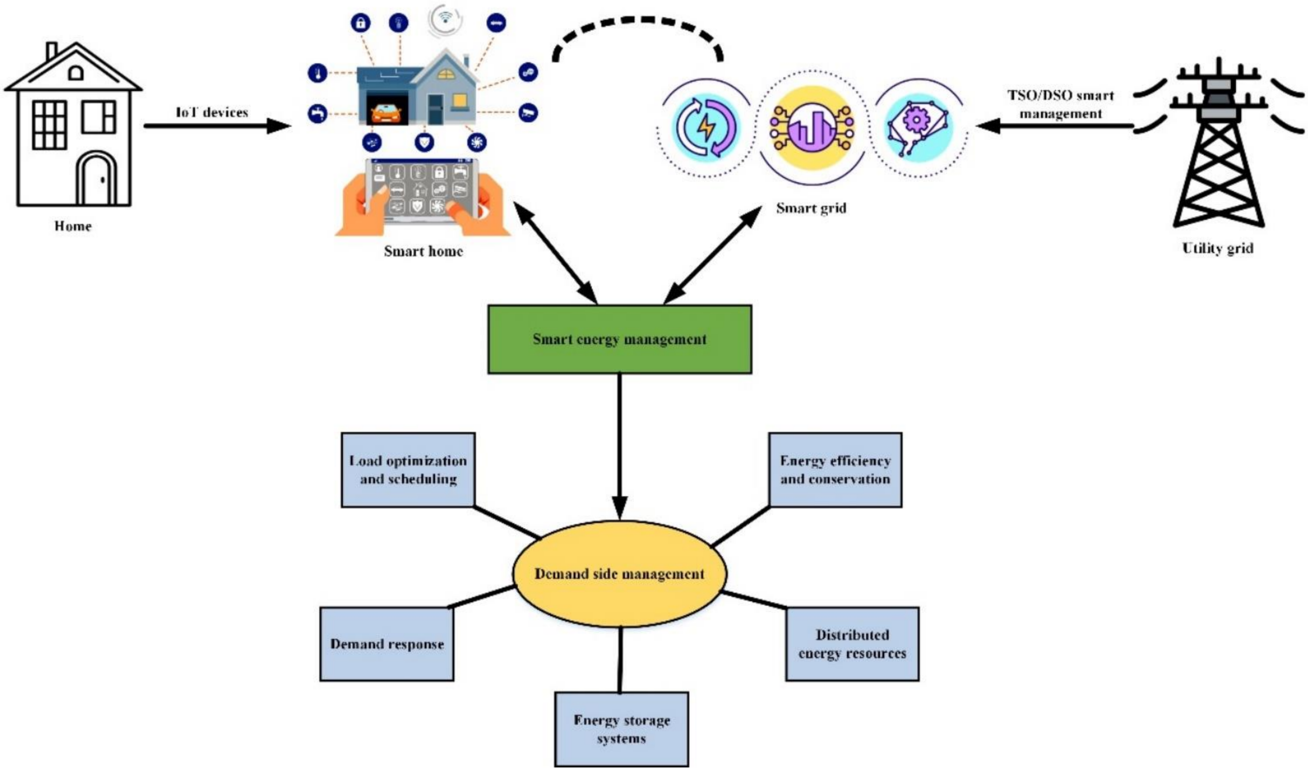

Figure 2. Principle of DSM in the smart grid environment.

The four methodologies outlined below and illustrated in Figure 3 can be used to classify various alterations that can be used to shape and define the electricity load profiles:

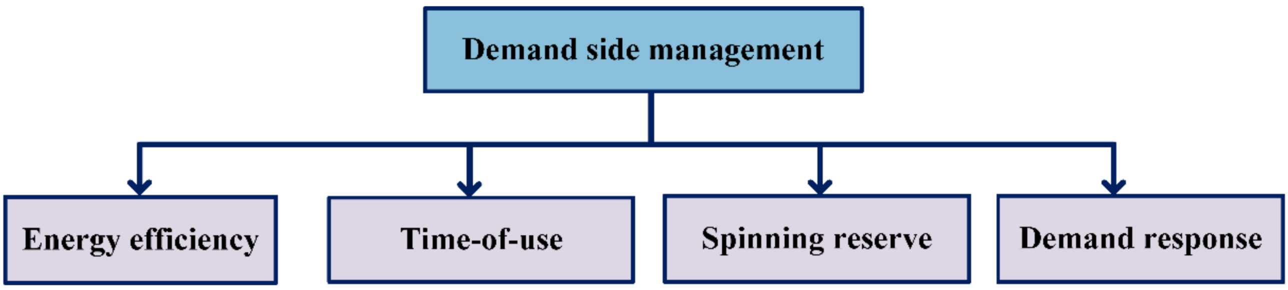

Figure 3. Basic principle of DSM.

Energy efficiency (EE): These are end-user, appliance-specific controls intended to reduce load utilization over time by employing energy-saving methods on the device level. Rather than relying on an event-triggered strategy for consumption profile minimization, energy efficiency refers to the reduction in overall load consumption achieved by providing more efficient power delivery for each unit with respect to the supplied input power to the appliance, decreasing consumption over time. An in-depth look at the energy efficiency improvement profiles, measurements, and roadblocks can be found in [14,15].

Time of use (ToU): The ToU pricing method divides the utility's fixed tariff into 24 h time blocks and then assigns a variable pricing profile for each period [16,17]. This method can help keep peak load rates and seasonal fluctuations in pricing tariffs under control based on the hourly block-based signal tariff of electricity units.

Spinning reserve: In the case of a drastic shortfall in generating levels, the spinning reserve is synonymously recognized with the electric power system's backup power, which may be utilized by the distribution network operator (DNO) to balance the difference or gaps between demand and supply in generation [18]. Power outages can be caused by various factors, including damage to producing units, inadequate load prediction, and dispatch scheduling [19]. In general, there are two types of spinning reserves: primary and secondary [16], with the central spinning reserve employing frequency regulation to limit active power output and the secondary spinning reserve injecting extra active power.

Demand response: Energy users depart from their usual use patterns in response to unit rate variations over time or incentive programs. The primary focus is to reduce load profiles during critical tariff periods in the energy wholesale market or when grid reliability is uncertain [20]. Short-term variations throughout the day's critical peak pricing/usage times, when demand is low and spinning reserve capacity is scarce, are of primary interest to DR. DSM is more concerned with long-term load profiles, which may be accomplished on the demand side by improving energy efficiency or adopting consumer-centric usage behavior.

4. Distributed Generations in Smart Grid

A distributed energy resource (DER) is an aggregation of distributed generators, as shown in Figure 4, or controllable loads (conventional or smart) connected to the network in a smart grid. A DER unit, or distributed generation (DG), often blends a variety of energy sources. They are classified into, essentially, two sorts of sources based on their dispatch capacity and source of generation type:

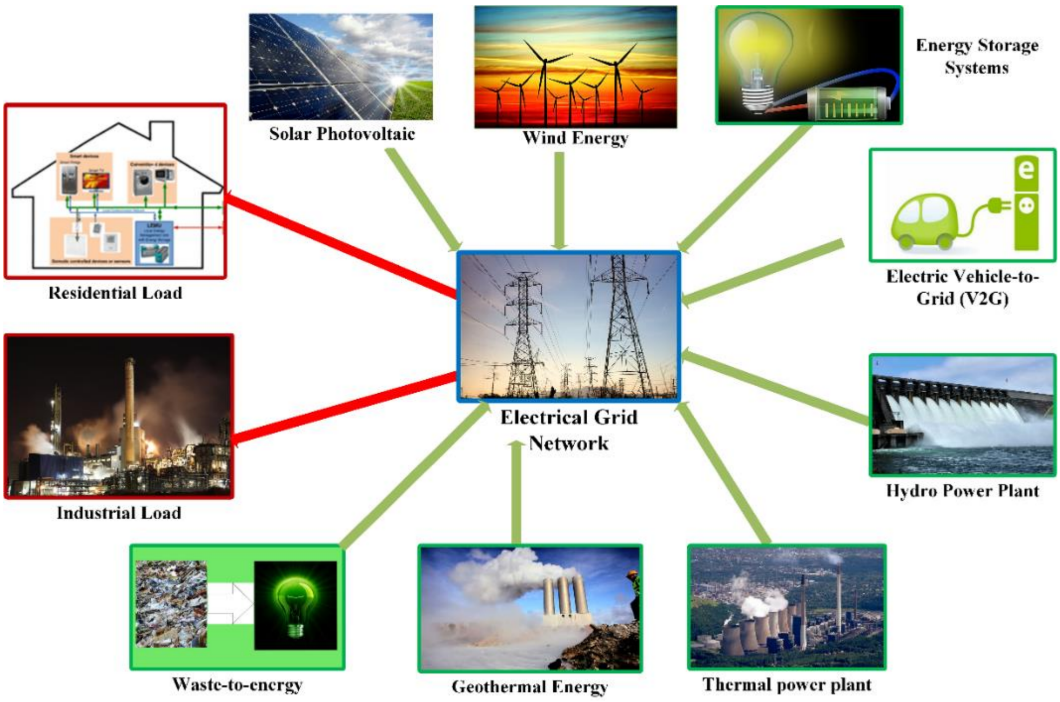

Figure 4. Various types of energy sources in the smart grid.

4.1. Renewable Energy Sources (RES)

Solar Photovoltaics: Converting solar energy to electrical energy via mounted semiconductor panels is the primary renewable generating source across the globe. It can produce energy in any mode, stand-alone or grid-integrated, and small-scale (such as rooftop PV in residential areas) or large-scale (centralized power plants). Scheduling, as per weather condition forecasting, boosts production capabilities.

Solar Thermal: Solar thermal power plants use solar energy to heat a fluid to a high temperature to generate electricity. The heat from this fluid is transferred to water, which subsequently forms superheated steam. In a power plant, steam is utilized to run turbines, and mechanical energy is transformed into electricity by a generator. This sort of generating is similar to electricity generation that uses fossil fuels, except that instead of burning fossil fuels, sunlight is used to heat steam.

Hydropower Plants: The flowing capacity of water is capable of rotating a turbine to generate electricity, which can be the centralized or decentralized mode of operations according to the availability of the water and the water head. Generally, small-scale hydropower stations are used for DSM operations, which are described in Section 5.

Wind Turbines: Wind energy conversion systems (WECs) are also a significant component of DGs where the appropriate wind reach is available. This generation unit is limited to smaller, low-capacity generation units. This allows for small-scale WT unit deployment on the customer side to be possible without affecting the operation of the entire power system as a whole.

