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Demand side management in microgrid: A critical review of key issues and recent trends

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ABSTRACT

In a deregulated power system, Demand Side Management (DSM) plays a vital role in handling the uncertain renewable power generation and load. The flat load-profile can be obtained using the Demand Response (DR) techniques with the storage elements and proper switching. The increasing penetration of Renewable Energy Sources (RES) and Electric Vehicles (EVs) supports the DR measures which facilitate both the utility and the consumer. The objective of DSM is to minimize the peak demand, electricity cost and emission rate by the effective utilization of storage with RES. This review article mainly focuses on the layers of microgrid, different techniques involved in DSM, mathematical models of DSM, latest optimization techniques and application of storage devices such as battery energy storage system and EVs in DSM. The state of the art of this article lies on the critical analysis related to datascience, advanced metering infrastructure and blockchain technologies which are the uniqueness of this article. The key issues and approaches are examined critically with the existing works to show how DSM implementation can be effectively done in the microgrids to reduce the electricity cost. This article helps the researchers to identify the research gap by gaining knowledge on the implementation of DSM in the microgrid and the factors affecting the DSM implementation. Few recommendations are discussed to provide future directions for researchers who started working in the DSM implementation.

1. Introduction

Over the decades, the electricity demand has increased more rapidly than the power generation. The demand growth could be handled by the Distributed Generation (DG) which is defined as the installation of generating units such as wind, solar, combined heat and power, diesel generator, small hydro and biomass plants at the user end. Among the DGs, the combined heat and power and diesel generator create environmental pollution which could be effectively handled by the Renewable Energy Sources (RES) based DGs [1]. The RES-based DGs have some advantages such as reduced emissions, no operation cost in terms of fuel, loss minimization, voltage profile improvement, and minimum maintenance [2]. Therefore, it may be used in both utility side and consumer premises such as residential, commercial and industrial. The installation cost and its subsequent cost/kWh is greater than the conventional DGs. Also, its usage is limited due to the drawbacks of uncertainty and intermittency which cause supply–demand imbalance. It requires more reserves to support the peak-time power scarcity. The cost associated with the system increases while increasing the additional reserve capacity in the system [3]. Storage units are the alternative solution to handle the uncertain power generation of RES and ensure the complete utilization of RES-based DG [4]. The power generated from RES on the consumer side deregulates the conventional power system structure and facilitates the system to exchange power from consumer to utility [5].

The International Council on Large Electric Systems (CIGRE) defined Microgrid as, “Microgrids are electricity distribution systems containing loads and distributed energy resources, (such as distributed generators, storage devices, or controllable loads) that can be operated in a controlled, coordinated way either while connected to the main power network or while islanded” [6]. Power mismatch between demand and generation is the major concern to be addressed in both grid-connected and islanded microgrids [7]. In a grid-connected microgrid, power exchanges between the microgrid to the utility grid and vice-versa. The power mismatch problem in grid-connected microgrids could be solved either by varying the generation or varying the demand. Another problem associated with the grid system (e.g., outage) can be decreased by increasing any one of the capacities such as generating capacity, storage capacity and reserve capacity [8]. Increasing capacity in the grid system may increase the investment cost. In islanded operation, the microgrid is not connected to the utility grid and the consumption is served from standalone DGs within the microgrid. The power mismatch problem in islanded microgrids could