Geothermal Energy: Geothermal energy captures the energy from the core of the earth. DGs can be localized around nearby natural geothermal energy sources, such as lava flows, hot springs, geysers, or places that experience direct contact between water and high thermal capacity surfaces. As part of the natural cycle of evaporation and replenishment, geothermal sources can be considered a viable source of renewable energy generation.

4.2. Traditional Energy Sources

Combined Heat and Power: Fossil fuels are the primary sources of CHP that are set to run as centralized power stations, mainly to fulfill the baseload requirement. Fossil fuels are burnt to produce steam, which rotates the turbine to produce electricity. Due to substantial carbon emissions, limited availability of sources, and environmental concerns, the focus has shifted toward renewables.

Fuel-based DERs: To supply supplemental power to the grid, diesel generators and fuel cell (FC) generators often employ readily available fossil fuels, waste-derived fuel, and hydrogen-based production, and they are typically run on-demand rather than always-on. Due to their simple dispatch mechanism and controllability, they are suitable DER units to link to a smart grid design. For the purposes of providing power to emergency loads, they are suitable as a DSM option.

4.3. Energy Storage Systems

ESS is now viewed as a novel technique for adjusting generating capacity to load demand changes, particularly as energy buffers in the situation of the high availability of non-dispatchable generation sources. These ESS capture and store surplus energy generated during off-peak hours, then dispatch it during peak periods when the extra load is needed. They also allow for the optimal redistribution of PV array and WT unit output power throughout the daily scheduling period. In terms of ESS concerned with energy supply, they are categorized as compressed air energy storage (CAES) and hydraulic pumped energy storage (HPES), depending on the method of application. Similarly, ESS focused on power supply include supercapacitor energy storage (SCES), superconductor magnetic energy storage (SMES), pumped storage, and flywheel energy storage (FWES) [21,22].

4.4. Waste-to-Energy (Bio-Energy)

An increase in urbanization is the cause of the generation of a large amount of waste, particularly MSW (municipal solid waste). The thermal treatment of municipal or industrial waste and sludge, as well as medical or industrial hazardous waste, decreases trash disposal in landfill sites dramatically. The produced energy yields a new revenue stream that helps both the local population and the environment through cleaner air, water, and soil. The process starts with collection, followed by segregation, then processing through various stages, such as pyrolysis, and then incineration to produce electricity. Taking into consideration the United Nations' Sustainability Goal of cleaner energy, waste is counted as one of many effective sources of conversion to electricity [23,24]. The different processes, which can be followed to convert the waste, are presented in Figure 5.

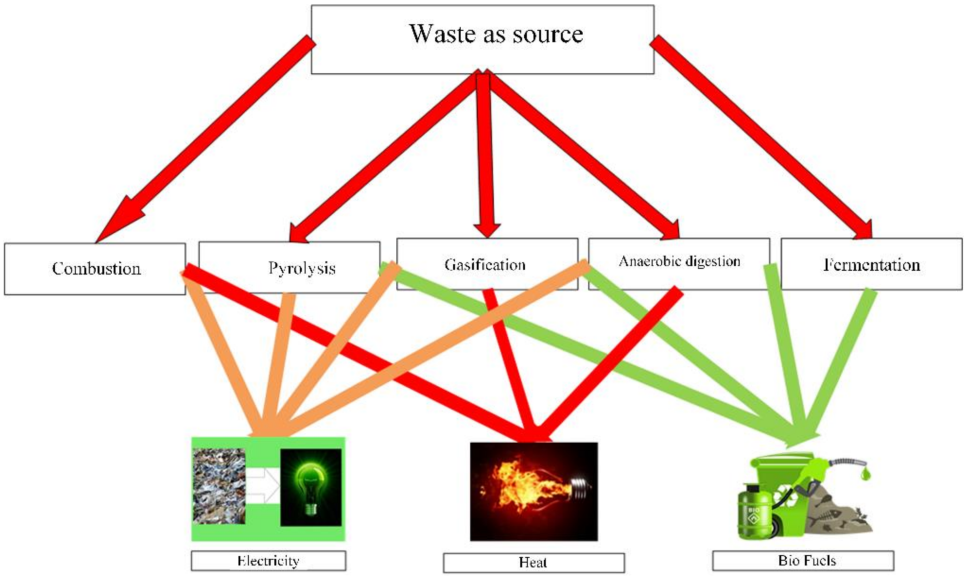

Figure 5. Different processes of waste-to-energy.

4.5. Electric Vehicle (V2G)

Vehicle-to-grid (V2G) is a system in which plug-in electric vehicles (PEVs), such as battery electric vehicles (BEVs), plug-in hybrids (PHEVs), and hydrogen fuel cell electric vehicles (FCEVs), communicate with the power grid to sell demand response services by returning electricity to the grid or throttling their charging rate. Electric vehicles with V2G storage capability can store and discharge power generated from renewable energy sources such as solar and wind, with output that varies based on weather and time of day [25,26]. The process of V2G is the same as in the case of the ESS shown in Figure 6.

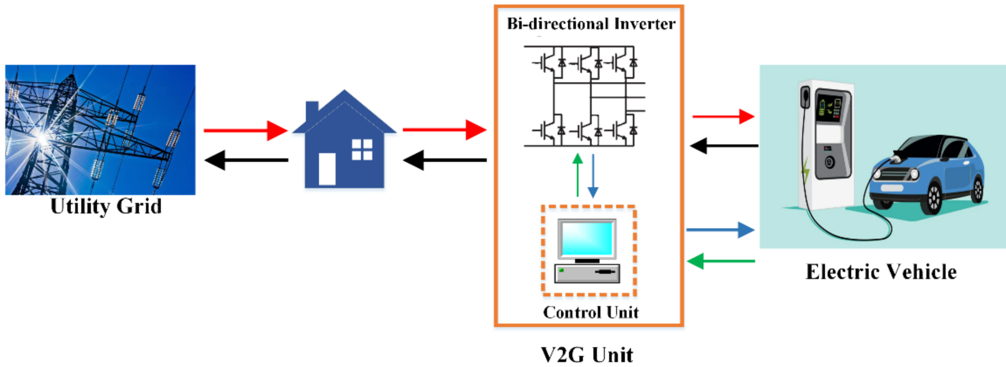

Figure 6. Electric vehicle as a source of energy.

5. DSM Using DGs and ESS

DSM is the systematic energy management in the case of using DGs and ESS. Using DSM can have a lot of benefits to industry, residents, nations, and the globe, which is shown in Figure 7. DSM can be implemented by using distributed energy resources such as solar, wind, waste-to-energy, etc. DSM generally involves load shape modification by applying different optimization techniques [27–29]. This modification is carried out by the significant DSM component, which is the load duration curve (LDC). LDC offers a general and analytical idea of off-peak hours and peak hours. Six techniques are used in load shaping, which are discussed below and in Figure 8.

a. *Peak Clipping*: This technique is used to reduce the peak demand at peak hours. Effective use of this method can reduce the chances of establishing new generating stations. Generation from DERs also helps in balancing load and can reduce the peak demand.

b. *Valley Filling*: This technique is set to rebuild the load during off-peak hours, which helps reduce tariffs. Charging electric vehicles at off-peak hours to work as V2G at the time of need is a possible example of valley filling.
c. *Load Shifting*: This is based on shifting load from peak hours to off-peak hours.
d. *Load Reduction*: This strategy is based on using energy-efficient equipment to reduce load demand. Rooftop solar installation in residential areas can reduce the load overall, which is an example of this technique.
e. *Load Growth*: Building up the load at the time of reduced load conditions or in off-peak hours. This technique is an example of charging ESS or EVs at non-peak times or during non-peak days.
f. *Flexible Load Shaping*: The rearrangement of LDC according to the conditions. WEC system generation is an example of this method.

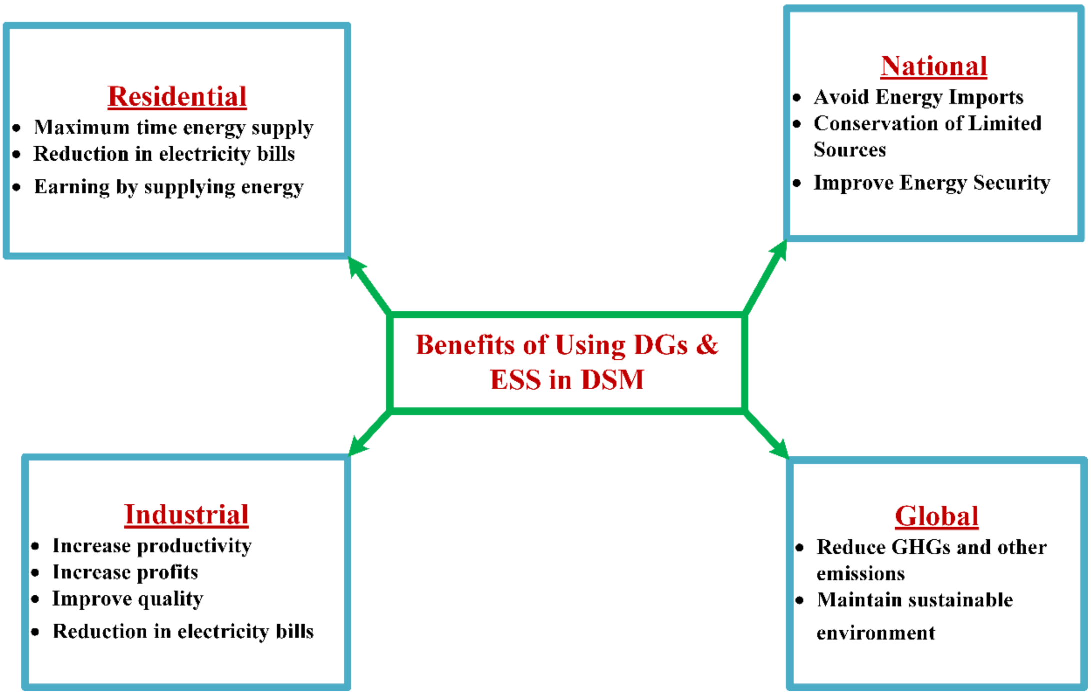

Figure 7. Benefits of using DGs and ESS in DSM.

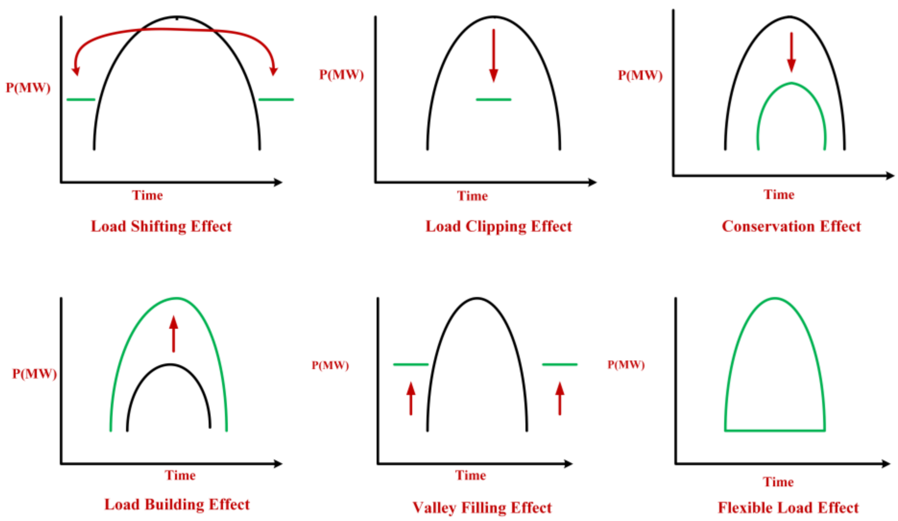

Figure 8. DSM techniques.

The discussed DSM objectives can be achieved by integrating the DERs described in earlier sections in a forecasted manner [29]. The reason for using all these renewables is as simple as the UN's Sustainability Goal of cleaner energy. Different types of available DERs and possible DSM techniques are discussed in Table 1, which is a new and innovative way of expressing the information in this paper.

Table 1. Different types of DERs with DSM applications.

DERs	Available for the Time (24 h)	Possible DSM Techniques	Types of Operations	Benefits
Solar [30,31]	Morning to afternoon (7–9 h)	Peak clipping Load reduction Load shifting Valley filling	Thermal: Converting solar heat energy to electrical energy.	Cleaner energy, reduction in the use of carbon.
			Photovoltaic: Converting solar radiations to electrical energy with solar cells.	Cleaner energy, tariff reduction, decentralized generation, residential mode generation.
Wind Energy [32]	24 h	Load reduction Load shifting Valley filling	Converting wind energy to electrical energy with induction generators	Cleaner energy, decentralized generation.
Hydro Energy [33]	24 h	Peak clipping Load reduction Load shifting Valley filling Flexible load growth	Pumped hydro: Water pumped during off-peak hours generates electricity during peak hours.	Emergency power, cleaner energy, small centralized power generation.
			Small hydro: Decentralized runaway water used for electricity generation.	Emergency power, cleaner energy, small centralized power generation, low-cost generation.
Waste-to-Energy [34,35]	24 h	Peak clipping Load reduction Load shifting Valley filling	Biogas: Anaerobic digestion of biodegradable waste into methane produces energy. Thermal: Combustion of waste to produce energy.	Cleaner energy, small centralized power generation, less carbon production. Cleaner energy, small centralized power generation, less carbon production.
ESS [36]	24 h	Peak clipping Load reduction Load shifting Valley filling Flexible load growth	Energy is stored at off-peak hours in various systems such as electric springs, pumped hydro, fuel cells, hydrogen cells, supercapacitors, etc.	Emergency power, cleaner energy, small centralized power generation, less carbon production, charging stations.
Vehicle-to-Grid [37]	24 h	Peak clipping Load reduction Load shifting Valley filling Flexible load growth	EV charging in off-peak hours can provide power to grid-like ESS at the time of need.	Emergency power, cleaner energy.
Geothermal Energy [38]	Available when water is in contact with lava	Peak clipping Load reduction Valley filling	Providing intermittent boosts to power levels.	Small centralized power generation, spinning reserve.

6. Energy Management System

An energy management system is an operational system used to plan, manage, mitigate, forecast, and continuously improve energy performance to establish a balance in the power flow network, including various DERs, as shown in Figure 9. An EMS optimizes the energy supplied by generating stations to the grid, taking into account various parameters, which are listed below:

- Energy consumption in the power flow network;
- Load behavior pattern on the demand side;
- Consumer energy consumption patterns;
- Seasonal forecasting of consumer data;
- Weather forecasting data;
- Time of pricing when it is highest.

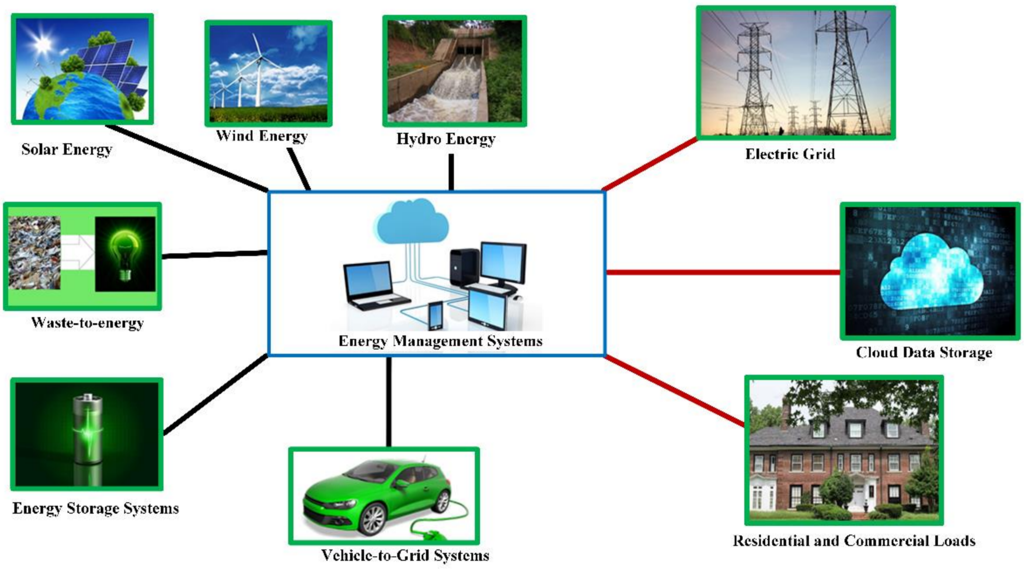

Figure 9. Energy management system.

Major components of EMS are measuring units, IoT-based tools to forecast data from collected data, various types of sources of generation, and generation scheduling. An EMS is operated by various optimization models with specific objectives, taking into account the constraints related to them, which are discussed in the later section.

6.1. Energy Monitoring, Measurement, and Analysis

An EMS includes monitoring, measuring, and analysis as major components to carry forward its operations, which will determine the energy flow performance and help it perform DSM effectively. Its key characteristics include [9,39]:

- Significant energy use in the SG network;
- Variables related to energy use;
- Energy performance indicators;
- Effective energy-efficient plans to achieve objectives and targets.

6.2. Standards Used for Communications in DSM Using DGs and ESS

There are specific standards used for communicating various DGs and ESS to the SG's power flow network, which are provided in Table 2 [40].

Table 2. Standards used for communication in DSM using DGs and ESS.

Code	Year of Implementation	Objective
IEEE 1547	2003	To find a bridge between distributed generation and the electric network.
IEEE 1547.1	2005	Specifies the test procedure for the interconnection.
IEEE 1547.4	2011	Deals with the planning and operation of integration.
IEEE 1547.7	2013	To standardize the DG integration system.
IEEE 1547.8	2014	It identifies and expands the innovative design, process, and operational procedure to achieve flexibility.
IEEE 2030	2011	Integration of information technology into the grid, the establishment of a framework of operation because of the prospects of a smart grid.
IEEE P2030.2	2015	Integration of hybrid energy storage systems into the power flow in the network.
IEEE 2030.3	2015	The test procedure for a single storage device in the power network.
IEEE2030.7	2017	Standards for microgrid energy management.
IEEE 802.1/ 802.3/802.15.4	2003	Interfaces the identifiers, which operate as the interconnecting modes and power control. Information exchange between the components.
EEC 61850-7-2	2003	Sets standards for abstract communication service interface (ACSI) as a paradigm used for vertical and horizontal communication for MC61850.
EEC 61970/ 61968/62325	2013	Sets standards based on information integration and the software framework of EMS for DGs
IEEE 2030.8	2018	Sets standards for microgrid energy management and control in a grid-tied or off-grid system.
IEC 61850	2019	Automation architecture requirement for utility subsystems, enabling communication and semantic interoperability among multi-vendor equipment, communication networking, and the communication front-end for the network.

7. Issues and Challenges

During the review process, several issues related to integrating DGs into the smart grid for DSM purposes were found, which are listed below, categorically segregating different types of DGs [41–48].

7.1. DSM with SPV

SPV energy conversion systems have been used for a long time since their discovery as a significantly cleaner energy source. Much of the maturity in semiconductor technology has allowed for vast improvements in the scope of SPV generation. The issues discussed below are the major difficulties in addressing stable grid operations with DSM.

- These sources of generation, albeit easy to install, are not flexible to operate. This is because the reactive power necessary to complement the generated active power from SPV is not readily sourced and is difficult to integrate when upgrading the primary SPV generation sources.
- SPV generation necessitates the use of ESS to avoid drops in power delivery and the energy buffer as and when power is not readily available for generation.
- The installation safety measures need to be stepped up, as they are prone to damage from meteorological and physical factors such as hurricane winds and rust in the installation equipment. This presents a potential hazard, hindering the safety aspect of SPV installation.
- Maturity in SPV panel technology has vastly improved since its inception, but the technology has still not reached its peak maturity for the maximum extraction of available solar energy using existing power conversion and extraction techniques, viz., MPPT.
- The manufacturing and disposal of SPV equipment leave behind a very high carbon footprint, presenting a deterrent toward adoption owing to environmental concerns.

7.2. DSM with Wind Energy Conversion System

Wind energy conversion systems integrated into DSM have been wholly realized for a long time; this includes wind turbines, wind monitoring systems, and related environmental protection systems, such as environmental protection stations and power generation systems. Still, it has proved challenging to synchronize wind and hydropower effectively in actual operations, which does achieve high efficiency at the same time each year [3]. The complexity can be seen in the following aspects.

There are three significant issues in the current use of wind turbines in DSM that challenge its high efficiency and stable operation [3,24]:

1. The prediction and forecasting are not accurate, as various sources influence the generation capacity. The meteorological uncertainty, coupled with the continuous available wind flow available at the tip level, influences the generation capacity of the wind turbine.
2. The transmission and distribution of the existing power grid are too complicated, making it more challenging to integrate with wind turbines effectively, as they have issues concerning intermittency and frequency deviations from the existing grid requirements.
3. The operation of wind turbines with the existing power grid is not sustainable during the nighttime, eventually leading to an increased load on the grid during the daytime.