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List of Abbreviations

AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
ANSI	American National Standards Institute
ASD	Adjustable Speed Drives
BEE	Bureau of Energy Efficiency
BESS	Battery Energy Storage System
BPSO	Binary PSO
CAES	Compressed air energy storage
CFL	Compact Fluorescent Lamp
CHP	Combined Heat and Power
CMP	Capacity Market Programs
CPP	Critical Peak Pricing
DADR	Data Analytical Demand Response
DB	Demand Bidding
DER	Distributed Energy Resources
DG	Distributed Generation
DISCOM	DIStribution COMpanies
DL	Deep Learning
DLC	Direct Load Control
DR	Demand Response
DSM	Demand Side Management
EDRP	Emergency DR Program
EMS	Energy Management System
ESS	Energy Storage System
EV	Electric Vehicle
GA	Genetic Algorithm
GWDO	Genetic Wind driven optimization
GWO	Grey Wolf Optimization
HEMS	Home Energy Management System
HPP	Hybrid power plant
I/Cs	Interruptible or Curtailable services
IBDR	Incentive-based DR
VPP	Virtual Power Plant
IBR	Inclined Block Rate
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
ILP	Integer Linear Programming
IP	Internet Protocol
IoT	Internet of Things
ISO	Independent System Operator
LAN	Local Area Network
MILP	Mixed Integer Linear Programming
MSEDL	Maharashtra State Electricity Distribution Company Limited
OSR	Optimum Stopping Rule
PAR	Peak to Average Ratio
PHEV	Plugged in Hybrid Electric Vehicle
PLC	Power Line Communication
PQ	Power Quality
PSO	Particle Swarm Optimization
PTR	Peak Time Rebate
PV	PhotoVoltaic
RDL	Reinforcement Deep Learning
RES	Renewable Energy Sources
RHO	Rolling Horizon Optimization
RL	Reinforcement learning
RTP	Real Time Pricing
SCADA	Supervisory Control And Data Acquisition
SCEM	Smart Compact Energy Meter
SERC	State Electricity Regulatory Commission
SGAM	Smart Grid Architecture Model
ToD	Time of Day
ToU	Time of Use
THD	Total Harmonic Distortion (THD)
V2G	Vehicle to Grid
WDO	Wind Driven Optimization
ML	Machine learning

be solved by implementing a proper control scheme to schedule the load, DGs and storage devices [9,10]. The consensus algorithm-based control has been implemented for resource allocation to reduce the supply and demand gap where the optimal scheduling has been done with the aid of distributed energy storage [11].

The load pattern should be changed for optimum operation of the system which can be obtained by Demand Side Management (DSM). DSM is the energy management technique that is used to modify the load pattern of the consumer. Energy efficiency and Demand Response (DR) are the two different categories of DSM implementation [12]. Energy efficiency includes the replacement of inefficient older equipment with efficient equipment whereas DR deals with pricing schemes that can provide the benefits on shifting the demand from peak-hour to an off-peak hour to reduce the Peak to Average Ratio (PAR). The DR program such as peak clipping, valley filling, load shifting, load growth, strategic conservation and flexible load curve can be utilized for changing the load pattern. It has many advantages such as cost reduction, improved reliability, lower number of blackouts, reduced dependency on fossil fuels and emissions. From the customer‘s point of view, DSM helps to reduce their electricity bill. On the utility side, it reduces the investment cost associated with the additional capacity. The implementation of RES-based DGs with DSM will get the maximum benefit on the utility side in terms of power balance during the peak demand period [12].

The installed capacity of RES in India is approximately 92550.74 MW which includes solar power, wind power, bio-power and small hydro-power. As per the ministry of new and renewable energy report, wind power has 38683.65 MW, solar power has 38794.07 MW, bio-power has 10314.56 MW and small hydro-power has 4758.46 MW [13]. The energy and resource institute in India has published a document which deals with the future planning of RES installation in India. The report specified that the installation should be 175 GW by 2022 out of which 100 GW from solar power, 60 GW from wind energy, 10 GW from small hydro-power, and 5 GW from biomass-based power [14]. The on-site generation of DSM implementation has become popular in India because of the installation of solar and other renewable energy resources in the consumer end for various applications [15]. Later, the DSM has been implemented for improving energy efficiency by replacing the existing load with the efficient one and encouraging the adoption of energy conservation measures.

The impact of grid integration in microgrids with Distributed Energy Resources (DER), protection schemes, Power Quality (PQ) [16] and stability of the microgrid have been critically reviewed in [17,18]. An exclusive review on central controllers [19] and protection schemes along with control techniques has been discussed in [20]. But the DSM implementation in microgrid has not been critically reviewed in the above-mentioned review articles. The policies related to DSM implementations have been discussed for various countries such as Kuwait [21], China [22] and UK [23]. DR techniques in residential buildings and their control techniques, optimization method and tariff structures have been studied in [24]. The business model of DSM for different segments of the electricity market such as operation, generation, transmission and distribution, retailing and load segments have been reviewed in [25]. The different DSM implementations, tariff structure and the impact of DSM on reliability and security have been reviewed in [26]. The critical assessment on the peak-load shifting for different kinds of consumers such as residential, industrial, campus and islanded microgrids has been done in [27] and also the importance of communication infrastructure has been insisted. DSM implementation in microgrids has been discussed in the above-mentioned review articles.