7.3. DSM with Hydro Energy Sources

Generation sources pertaining to hydro-based sources are a major part of the power supply to grids. Complex hydropower-generating units installed in dams and tidal-based generation can be leveraged to a high extent, owing to their pollution-free generation and the replenishable source of waterbodies, which are naturally replenished via the water cycle. The major issues that are present in the existing power generation scenario that can affect DSM operation, to a certain extent, are highlighted as follows:

- The availability of water sources for potential generation is not feasible in every possible geographical location. Large-scale generation is only possible if the geographical arrangement allows for dams to be constructed or the waves to be harnessed suitably without causing ecological imbalance to nearby flora and fauna.
- The ratios of cost-to-establishment and revenue generation-to-cost are generally low, owing to high recurring and installation expenditures. However, these can be leveraged by using an environmental outlook to justify the cost.
- Maintaining the frequency of the power generated is complex due to the intermittent nature of water flow at the available head level. This prevents the energy generated from the wind turbines to be directly integrated into the transmission system, as pre-conditioning the power supplied is necessary for reliable grid operation. This adds significantly to the power generation costs as additional power conditioning units are required to bring the frequency and other parameters up to an acceptable generation level.

7.4. DSM with Waste-to-Energy Sources

In recent times, waste-to-energy has gained significant potential in the renewable and biologically eco-friendly energy market owing to its nature-oriented disposal and pollution-free generation. DSM can be implemented at the prosumer level, with the prosumers being active power generation sources putting greater emphasis on waste-to-energy potential as their preferred source of energy to defer them from using conventional grid-supplied electricity. However, the present scenario is plagued with many issues, some of which affect DSM integration with waste-to-energy potential as a potent source of power generation. Some of these issues are:

- Waste segregation and management on the ground level are the primary tasks that need to be focused on. In developed countries, this is not a major issue, as the general population is aware at a high level in comparison to countries with developing economies. Better awareness among the general masses can be a solution to the segregation and management of waste.

- Complex techniques are involved in waste-to-energy-based generation, such as pyrolysis in controlled environments and the use of a specific mixture of substances to keep the entire process pollution-free.
- High investment costs are required for setting up the incineration and biogas plants.

7.5. DSM with EV and ESS

The automobile sector is presently witnessing a surge in sales of EVs with the transition to battery-based power delivery from conventional gasoline and diesel as sources of transportation fuel being the prime focus. This has seen a rise in the adoption of more efficient and high power density battery systems to be implemented at the EV end-user side. Higher capacity batteries can be configured from a backup or buffer storage system standpoint. A bidirectional implementation of these battery-enabled mobile EVs can allow for dispatch strategies to be collectively aggregated and disbursed by DNOs as a virtual power plant system through DSM strategies. Similarly, DSM can allow intelligent control of EVs, charging and discharging according to adaptive schedules, which will benefit the power system. Nonetheless, issues pertaining to EV adoption prevent the large-scale integration of DSM in EV-based programs due to:

- High investment costs and costs of ownership from the perspective of the manufacturers, grid utility operators, and consumers. The careful economic and technical planning of charging stations, the grid's capacity to accept increased loading, and the minimization of losses along the transmission and distribution systems to allow for efficient use of available energy are the primary concerns from the maintenance and setting-up perspective.
- Consumer acceptance is still low in developing countries due to a range of anxieties about reliability and initial expenditure during purchase as compared to fossil fuel-based automotives [46].
- Battery degradation and better health are also major concerns; the periodic maintenance of fossil fuel vehicles is a fuss-free ownership experience in the long run, as battery degradation does not hinder the performance of the vehicle to a great extent. In contrast, in the case of EVs, the batteries eventually require replacement at their end-of-life stage unless they find use as second-life batteries.

These issues and challenges must be addressed to make EMS architecture more robust and reliable. After resolving these challenges, the optimization techniques can be integrated seamlessly into the EMS architecture.

8. Optimization Methods

The earlier literature presents various ideas about different types of mathematical approaches to solve the DSM problem. Techniques such as linear programming, dynamic programming, non-linear programming, game theory approach, and particle swarm optimization set a mark for solving the DSM objectives. Recently, hybrid techniques, such as gray wolf optimization (GWO), harmony search (HS) algorithm, enhanced differential evolution (EDE), etc., have drawn the interest of researchers in this field. Many of these optimization approaches and real-world implementations of DSM (mostly on residential premises) were discussed in [26], with distinct classifications between each approach and classification. The various objectives and constraints are discussed in Table 3, and different types of optimization techniques are broadly listed in Table 4, below.

Table 3. Classical technique-based single objective optimization.

Refs.	Objective	Objective Function	Concepts Employed					
			LS	PC	VF	LS	LG	LR
[47]	To facilitate EMS to reduce the total cost of energy consumption and generation.	$F(x) = \min\left(\sum\limits_{i \in I} E_{con,i}.P_i - \sum\limits_{j \in J} E_{gen,j}.P_j\right)$	✔	✔				
[48]	To assign a thermal management system for peak load shifting.	$F(x) = J(s,p) = \sum\limits_{t=1}^{T} \Delta t(p_{load}(t) - \overline{p_{load}}(t))^T \times K\Delta t(p_{load}(t) - \overline{p_{load}}(t)) + (s(t) - \bar{s}(t))^T M(s(t) - \bar{s}(t))$	✔					
[49]	To reduce power consumption in classroom-based smart buildings.	$F(x) = E^{obj} = \min\left(\sum\limits_{r=1}^{c} \sum\limits_{t=1}^{h} E_r \alpha_{rt} + \sum\limits_{r=1}^{c} E_r^{\alpha}\right)$		✔				✔
[50]	To reduce a building's peak electrical demand through customer-side load control.	$F(x) = \min\left(\sum\limits_{\mathrm{h}} E_{DG}^h.C^h\right) \forall h \in H$ $E_{DG}^h = \left(P_{NINSLs}^h + P_{INSLs}^h + P_{SLs}^h + P_B^h - P_R^h\right) \cdot \left(\frac{D_S}{60}\right)$		✔				
[51]	To propose reduction values for home energy management.	$F(x) = \min\left\{\begin{array}{c}\sum\limits_{Load=1}^{nLoad} \lambda_{Load} \times P_{Load} + \lambda_{Grid} \times P_{Grid} + \lambda_{Down} \times \mathrm{Reg}_{Down} - \\ \sum\limits_{DG=1}^{nDG} \lambda_{DG} \times P_{DG} + \lambda_{Up} \times \mathrm{Reg}_{Up}\end{array}\right\}$		✔		✔	✔	
[52]	To minimize the electricity cost and lower the delay of equipment running.	$F\ (x) = W_1 \frac{(\sum_{u=1}^{120} pr\, Cu\, P_{scd}{}^{(u)}) P_{scd}{}^{(u)}}{((\sum_{u=1}^{120} pr\, Cu\, P_{scd}{}^{(u)}) P_{scd}{}^{(u)})\max} + W_2 \frac{\sum_{a \in A} \rho^{DT\,R_a}}{(\sum_{a \in A} \rho^{DT\,R_a})\max}$		✔				
[53]	To minimize the cost of use on the generation side.	$F\ (x) = (E_{\max n} e_n\ -\ 1/2\alpha \frac{E_{res\,n}}{E_{\max n}} e_n{}^2 - \beta \frac{p_m}{p_{\min}} S_w e_n$			✔			✔
[54]	To minimize the cost, including overall energy costs, scheduling costs, and climate comfort.	$F\ (x) = \alpha_{EC} \overline{C}_{EC} + \alpha_{PR} \overline{C}_{PR} + \alpha_{CC} \overline{C}_{CC}$						✔
[55]	To minimize the cost of use on the consumer side.	$F\ (x) = \sum_{i,j} F_{i,j} x_{i,j} + \sum_{i,j} G_{i,j} d_{i,j}$		✔				
[56]	To minimize the generation costs, including all possible types of DGs.	$F = \sum\limits_{t=1}^{T} \left\{ \sum\limits_{i=1}^{N_g} \left[u_i(t) P_{gi}(t) \left(B_{gi}(t) + K_{OMi}\right) + S_{gi} \lvert u_i(t-1) \rvert\right] + \sum\limits_{j=1}^{N_{ES}} \left[u_i(t) P_{Sj}\ (t) B_{Sj}\ (t)\right] + P_{Grid}\ (t) B_{Grid}\ (t) \right\} + \sum\limits_{t=1}^{T} \left\{ \left(\sum\limits_{i=1}^{T_E} \sum\limits_{j=1}^{N} EF_{ij} P_{gi}\ (t) \right) + P_{Grid}\ (t) EF_{grid} \right\}$		✔				
[57]	To reduce the charge and discharge costs.	$F = \sum\limits_{t=1}^{m} \left(C_t^g + C\iota_t^g + C_t^{ES-} - C_t^l - C_t^{ES+} + \Omega_t\right) \times \Delta t$		✔				

Table 3. *Cont.*

Refs.	Objective	Objective Function	Concepts Employed					
			LS	PC	VF	LS	LG	LR
[58]	To reduce NPC, taking into account all types of sources.	$F = NPC + \sum_{t=1}^{8760} P_b(t) + \sum_{t=1}^{8760} P_{H_2}(t) + \sum_{t=1}^{8760} P_w(t) + P_{wt} + P_{H_2T}$	✔					
[59]	To reduce operation costs, emissions, and the reliability of SG.	$F = CF_t^{OPR} + CF_t^{EMI} + CF_t^{RLB}$ $F = C_{in}^{MG} + C_{op}^{MG}$	✔					
[60]	To reduce the investment and operating costs.	$C_{op}^{MG} = \sum_{i=1}^{L} (C_{Fi} + C_{OMi} + C_{Si} + C_{Ei}) + \sum_{j=1}^{M} C_{OMj}^{ESS} - C_G^{MG}$				✔		
[61]	To minimize the operating and emission costs, including startup and shutdown costs, reverse costs, and exchange of power costs.	$F = \mathrm{Cost}^{Operating} + \mathrm{Cost}^{Emission}$ $\mathrm{Cost}^{Operating} = \sum_{t=1}^{T} (\cos t_{DG}(t) + ST_{DG}(t) + \cos t_s(t) + \cos t_{Grid}(t) + \cos t_{DR}(t))$ $\mathrm{Cost}^{Emission} = \sum_{t=1}^{T} \{emission_{DG}(t) + emission_S(t) + emission_{Grid}(t)\}$ $F = F_{\mathrm{Cost}}^{start-up} + F_{\mathrm{Cost}}^{reserve} + F_{\mathrm{Cost}}^{generation} + F_{\mathrm{Cost}}^{DR} + F_{Emission}$		✔				
[62]	To minimize the overall costs of generation.	$F = \sum_{t=1}^{ND} \left\{ \sum_{a=1}^{A} [(AT_{at}.ut_{at} + (MTC_a + BT_{at}).pt_{at}).H/ND \right.$ $+DT_a.yt_{at} + FT_a.zt_{at}] + \sum_{b=1}^{B} [((MFC_b + CF_b).pf_{bt} + \zeta_b.dpf_{bt})$ $\left. ..H/ND + EF_b.yf_{bf} + GF_b.zf_{bt}\right] + \sum_{c=1}^{C} [(CC_c.pdc_{ct})..H/ND]$ $+[BP_t.pgb_t - SP_t.pgs_t + CD.pde_t + CE.pex_t]..H/ND\}$		✔				
[63]	To reduce the operating costs.	$F = \sum_{s \in S} \lambda_s \left[\sum_{k \in K} \sum_{j \in J} (C_j(P_{j,k,s}) + SU_{j,k}) + \sum_{k \in K} C_{ES}.\left(V_{k,s}^{CH} + V_{k,s}^{DCH}\right) \right.$ $\left. + \sum_{k \in K} P_{k,s}^{Int,R-C-I}.C_k^{Int,R-C-I} + \sum_{k \in K} \Delta P_{k,s}^{do,R-C-I}.C_k^{DR,R-C-I} \right]$	✔					
[64]	To minimize short-term variable generation costs.	$Minimize \quad f = C_{HV}(P_{HV}, Q_{HV})$		✔				
[65]	To maximize economic benefit by integrating small CPPs, ESSs, RES, and interruptible demand loads.	$\max \sum_{t=1}^{T} \sum_{i=1}^{I} \rho_{s,t} P_{dl,i,t} - C_{dg,i,t}(P_{dg,i,t}) - C_{es,i,t}(P_{es,i,t}) - \rho_{b,t} P_{b,t}$		✔				
[66]	To provide a self-scheduling program for an SG.	$Maximize \sum_{t=1}^{T} (\sum_{w=1}^{n_w} \pi(w). \sum_{s=1}^{N_s} \pi(s). \sum_{p=1}^{N_p} \pi(p).(\lambda^p(t).G^{wsp}(t)$ $-C_{conv}^{wsp}(t) - y_{conv}^{wsp}(t).S_{conv}))$	✔					
[67]	To maximize the SG's short-term profit.	$Max \sum_{t=1}^{T} \sum_{w=1}^{nw} \pi_w \sum_{p=1}^{np} \pi_p \sum_{r^{down}=1}^{n_r^{down}} \pi_r^{down} \sum_{r^{up}=1}^{n_r^{up}} \pi_r^{up} [\lambda_p(t)(G_{wp}(t) + bm_{wp}^{down}(t).\psi_r^{down}(t)$ $-bm_{wp}^{up}(t).\psi_r^{up}(t)) - C_{wp}^c(t) - SUC^c.v_{wp}^c(t)]$	✔					
[68]	To minimize the cost, as well as the carbon emission percentage.	$\mathrm{Profit} =$ $\max \sum_{s=1}^{N_s} \pi_s \times \sum_{t=1}^{24} \left\{ \begin{array}{c} -\sum_{p=1}^{N_p} \left\{ C_{t,p}^{chp} + C_{t,p}^{ho} \right\} \\ \left\{ \rho_{s,t}^{em} \times P_{s,t}^{grid} + \sum_{p=1}^{N_p} \left\{ \rho_t^{ret\_e} \times P_{s,t,p}^{sel} + \rho_t^h \times H_{t,p}^{tl} - C_{s,t,p}^{ens} \right\} \right\} \end{array} \right\}$ $Emission = \min \sum_{s=1}^{N_s} \pi_s \times \sum_{t=1}^{24} \left\{ \begin{array}{c} \sum_{p=1}^{N_p} \left\{ E_{t,p}^{chp} + E_{t,p}^{ho} \right\} \\ E_{s,t}^{grid} \end{array} \right\}$		✔		✔		

Table 3. *Cont.*

Refs.	Objective	Objective Function	Concepts Employed					
			LS	PC	VF	LS	LG	LR
[69]	To minimize of average generation cost of DG units.	$MinS_{VPP} = \frac{\sum_{i=1}^{n} P_{DG\_C,i} * v_{DG\_C,i}(P_{DG\_C,i})}{\sum_{i=1}^{n} P_{DG\_C,i}}$ $MinC_{VPP} = \sum_{i=1}^{n} P_{DG\_C,i} * v_{DG\_C,i}(P_{DG\_C,i})$		✔				
[70]	To maximize the worst-condition expected profit of SG.	$\max_{\psi M} \sum_{\omega \in \Omega} \pi_{\omega} \left[\sum_{t \in \tau} [\lambda_{t\omega}^{E} p_t^E \Delta t + \hat{\lambda}_{t\omega}^{R} + p_t^R + \hat{\lambda}_{t\omega}^{R} - p_t^R - \right.$ $-(C^{C,F} u_t^C + SUC^C v_t^{C,SU} + SDC^C v_t^{C,SD})] + v$		✔				✔
[71]	To maximize the SG profit.	$Max\ Z_{\mathrm{Profit}} = -\sum_{i \in DG} (P_{it}^{DG}.\lambda_i^{DG,\cos t} + y_{it}^{DG,start}.\lambda_i^{DG,start\cos t} + z_{it}^{DG,shut}.\lambda_i^{DG,shut\cos t}$ $\sum_{t=1}^{T} (P_t^D.\lambda_t^{DSO,charge} + \sum_{k \in GSP} P_{kt}^{Upstream}.\lambda_{kt}^{LMP}$ $-\sum_{j \in SG} P_{jt}^{SG}.\lambda_j^{SG,\cos t} - P_t^{FL}.\lambda_t^{FL,\cos t})$		✔		✔		
[72]	To integrate EV, ESS, and wind generation for participation in the day-ahead and reserve electricity market.	$\max Y = \sum_{t=1}^{T} \left(\lambda_t^{DA} e_t^{DA} + P_{res} \lambda_t^{\mathrm{Res}} e_t^{\mathrm{Res}} + call_t \lambda_t^{\mathrm{Res}} e_t^{\mathrm{Res}} - \sum_{n=1}^{N} \cos t_{t,n}^{\deg} \right) + \sum_{n=1}^{N} (\lambda^S E_n^{dem})$	✔					
[73]	To minimize the SG cost and emissions using day-ahead scheduling.	$Minimize\ C^{DN} = \Delta T.\sum_{t=1}^{T} \begin{pmatrix} k_t^P.P_t^{DN}.Q_t^{DN} + \sum_{i=1}^{NB} \left[c_i^{RES}.P_{i,t}^{RES} + F_i^{DG}\left(P_{i,t}^{DG}\right) \right] \\ -\sum_{k=1}^{N_{VPP}} \left(\pi_{k,t}^{P}.P_{k,t}^{VPP} + \pi_{k,t}^{Q}.Q_{k,t}^{VPP} \right) \end{pmatrix}$ $Maximize\ B_i^{VPP,k} = \Delta T.\sum_{t=1}^{T} \begin{pmatrix} U_k^{DR}\left(P_{k,t}^{DR}\right) - F_k^{DG}\left(P_{k,t}^{DG}\right) \\ -c_k^{RES}.P_{k,t}^{RES} - \left(\pi_{k,t}^{P}.P_{k,t}^{VPP} + \pi_{k,t}^{Q}.Q_{k,t}^{VPP} \right) \end{pmatrix}$		✔		✔		
[74]	To minimize the total operating cost of SG.	$Minimize \quad f = \sum_{t=1}^{T} Cost = \sum_{t=1}^{T} \begin{pmatrix} P_{Grid}(t) \times C_{Grid}(t) \\ +U_{WT}(t) \times P_{WT}(t) \times C_{WT}(t) \\ +U_{PV}(t) \times P_{PV}(t) \times C_{PV}(t) \\ +U_{FC}(t) \times P_{FC}(t) \times C_{FC}(t) \\ +U_{MT}(t) \times P_{MT}(t) \times C_{MT}(t) \\ \sum_{j=1}^{N_s} U_j(t) \times P_{Sj}(t) \times C_{Sj}(t) \\ +\sum_{i=1}^{N_g} S_{Gi} \lvert U_i(t) - U_i(t-1) \rvert \\ +\sum_{i=1}^{N_s} S_{Sj} \lvert U_j(t) - U_j(t-1) \rvert \\ -\Delta P(t) \times C_{\Delta P}(t) \end{pmatrix}$	✔					
[75]	To maximize the profit.	$Profit_{increase} = \left[\sum_{j=1}^{n} profit_j (1+i)^{-j} \right] - C_{cap}$ $= \left[\sum_{j=1}^{n} (price_{VPP} \times power_{VPP} - Income_{baseline}) \times (1+i)^{-j} \right] - C_{cap}$		✔		✔		
[76]	To minimize the generation costs.	$F = \sum_{t=1}^{T} \left(\sum_{i=1}^{N^{cpp}} F_{i,t}^{cpp}\left(P_{Gi,t}^{cpp}\right) + \sum_{j=1}^{N^{vpp}} F_{j,t}^{vpp}\left(P_{Gj,t}^{vpp}\right) \right)$		✔				
[77]	To minimize congestion based on the day-ahead scheduling of DERs.	$\min \sum_{s=1}^{N_s} p_s (\sum_{t_h=1\tau_{da}}^{H_{da}} (\sum_{i=1}^{N_{chp}} C_{f,chp,i,s}(t_h)$ $+ \sum_{i=1}^{N_{e,sto}} C_{op,e,sto,i,s}(t_h) - P_{m,da}(t_h) c_{m,da}(t_h) \tau_{da}))$ $\min \sum_{t_h=1\tau_{id}}^{H_{id}} (\sum_{i=1}^{N_{chp}} C_{f,chp,i}(t_h) + \sum_{i=1}^{N_{e,sto}} C_{op,e,sto,i}(t_h) + C_{pen,imb}(t_h))$		✔	✔			