In earlier days, DSM techniques were implemented on energy conservation and energy efficiency due to lack of on-site generation, communication technologies including Advanced Metering Infrastructure (AMI), data storage & handling techniques and soft computing techniques. The AMI with secure IoT has been developed for DSM implementation in [28]. Recently, the Reinforcement Learning (RL) [29], Deep Learning (DL) [30] and Machine Learning (ML) [31] models have been suggested for enhancing either the load or source forecasting to achieve energy supply–demand balance. Blockchain technology has been suggested for secure data storage and data handling with more privacy in [32]. Thermostatically controlled devices with DSM implementation have been given more importance than electrically controlled devices due to their behavior of decreasing the energy demand. The energy trading with DSM implementation among consumers in real-time frameworks has been suggested for community-based microgrids to reduce the electricity cost. For real-time implementation, sensor network applications have been considered as the major requirement for optimizing energy usage in smart cities and intelligent buildings.

Based on the above discussion, most of the review articles contemplate either only the microgrid control techniques or types of DSM techniques. For a better understanding of DSM implementation in the microgrid, it is necessary to study the microgrid structure including components and controllers. Also, it is imperative to understand the impact of DSM implementation in the microgrid based on the performance parameters which is discussed in Section 6. The performance parameters are the PQ, reliability and stability of the microgrid. Therefore, this article consolidates all the components involved in the implementation of DSM in the microgrid. The available literature provides knowledge about economic performance, environmental, operational and reliability issues in the microgrid without co-relation of each other. In this case, there is a possibility to degrade the microgrid performance if any one of the parameters is considered alone. This review article tries to showcase the joint investigation on the impacts of DSM in the above-mentioned performance parameters which are the uniqueness of this article. Also, this review article discusses the implementation of data science in DSM such as big data, blockchain, Internet of Things (IoT) and ML etc. As a result, this review article provides in-depth and cutting-edge knowledge on the implementation of DSM in the microgrid. Also, it helps the researcher to identify where the DSM could be implemented and how the implementation affects the performance parameters in the microgrid.

The remaining sections of this article as follows: Section 2 deals with the architecture model, major components of the microgrid and the contribution of each layer of the microgrid for DSM implementation. Section 3 elaborates the different DSM implementations and comparative study based on their application, physical components, optimization methods used. Also, this section discusses the utilization of advanced soft computing techniques that makes the DSM implementation simple and accurate. The major physical components in the microgrid that supports the DSM are RES and energy storage devices. So, Section 4 describes the contribution of batteries and EV for the implementation of DSM in the microgrid. Section 5 deals the advanced technologies in terms of metering, data science and communication in the application of DSM in microgrids. Section 6 deals the performance parameters for the implementation of DSM in the microgrid. Finally, the article ends with the conclusion.

2. Microgrid

The microgrid can be defined as a network consisting of loads and DER either connected to the grid known as "grid-connected mode" or isolated from the grid known as "islanded mode". The requirements of a microgrid are (i) distinct from the network, (ii) local control of the energy resources instead of centralized control from the remote control center, and (iii) either grid-connected or islanded mode of operation. To satisfy the requirements, the microgrid needs the appropriate control and maintenance which are monitored by the control centers [33]. The control measure may vary with respect to the grid type. The microgrid is classified based on the application in [33] and size in [34]. Based on the application, the microgrid can be classified as campus/institutional microgrids, military microgrids, residential, remote and rural microgrids. Based on the size of the microgrid, it is classified as nanogrid and picogrid. Nanogrid is one of the types of microgrid consists of the DG and industrial consumers whereas picogrid consists of the small-scale DG and residential consumers [34].

The Smart Grid Architecture Model (SGAM) has been discussed in [35]. The architecture model has been illustrated in Fig. 1. The component layer includes the physical components of the grid such as DGs, storage devices, smart meters, sensors and actuators. The communication layer includes the network and protocols that are connected with other layers to share the data from the information layer. The function layer describes the logical functions and applications of the entire grid. The Business layer handles the business model of the electricity market and its regulatory framework [36].