Table 3. *Cont.*

Refs.	Objective	Objective Function	Concepts Employed					
			LS	PC	VF	LS	LG	LR
[78]	To schedule optimally using EMS, taking into account all possible types of DGs aimed toward profit and the minimization of carbon emissions.	$Maximize \quad Income = \sum_{t=1}^{T}\left[\left(\begin{array}{c}\sum_{L=1}^{N_L} P_{Load(L,t)}.MP_{Load(L,t)} + \sum_{M=1}^{N_M} P_{Sell(M,t)}.MP_{Sell(M,t)} + \\ \sum_{E=1}^{N_E} P_{Discharge(E,t)}.MP_{Discharge(E,t)} + \sum_{V=1}^{N_V} P_{Discharge(V,t)}.MP_{Discharge(V,t)}\end{array}\right).\Delta t\right]$ $Minimize \quad OperatingCost = \sum_{t=1}^{T}\left[\left(\begin{array}{c}\sum_{I=1}^{N_{DG}} P_{DG(I,t)}.c_{DG(I,t)} + \sum_{S=1}^{N_S} P_{Supplier(S,t)}.c_{Supplier(S,t)} + \\ \sum_{L=1}^{N_L} P_{LoadDR(L,t)}.c_{LoadDR(L,t)} + \sum_{I=1}^{N_{DG}} P_{Discharge(E,t)}.c_{Discharge(E,t)} \\ \sum_{V=1}^{N_V} P_{Discharge(V,t)}.c_{Discharge(V,t)} + \sum_{L=1}^{N_L} P_{NSD(L,t)}.c_{NSD(L,t)} \\ \sum_{I=1}^{N_{DG}} P_{GCP(I,t)}.c_{GCP(I,t)}\end{array}\right).\Delta t\right]$ $Minimize \quad E = \sum_{t=1}^{T}\left[\left(\begin{array}{c}\sum_{I=1}^{\Omega_{DG}^{d}} P_{DG(I,t)} \times E_{DG(I,t)} + \\ \sum_{S=1}^{\Omega_{SP}^{e}} P_{Supplier(S,t)} \times E_{Supplier(S,t)}\end{array}\right).\Delta t\right]$		✔		✔		
[79]	To minimize the operating cost of SG over 24 h.	$Minimize \;\; F = \left[\sum_{t=1}^{24}\left[\left(\begin{array}{c}P_{WT}(t).K_{WT}(t) + P_{PV}(t).K_{PV}(t) \\ +P_{FC}(t).K_{FC}(t) - P_{Ch}(t).K_{Ch}(t) \\ +P_{Dch}(t).K_{Dch}(t) - P_{Sp}(t).K_{Sp}(t) \\ +P_{Ns}(t).K_{Ns}(t)\end{array}\right)\Delta t\right]\right]$			✔		✔	

Table 4. The optimization papers surveyed across DGs DSM optimization problems.

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[80]	ANN	• RTP	• Minimization of the total cost to consumers	• Battery SoC • Battery charge/discharge power	• RTP pricing values • PEV charging/discharging rate
[81]		• Peak shaving (PS)	• Minimization of transformer loading	• Transformer limits • Line current carrying capacity	• Transformer parameters • Number of EVs • EV charging power
[82]		• PS • IBR	• Minimization of energy cost • Minimization of network losses • Minimization of voltage magnitude deviation	• EV battery SoC • EV charging power • DG power balance limits	• Participating active loads • Power injected into the grid
[83]		• PS	• Maximization of revenue	• Load charge/discharge limits • EV SoC • Maximum charge/discharge power • Charging time constraints	• Charging tariff • Day-ahead forecasted prices • EV drive cycle
[84]		• ToU	• Minimization of the total cost • Maximization of revenue	• RES generation limits • DG unit operating costs	• Available tradeable power • RES generation-dependent parameters

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[85]	DP	• Load shifting (LS)	• Minimization of energy costs without sacrificing user preferences and satisfaction	• EV charge/discharge power • EV battery SoC	• RES generation parameters • Utility tariff rates
[86]	Fuzzy Logic (FL)	• LS • PS	• Minimization of total operation cost	• Power balance constraints • Spinning reserve constraints • Generator limits • Wind power penetration rate	• Fuel cost • Startup cost
[87]		• ToU • CPP • Valley filling (VF)	• Minimization of peak load demand	• EV SoC • Bus voltage limits	• EV charge/discharge time • Market pricing signals
[88]		• ToU • VF • LS	• Maximization of profit of consumers through maximum EV integration	• EV SoC • Charging preference limits consumers	• Electricity tariff • EV availability
[89]		• LS	• Minimization of generation costs, emissions, and energy losses	• Active power output limits • Generator limits • Total flexible load limits	• Flexible load operation time
[90]		• VF	• Minimization of high ramp rates in G2V mode	• EV SoC • Ramp rate limits • Wind power output limits	• EV charging current
[91]	Game Theory	• LS	• Minimization of cost for residential users	• The discharge rate of PEV	• Hourly electricity tariff • PEV energy consumption
[92]		• PS	• Minimization of energy cost	• Transmission limits • EV charge/discharge limits	• Total load demand • Cost function • Welfare function
[93]		• LS • PS	• Minimization of peak demand using distributed EV integration	• Charging outlet limits • Energy trading limits	• EV charging time • Number of participating EVs under the same aggregator

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[94]	Game Theory	• PS • ToU	• Minimization of electricity costs • Minimization of deviation between predicted and actual load demand	• EV storage limits • ESS storage limits • EV SoC limits	• EV availability • Load demand
[95]		• ToU • PS	• Minimization of the peak-to-average ratio (PAR) of the total energy demand	• Energy balance limits • PEV discharge limits • Charging/ discharging time limits	• Cost function • Load demand
[96]		• ToU	• Maximization of profits in the market environment	• EV charging limits	• Number of participating EVs • Bidding tariff
[97]		• PS • ToU • VF	• Minimization of charging the cost of EV	• Grid power limits • EV SoC limits	• Satisfaction income of EVs • Battery loss of EV • Charging cost
[98]		• PS • VF	• Minimization of energy cost • Minimization of battery degradation	• Client usage parameters	• Cost function • Residential load demand • PHEV driving behavior
[99]		• ToU • RTP	• Minimization of electricity tariff for the customers	• Hourly power demand limits • Total energy consumption limits	• Availability of EVs in the parking lot • SoC of EVs • Battery power rate • Load demand
[100]		• RTP • ToU	• Maximization of system stability • Maximization of profits	• Average power generation limits • Daily energy usage limits	• EV availability • Load demand
[101]		• RTP	• Maximization of profits of utility companies	• Charging rate limits	• Price function of utility
[102]		• RTP	• Maximization of retailer profits • Minimization of generation cost	• Charging rate limits	• Charging period of EVs • Battery charging efficiency
[103]	LP	• PS • VF	• Minimization of energy expenses of individual customer	• Charging rate limits • Battery SoC for driving cycle	• Appliance operating time • Appliance power demand

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[104]	LP	• LS • RTP • ToU	• Minimization of peak load in the distribution network • Minimization of consumer tariff	• Power limit of EV	• Availability of appliances • Power generation
[105]		• PS • VF • ToU	• Minimization of difference between peak and off-peak tariff • Minimization of EV charging cost	• Base tariff limits • Price deviation limits • EV SoC limits • EV charging power limits • Feeder baseload limits	• Electricity tariff • Operation time slot
[106]		• VF	• Maximization of EVs availability in charging • Minimization of monetary expenses	• Charging load limits • EV SoC limits	• Charging decision value/vector
[107]		• PS • ToU	• Minimization of home electricity expenses	• EV availability period	• EV demand • Electricity tariff
[108]		• RTP • ToU	• Minimization of the operation cost of EVCS and energy management system (EMS)	• Power supply constraints • ESS constraints • Heating system constraints • EV power balance limits	• Load demand • EV and ESS reserve tariff • Heating compensation prices
[109]		• PS	• Minimization of variation of the load curve	• EV SoC	• EV charging load
[110]		• PS • LS	• Maximization of revenues	• EV charging level limits • Grid power limits	• Hourly tariff • DG power generation capacity • Hourly critical load demand
[111]		• RTP • ToU	• Minimization of PAR and system costs	• PV power trade limit • EV SoC limits	• PV generation capacity • EV charging load • EV availability
[112]		• RTP	• Minimization of costs, peak charging load • Maximization of PV integration	• EV charging demand limit	• EV availability • EV charging load

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[113]	LP	• RTP	• Minimization of cost of the system	• EV charging limits • EV SoC limits	• Grid power consumption • Appliance schedule • Hourly tariff
[114]		• PS	• Minimization of operational costs and emissions	• Thermal unit limits • Power flow and grid constraints • PEV constraints • Power balance limits	• EV SoC • Thermal generation requirement
[115]		• ToU	• Minimization of the total cost for the consumer	• Power balance limits • EV SoC limits • Power transaction limits	• EV charging/discharging time • The usable capacity of EV ESS
[116]		• ToU	• Minimization of the total cost for the consumer	• EV charging limits • EV operation time limits • EV battery capacity limits	• Real-time tariff
[117]		• RTP	• Minimization of the total energy cost of a smart home	• Power balance limits • Power trading limits • EV SoC limits • PV generation limits	• PV generated power • EV availability
[118]		• PS • LS	• Minimization of individual consumer costs at lower participation levels	• EV SoC limits • ESS storage limits • DER generation limits	• Price indicators • Customer fairness index
[119]		• ToU	• Maximization of EVCS operating profits	• EV SoC limits • ESS charge/discharge power limits • Efficiency limits	• Short-term forecasted loads • Load reduction signal
[120]		• ToU • PS	• Minimization of energy cost	• EV charging limits	• Cost function • Total charging demand
[121]		• RTP • LS	• Minimization of generation costs for the customer and utility	• Shiftable load power limits • EV SoC limits	• EV availability
[122]		• PS	• Minimization of PAR of the system	• Grid power injection limits • EV SoC limits	• EV charging efficiency

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[123]	LP	• ToU	• Minimization of overall system cost	• ESS power limits • EV charge/discharge power limits	• Cost function
[124]	PSO	• ToU	• Maximization of revenues • Minimization of load fluctuation	• EV aggregator power limits • Grid power limits • EV charge/discharge power limits	• Charging tariffs from the grid • Service revenues of EV aggregator
[125]		• LS • PS	• Minimization of operating costs for the network operator	• Grid power balance limits • Bus voltage limits • Line thermal limits • EV charge/discharge limits	• EV SoC • Network power injection • DG power injection
[126]		• PS	• Minimization of fuel and startup costs	• Power balance constraints • Generation limits • Up/downtime constraints • Spinning reserve limits • EV charge/discharge power limits	• Fuel economics cost • Startup/shutdown time
[127]		• RTP	• Minimization of the load curve • Maximization of customer profit	• Power capacity and balance constraints • EV charge/discharge limits • EV charging time limits	• EV availability • The power exchanged from the grid
[128]	Evolutionary PSO	• ToU	• Minimization of system cost	• Active and reactive power generation limits • Grid voltage limits	• Power flow from the grid • EV availability
[129]	ACO	• PS	• Minimization of overall system cost	• DG generation limits • Grid power balance limits	• Cost function
[130]	GA	• PS	• Minimization of cost variance • Maximization of user satisfaction	• EV SoC limits • EV charge/discharge power limits	• EV availability • Load demand from the grid
[131]		• VF • PS	• Minimization of PAR	• EV SoC limits	• EV availability