The five layers of smart grid (business, function, information, communication, and component layer) have been extracted from eight stacks of the grid-wise architectural council in [37]. Among the eight stacks, economic /regulatory policy and business objectives have come under business layer. The function layer has business procedures and context whereas the information layer has data/information that could be communicated between the different systems. The communication mode and infrastructure have been listed under the communication layer whereas the component layer has been included the components required for the grid operation and connectivity. The SGAM in European projects has been critically reviewed in [38]. The wide range of applications, benefits of SGAM and challenges on the implementation of SGAM have been critically reviewed in [38]. It has also discussed the points to be considered for future research in terms of development tools and their implementation/testing.

The architecture of a microgrid consists of five layers such as the component layer, communication layer, information layer, function layer and business layer. The function of each layer has been explained in the subsequent sections. Section 2.1 describes the function of component layer, Section 2.2 discusses the function of communication layer, Section 2.3 discusses the function of both the information layer and the function layer and Section 2.4 discusses the function of the business layer.

2.1. Component layer

The component layer (physical layer) contains the physical components such as DG, storage unit, power electronic converters and loads. A hybrid energy system consists of the combination of the grid-connected DG, storage and load which may be configured as series, parallel and switched [39]. The different DGs used in the residential sector are solar PhotoVoltaic (PV) panels, small wind turbines, natural-gas-fired fuel cells, and diesel generators. The different DGs used in both the commercial and industrial sectors are combined heat and power systems, solar photovoltaic panels, wind, hydropower, biomass combustion or co-firing, municipal solid waste incineration, fuel cells, diesel generators [40]. The utilization of the loads in the microgrid can be traditional or smart. Smart loads are flexible to adopt any advanced technique for implementing the DR whereas the traditional loads can measure only energy efficiency.

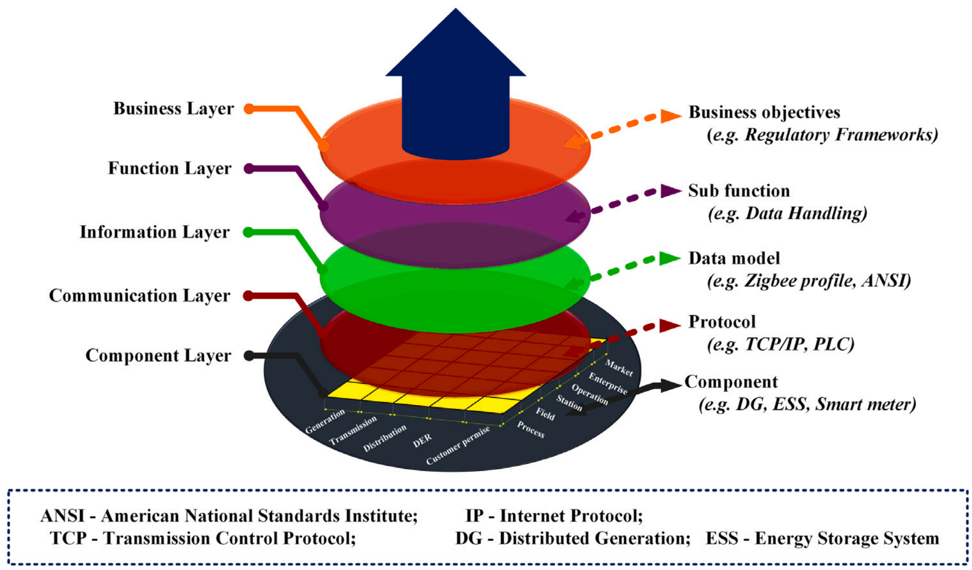

Fig. 1. Smart grid architecture model.

2.1.1. Distributed generation

DG is the small-scale generation of electricity at the consumer end. DG technologies consist of modular generators (e.g. diesel generators) and RES. Generally, DGs can provide electrical energy at a low cost or even without cost at higher reliability and security with fewer environmental impacts [41]. Instead of using few large-scale generating stations located far away from load centers, the numerous DG systems may employ as small plants. It possess various potential benefits such as reduced transmission losses at the distribution end and minimum operation cost.

Photovoltaic systems. PV systems convert directly the solar energy into electricity [42]. In [43], PV has been used for the DSM implementation in different types of consumers (residential, industrial and commercial) to minimize the electricity cost. In [44], prosumer-based energy management with the PV power has been implemented with three different tariff structures: Real Time Pricing (RTP), feed-in tariffs and net purchase/ net sale. It was concluded that the net purchase/ net sale was the most economical tariff structure and RTP was the second option. In [45], a Home Energy Management System (HEMS) was developed for a consumer with PV power generation. The efficiency of the developed model has been proved by comparing their electricity cost and peak demand with the traditional consumer and HEMS without PV installation. Energy trading among the neighbors has been suggested in [46,47] for minimization of electricity cost and peak demand. In [46], a multi-agent model has been utilized to share the PV and battery powers among the neighboring consumers. In [47], shared energy storage was developed with the implementation of incentive-based DR and obtained the electricity cost minimization. For a residential consumer, the implementation of DSM with the combination of PV, Battery Energy Storage System (BESS) and EV has reduced the peak demand up to 96% [48].

Wind energy system. Wind power plants convert the kinetic energy of the wind into electrical energy. Distributed wind energy system ranges from a 5 kW turbine at a home to few megawatt turbines at the industrial premises [49]. Variable-speed wind turbines can extract the maximum power at a wide range of wind speeds. The dynamic modeling and control of the small wind-turbine via furling dynamics at high wind-speed maintains the steady-state power. In [50], the hill climbing control has been used to obtain the maximum annual energy capture. In [51], DSM was used for the integration of wind power with the grid to manage the intermittency of wind power generation, minimize the peak-load and avoids the reliability problems. The minimization of operating cost and emission rate was obtained with the implementation of DR program and wind power along with solar power in [52]. DR program with Plugged-in EV (PHEV) and wind power have been implemented for cost savings of the consumer [53]. The electricity cost for the energy consumption of 50 users have been compared with and without DSM implementation where the cost saving for the users have been obtained by DSM implementation [54]. The maximization of wind energy utilization and minimization of cost and carbon emission have been obtained by the coordination of DSM, wind power and BESS [55]. In [56], the energy management of a hybrid system with solar, wind and BESS has been utilized for improving the reliability of the microgrid.

2.1.2. Loads

An electrical load is an appliance or equipment that consumes the electrical energy [57]. It plays a vital role in DSM implementation for load management to modify the load pattern [58]. Electrical appliances, types of equipment, and types of machinery in residential, commercial, and industrial consumers are the different possible loads in a microgrid system [59].

Industrial consumers are the large-scale energy consumers with advanced measurement, control, and communication infrastructures that possess the various advantages such as fast and accurate scheduling [60]. In absence of DG, the modification of industrial consumers load pattern by proper scheduling for minimizing the peak demand [59]. As most of the loads in production industry are uninterruptible. But the interruption in any one of the load may affect the subsequent processes which it requires the technical and financial barriers to be handled along with the DR implementation [60].

Residential consumers are the second largest consumers after industrial consumers. The most common categories are controllable, interruptible, and uninterruptible. Controllable, interruptible, and uninterruptible appliances have been scheduled for minimization of electricity cost, peak load, and PAR. Recently, many research works have focused on the residential consumer along with the implementation of EV [61]. The classification of smart residential appliances for DSM implementation along with tariff has been tabulated in Table 1. From Table 1, it is understood that the classification of different appliances in each category of the residential consumers to the effective DSM implementation.

In [62], the price bound has been communicated with commercial consumer to modify the load pattern for minimizing the electricity cost.

Table 1
Classification of residential appliances.

Ref No	Classification of residential appliances						Tariff
	Controllable	Uninterruptible controllable	Interruptible controllable	Thermostatically controllable	Uncontrollable	Continuous operation	
[61]	Iron box, Induction motor, Electric water heater, Refrigerator, Compact Fluorescent Lamp (CFL),light emitting diode lamp	Ceiling fan, Grinder, Tube light, Television, Air conditioner, Computer, Laptop, Mobile charger	Washing machine				RTP
[64]	Washing machine, Television, Air conditioner, Lighting						Optimal bidding strategy
[65]	Air conditioner, Oven, Clothes washer, Lighting, Television, Refrigerator						Time of Use (ToU)
[66]	Dish washer, Washing machine, Lighting, Oven, Sprinkler				Stove, Television, Laptop, Iron box, Coffee machine, Shaver, Game consol	Refrigerator, Outdoor lighting	Fixed tariff, Consumption based tariff, Rewarding tariff
[67]	Washing machine, Clothes dryer			Air conditioner, Water heater, Refrigerator, Water dispenser	Water pump, Oven, Dish washer, Vacuum pump		RTP
[68]	Dish washer, Plug-in EV, Electric water heater, Air conditioner Electric rice cooker						ToU
[69]	Battery, EV (Power Shiftable)		Washing machine, Dish washer, Clothes dryer, Automatic defrost (Time shiftable appliances)	Electric water heater, Refrigerator, Air conditioner			ToU, Feed in tariff
[70]	Washing machine, EV, Dish washer, Cloth dryer				Refrigerator, Lighting, Microwave, Television, Vacuum cleaner, Computer, Laptop		RTP
[71]	Washing machine, EV, Spin dryers, Dish washers, Cooker hub, Cooker oven Microwave, Computer, Vacuum cleaner, Laptop			Heating, Ventilation, Air conditioner		Refrigerator	ToU