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[132]	GA	• PS	• Minimization of PAR	• EV SoC limits	• Power demand • EV availability
[133]	GA	• ToU	• Maximization of profit • Minimization of PAR • Minimization of variance	• EV SoC limits • EV charge/discharge power limits	• EV availability • EV charging power
[134]	Improved partheno-genetic algorithm (IPGA)	• LS	• Minimization of annual construction maintenance cost	• Grid power limits • System reliability constraints • DG and ESS penetration limits • EVCS charging power limits	• EV availability at EVCS • DG power generation capacity
[135]	Hyper-heuristic optimization	• LS	• Minimization of total cost and emission	• EV SoC limits • Electricity tariff limits	• Emissions from CPP • DG is active in the grid
[136]	DE	• PS	• Maximization of energy consumption using EV-ESS • Minimization of PAR	• EV SoC limits	• EV availability
[137]	Virus colony search (VCS) optimization	• PS	• Minimization of smart parking costs	• Upstream grid power limits • EV SoC limits • Power equilibrium limits	• Cost function
[138]	Hybrid GA and PSO	• LS • ToU	• Minimization of total tariff for customers in 24 h	• Energy balance limits	• EV availability
[139]	Model predictive control (MPC)	• PS • RTP	• Minimization of total operational cost for energy management	• Heat pump capacity limits • Heat pump thermal capacity limits • SoC of EV limit	• Heat pump generated power • EV availability • Fuel price • Natural gas price
[140]	Model predictive control (MPC)	• RTP	• Minimization of ramping requirements from power plant	• Power balance constraints • Service quality constraints of EVs	• EV charging load request vector
[141]	Model predictive control (MPC)	• RTP	• Minimization of cost of energy consumption considering EV owner preferences	• EV SoC limits	• EV SoC level • Price signal • Volume signal

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[142]	Model predictive control (MPC)	• PS	• Minimization of electricity bills and peak load	• EV SoC limits • EV charge/discharge power limits • Grid power balance limits	• Energy tariff • Capacity tariff
[143]	Nonlinear programming (NLP)	• RTP	• Maximization of total profit considering social welfare	• EVCS EV loading limits • EV SoC limits • EV BESS temperature limits	• EVCS operation time
[144]	Robust programming	• PS • LS	• Maximization of EV-V2G power integration	• Grid power balance limits • EV power trajectory limits	• EV availability
[145]	Robust mixed-integer linear programming (RMILP)	• LS	• Minimization of total operational costs and emissions	• CAES operational limits • BESS charge/discharge limits • EV SoC limits • RES generation limits	• EV availability • Grid power injection
[146]	Robust mixed-integer quadratic programming (RMIQP)	• PS • LS	• Minimization of PAR and energy cost for the users	• RES generation limits • Appliance loading limits • EV SoC limits • Power demand-supply balance limits	• Appliance operation time • Grid power exchange tariff
[147]	Stochastic programming	• RTP • PS	• Minimization of operational cost	• DG power limits • Fuel cell power limits • EV SoC limits • Grid power balance limits	• Cost of power at DG units
[148]		• ToU	• Maximization of expected profits of EV aggregator	• Bidding amount capacity limits • EV charger capacity limits	• EV charge/discharge power • Grid electricity tariff
[149]		• ToU • CPP • RTP • Incentive-based pricing	• Maximization of a parking lot profit	• EV SoC limits • Parking lot stored energy limits	• EV arrival and departure SoC

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[150]	Stochastic programming	• ToU • DLC	• Minimization of maximum transformer loading during the charging operation	• EV SoC limits • EV charge/discharge limits • Grid power balance limits	• Load demand curve • EV availability • Transformer loading capacity
[151]		• ToU • Incentive-based pricing	• Maximization of a parking lot profit	• EV SOC limits • EV battery efficiency	• EV battery capacity • Cost of degradation • Availability of EVs • EV charge/discharge tariff
[152]		• ToU	• Maximization of EV aggregation profit	• EV SoC limits	• Market electricity tariff • Spinning reserve capacity • EV availability
[153]		• ToU	• Maximization of expected profit • Minimization of risks and costs associated with DR	• Available DR limits • EV charging/discharging power limits • EV SoC limits	• Intraday price • RES generation capacity
[154]	Conditional value at risk (CVaR) function optimization	• RTP	• Minimization of EV charge/discharge cost	• EV charge/discharge rate limits • EV SoC limits • EV charging time limits	• EV charge/discharge power
[155]	CVaR-based stochastic programming	• LS	• Minimization of operation cost, emissions, and renewable power curtailment	• Active and reactive power limits • Power flow and balance limits • EV SoC limits	• Shiftable appliance schedule • EV availability
[156]	Multi-period security constraint optimal power flow (MPSOPF)	• ToU	• Minimization of generation costs, contingency costs, load-following costs, and load shedding costs	• EV SoC limits • Distributed energy resource (DER) generation limits • Load shedding and load following reserve limits	• Electricity ToU tariff • Electricity load curve
[157]	Techno-economic optimization	• ToU • CPP • RTP	• Maximization of income of distribution operator • Minimization of operational costs	• RES generation limits • Bus and line voltage limits • Available DR limits • EV SoC, efficiency, and power exchange limits	• EV energy trading tariff • Bidirectional power flow tariff • Battery depreciation cost

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[158]	Stochastic dynamic programming (SDP)	• ToU	• Minimization of customer's energy charges considering residential power demand and EV charging	• EV SoC limits • EV charger power limits • Grid power injection limits	• Time index • Residential load demand
[159]	Deep learning (DL)	• ToU • PS	• Minimization of overall vehicle energy cost	• EV SoC limits • EV charger efficiency limits	• Cost function • Real-time electricity tariff • EV availability
[160]		• ToU	• Minimization of energy costs in the real-time market	• Voltage and current limits • EV SoC limits	• Real-time electricity tariff • EV load demand
[161]	Robust adversarial reinforcement learning (RARL)	• ToU	• Minimization of customer's electricity bill considering privacy concerns	• RES generation limits • EV SoC limits	• Dynamic electricity tariff • Appliance schedule
[162]	Reinforcement learning (RL)	• PS	• Minimization of monetary and non-monetary costs in DSM	• EV battery SoC limits	• Energy prices • Load demand curve • Total cost function
[163]		• ToU	• Minimization of the load demand curve of the system	• EV SoC limits • EV charge/discharge power limits	• Charging reward function
[164]		• ToU	• Minimization of charging cost over the day-ahead time frame	• EV BESS charge/discharge time limits • EV charge/discharge rate limits	• EV availability • Real-time electricity tariff
[165]	Hierarchical reinforcement learning (HRL)	• PS	• Minimization of hydrogen consumption	• EV SoC limits • Fuel cell operation limits	• Fuel consumption • Fuel cell operation status
[166]	RL-based pursuit algorithm (PA)	• RTP • ToU	• Minimization of total energy cost	• EV SoC limits • EV charge/discharge time limits	• Reward function
[167]	Correlation optimization algorithm (COA)	• ToU	• Minimization of electricity cost of the consumers considering PV generation and ToU pricing	• PV generation limits • EV operation time limit	• Grid supply of power • Electricity price

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[168]	Market-based multi-agent system optimization	• PS	• Minimization of total operation costs	• Aggregated energy constraints • Power limit of EV fleet • EV battery capacity limits	• Cost function • Demand function
[169]	Alternating direction method of multipliers (ADMM)-based decentralized optimization algorithm	• PS	• Minimization of the load curve	• EV SoC limits • EV charging efficiency limits • EV charge rate limits • Network constraints	• EV charging load
[170]		• VF • LS • PS	• Minimization of total generation cost	• EV charging/discharging efficiency limits • EV ESS capacity limits • EV SoC limits	• Load demand curve • EV availability
[171]	Multi-EV reference and single-EV real-time response (MRS2R) online algorithm	• PS • VF	• Minimization of payment by EV customers	• EV SoC limits • EV BESS capacity limits	• EV availability
[172]	Interior point optimization	• VF	• Minimization of peak valley difference and improvement of stability	• EVCS charging/discharging time limits • Grid power limits	• Active power load • Grid bus voltage magnitude
[173]	Constrained nonlinear optimization problem with Karush–Kuhn–Tucker (KKT) conditions	• PS	• Minimization of charging the cost for EV owners	• Charging power limits • Grid power limits	• Cost function
[174]	Decision-table-based control optimization	• PS	• Maximization of economic benefits • Minimization of grid power consumption	• EV BESS SoC limits • Balancing current limits	• PV generation during daytime • SoH of BESS
[175]	Monte Carlo simulation using mixed-integer linear programming (MILP)	• ToU	• Minimization of building energy consumption	• EV charging time limitations • EV SoC limits • Energy balance limits	• Load demand curve

Table 4. *Cont.*

Refs.	Optimization Algorithm	DR Programs Used	Objective Function	Constraints	Decision Variables
[176]	Convex optimization	• VF	• Minimization of EV charging costs	• ESS charging rate constraints • ESS SoC limits	• ESS availability
[177]		• RTP • VF	• Minimization of electricity costs	• Consumer comfort limits • EV charging time constraints	• ESS availability
[178]		• PS	• Minimization of total electric energy costs	• Power balance limits • SoC limits • Home ESS SoC limits	• Number of available EVs
[179]		• RTP	• Minimization of electricity cost for the consumer	• Charge/discharge power limits • Load threshold • SoC limits	• Number of available EVs • Real-time energy tariff
[180]	Quadratic programming	• PS	• Maximization of vehicle's fuel economy	• Power flow limits • SoC limits	• Cost function
[181]	Non-intrusive load extracting (NILE) algorithm	• LS • PS	• Minimization of the daily cluster charging costs of EVs	• Power balance limits • Ramping rate limits • User comfort constraints	• EV charging power • Availability of EVs
[182]	Monte Carlo-based risk-averse charge scheduling optimization	• ToU • RTP	• Maximization of profits	• SoC limits • Charging period limits	• Electricity tariff • EV drive cycle

9. Discussion and Findings

During the systematic review of the papers as a part of the literature survey, several research gaps were identified in the present research scenario, as well as implementations in various projects across the research domain. Some of the key findings identified during the survey include:

- Most of the research papers addressed DSM formulation in the EV scenario by incorporating bidirectional power flow, but the uncertainty in demand and supply forecasting leads to inefficient control over power flow.
- The limited participation of DGs, mainly on the distribution level, restrains the individual customers, and they cannot directly participate in ancillary services and energy markets [183,184]. Clustered DGs must be able to collectively participate in the formation and maintenance of such groups in the proper sizing and architecture, which should be scalable in future implementations.
- The clustering of uncoordinated DGs, which generally operate in a decentralized setup among different utility operators, seems challenging. It is necessary to implement a proper service-oriented architecture to group together the operation and participa-

tion of different DG aggregating companies to make DG-DSM integration into the commercial markets more profitable and easier to implement on a technical front.

- The drive cycle of the EV owners, on an individual basis, has not been taken into consideration on an end-user level. The optimization of charging and discharging can be improved, to a great extent, with the personalized scheduling of EV and ESS charge/discharge operations based on the user's comfort and usage cycle.
- ICT technologies are currently implemented mainly on the transmission system operator (TSO) and DSO levels. They need to be integrated directly into the end-user location with a two-way communication channel to ensure more engaging and detailed EV and ESS charge scheduling operations. The EV and ESS can provide personalized data collected during diagnostic and data collection schedules to supply the EV aggregator with proper charge schedule data. This will allow the EV aggregator to optimally dispatch loads based on detailed SoC, SoH, BESS capacity, and drive cycle condition data.
- The customer's security and privacy are prioritized in the public domain. Consumers need to be made aware that their privacy is assured when they avail themselves of services in public locations, such as when sharing the consumer's charging location history and charging and discharging profile. The public charge scheduling setup presents the issue of DGs sending private information or erroneous data to affect grid operation and load dispatch scheduling. Even though there is research on DGs, communication strategies concerning privacy issues, their effect on DG DSM scheduling in coordination with secure communication protocols, and procedures to mitigate them have not been explored in detail.
- Meta-heuristic optimization techniques have been studied in a few research formulations, and their efficiency in forecasting the load and charge schedule of DGs in DSM operation can be exploited to a greater extent with the discovery of newer and more efficient meta-heuristic techniques. This would ensure better computation with less complexity in arriving at a proper solution.
- Consumer comfort needs to be given a higher priority in DSM operations regarding their drive cycle usage and charge/discharge patterns.
- The maximum penetration of EVs in the grid system can facilitate the better usage of RES generation, and the high capacity of EV BESS can provide ample reserves for power relaying, which are necessary in cases of intermittent generation sources. The DSM operation, in the case of DGs, ensures the maximum utilization of the BESS capacity in conjunction with RES generation.
- The centralized control architecture of DGs is necessary for setting up standards of DSM operation and charge scheduling.
- The higher penetration of DGs into the distribution grid and the DSM operation associated with them can cause problems during peak usage periods, when other factors such as voltage drops and thermal overloading of transformer equipment and cables might occur.
- Robust control and device monitoring and remote upgrade capabilities in DG DSM architecture are important, as they may facilitate further upgradation and provide better and more reliable operation and communication.
- Most DGs can be connected to the Internet through the global system for mobiles (GSM), Wi-Fi, ZigBee, and other communication networks, which aggregators can exploit and coordinate the operation thereof among constituent EVs as dispatchable loads to the distribution grid [185].
- In the DSM environment, DGs lack methodologies to maximize revenues and grid utilization. The primary reason can be attributed to the lack of policies for participating entities in wholesale electricity markets, and low priority being given to commercializing DSM due to environmental, economic, and social barriers [186,187].

10. Future Research Direction

This literature survey carefully examined the current research and the advances in the domain of EV-based DSM, and after thoughtful discussion, based on the identified research gaps, some valuable suggestions regarding future research directions and prospective areas of research are suggested:

- DG integration on a system-wide scale can be a beneficial front for the maximum utilization of intelligent loads and appliances to participate in DSM, with EVs being smart energy hubs concerning energy dispatch and storage [188,189].
- Data collection and data handling for relevant information extraction and calculation should be prioritized in the future since information gathering and processing have a significant influence on performance.
- Hybrid incentive-based and tariff-based financial models can be formulated for the optimization of load control features, such as the DSM response speed, the duration of the program, advanced alert and notification systems, geolocation sensitivity-based analysis, and real-time load monitoring rates [190–192].
- Meta-heuristic-based optimization can be hybridized, or newer, more efficient heuristic algorithms can be used for better computation in the scheduling of DSM operations. PSO, GA, wavelet transform-modified ANN, adaptive FL, support vector machine computation, and autoregressive moving average value integration with models can be implemented to obtain higher load forecast accuracy considering the regulation of loads, dispatch, scheduling, and the unit commitment problems of smart grids [193,194].
- K-map algorithms, fuzzy constrained algorithms, self-reorganizing maps, multilevel hierarchy-based clustering techniques, artificial bee colony (ABC) optimization, and an ACO can be implemented for the extraction of crucial information from aggregated load consumption profiles and in the classification of various load types in intelligent distribution systems [195].
- EV DSM models need to be more comprehensive in their operation for better practical implementation, i.e., varying charging rates, standards implemented on EVCS premises, standardized BESS swapping station methodologies, and the active participation of EVs in overall market trading and ancillary service support scenarios. More research needs to be focused on obtaining an optimized tradeoff between the performance of the system and computational complexity.
- Through data-mining and decision-making processes, diverse and hybrid optimization techniques, such as game theory and Bayesian probability theory, among others, should be explored further for internal energy dispatch, external market participation, risk evaluation, information and strategy coordination, and bidding strategy.
- The practical and easy implementation of the management of charging demand during peak/off-peak usage periods, with price-sensitive scheduling, is an excellent prospect for DSM aggregators. With large-scale EV integration into smart grids, it is a very feasible research direction to be focused upon, with an emphasis on EV charging strategies based on price response and price elasticity dynamics [196].
- Climate-based EV-DSM scheduling should be researched further, as it would affect RES generation to a large extent, and forecasting-based scheduling could help the RES to be dispatched more efficiently based on meteorological data [197].
- There is a severe lack of datasets necessary for training machine learning and deep learning models. Only five well-known EV charge scheduling datasets are available in the open research domain for researchers [198–202]. Other datasets that have been developed are available to commercial companies. More machine learning models and bio-inspired optimization techniques need to be developed to represent varying architectures and geographical locations [203].
- Big-data analysis should be emphasized to establish appropriate information to improve the perception of the energy market to bring compatibility, universality, and competitiveness.

11. Conclusions

In this review paper, existing research on DSM operations, including the various DGs and an area that has witnessed significant interest in the energy management domain in the last few years, was reviewed extensively. The general structure, operation, and optimization models of DSM and DG-DSM integration into the present smart grid scenario were discussed and represented. New concepts such as waste-to-energy were explored through a brief study, as were their implementations in test case scenarios. The optimization aspect of DG-DSM scheduling was tabulated and represented, with emphasis placed on the objective function formulation, constraints or limitations, and the selection and parameterization of decision variables. With the expectation of an increase in the adoption of various types of DG, it is estimated that DSM operations can play a valuable opportunity for the customers and utility aggregators to be active participants in the scheduling, dispatch, and market-oriented trading of energy. The research directions that this review article provides can help researchers identify potential gaps, which have been discussed previously, and they can be given due importance in finding solutions to the existing issues and challenges.

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Nomenclature

DG	Distributed Generation
DR	Demand Response
RES	Renewable Energy Sources
DERs	Distributed Energy Resources
EMS	Energy Management System
CPP	Critical Peak Pricing
V2G	Vehicle to Grid
EVCS	Electric Vehicle Charging Station
BESS	Battery Energy Storage System
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaic
PEV	Plug-In Electric Vehicle
DG	Distributed Generation
DP	Dynamic Programming
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
FL	Fuzzy Logic
PAR	Peak-to-Average Ratio
VCS	Virus Colony Search
NLP	Nonlinear Programming
RMIQP	Robust Mixed-Integer Quadratic Programming
DER	Distributed Energy Resource
SBP	Stochastic Dynamic Programming
RARL	Robust Adversarial Reinforcement Learning

HRL	Hierarchical Reinforcement Learning
ADMM	Alternating Direction Method of Multipliers
KKT	Karush–Kuhn–Tucker
PC	Peak Clipping
VF	Valley Filling
LG	Load Growth
$P_{grid}(h)$	Transfer of Power from the Grid to Load (kW)
$D_e(h)$	Electrical Energy Demand at Hour h (kWh)
$SoC_{min}(h)$	Minimum SoC at Hour h
$E^h{}_{batt}$	The Battery Energy at Hour h
$\mathrm{d_r}$	Load Duration
$P^{max}{}_{grid}(h)$	The Maximum Power Draw by Load from the Grid at Hour h
$B_{sj}(t)$	The Energy of jth Storage Device
P_{sj}	Power Emission from jth Storage
$Cr_t{}^g$	Cost of Renewable Energy Production
P_b	Penalty of Battery
P_H	Penalty of Hydrogen
P_{HT}	Penalty Hydride Tank
CFt^{RLB}	Cost of Reliability Operations
DSM	Demand-Side Management
EV	Electric Vehicle
SG	Smart Grid
EE	Energy Efficiency
SoC	State of Charge
SoH	State of Health
RTP	Real-time Pricing
DoD	Depth of Discharge
ISO	Independent System Operator
ADR	Automated Demand Response
UC	Unit Commitment
ANN	Artificial Neural Network
LP	Linear Programming
ACO	Ant Colony Optimization
DE	Differential Evolution
EMS	Energy Management System
IPGA	Improved Parthenogenetic Algorithm
MPC	Model Predictive Control
RMILP	Robust Mixed-Integer Linear Programming
CVaR	Conditional Value at Risk
MPSOPF	Multi-Period Security Constraint Optimal Power Flow
DL	Deep Learning
RL	Reinforcement Learning
PA	Pursuit Algorithm
MRS2R	Multi-EV Reference and Single-EV Real-time Response
MILP	Mixed Integer Linear Programming
TSO	Transmission System Operator
LS	Load Shifting
LS	Flexible Load Shifting
LR	Load Reduction
$P_{batt}(h)$	The Net Output Power of the Battery in (kW)
$SoC_{max}(h)$	Maximum SoC at Hour h
$SoC(h)$	SoC at Hour h
$P_{ch}(h)$	Power for Charging at Hour h (kW)
$P_{max}(h)$	Maximum Power at Hour h (kW)
$B_{gi}(t)$	Energy Bids of $\mathrm{i^{th}}$ DG
P_{gi}	Power Generations of $\mathrm{i^{th}}$ DG

$C_t{}^{g}$	Cost of Energy Production
$C_t{}^{ES-}$, $C_t{}^{ES+}$	Cost of Energy Storage Charge (+) and Discharge (−)
CFt^{OPR}	Cost of Operations
P_w	Penalty for Water Tank
2 CFt^{EMI}	Cost of Microgrid Installation

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