In [63], automated DR has been analyzed for both industrial and commercial consumers. The peak load has been minimized and reliability was improved by implementing incentive-based DR for industrial and commercial consumers in Delhi.

2.2. Communication layer

The communication layer is responsible for information exchange between the utility and consumers. It supports the energy management and stability of the system [72]. Wide area network [73], field area network, neighborhood area network [73,74] and Local Area Network (LAN) [75] are the communication protocols used in the microgrid. LAN consists of building area network, industrial area network and home area network. In these types of wireless networks, the protocols such as Wireless Fidelity, home plug, digital subscriber line, ZigBee, Dash7 have been chosen based on standards of the Institute of Electrical and Electronics Engineers (IEEE) 802.15.4/Internet Protocol (IP), International Electrotechnical Commission (IEC) 61850, International Organization for Standardization/IEC 18000-7, IEEE 802.15.1, IEEE 802.11 (Wireless Fidelity) and IEEE 802.16 (Worldwide interoperability for microwave access) [76]. In [77], wireless communication has been used for DSM with microcontroller-based control. DSM has been implemented and the flat load profile was obtained without any storage devices. For an urban environment, mobile communication has been suggested for DSM in [78]. It has been proved that a long-range wide area network architecture of mobile communication with DSM implementation for minimization of PAR.

2.3. Intelligence layer

An Intelligence layer is the combination of information and function layers. It monitors the control of physical layer components. The control can be either centralized or decentralized. In the centralized control, the resource allocation has been done by Independent System Operator (ISO) [43]. The demand and DG of a consumer is communicated to the ISO periodically and the ISO manages the supply–demand balance. In decentralized control, the control of load allocation lies within the individual consumer. The consumer can make the scheduling based on the price of electricity on a particular period, storage availability and DG availability. Then, the consumer communicates the demand to the central utility and the utility acts based on the requirement from the consumer [79]. If the demand level quoted by the consumer is very high, the utility will impose a fare for that excessive power consumption. In intermediate control, the individual consumers are given rights to control their demand. If the demand exceeds the threshold, the central controller can keep it within the limit. The different controllers for microgrids [80] are droop control [81], V-f control [82], P-Q sharing [83], Energy Management System (EMS) [84] and several other miscellaneous functions. The energy management in a microgrid with DG is handled by DSM. EMS is classified into two types such as Direct Load Control (DLC) and indirect load control [84] which will be further explained in Sections 3.1 and 3.2.

2.3.1. Centralized control

In centralized control, an aggregator or control center maintains the load pattern of the consumer which does not consider the consumer satisfaction level [85]. Fig. 2 represents the centralized control of microgrid architecture. From Fig. 2, it is evident that the microgrid consists of DGs such as solar PV, wind & diesel generator, battery, EV and load (consumer with different appliances and smart meter). Each microgrid is connected to the grid as well as the other microgrids through a centralized control center. The centralized control center monitors and controls the power generation, power demand and power-sharing among the microgrids. The consumer response for changing the load pattern could be improved while implementing the ToU, RTP and Critical Peak Pricing (CPP) tariffs in a centralized control environment [85]. In addition, the environmental and security signals may be added along with tariff signals to get effective performance. In [43, 44], the centralized control on price-based DR program for residential appliance scheduling to minimize the electricity cost and PAR has been discussed. The control suggested in the article [43] provided the cost savings in the prosumers than the traditional end-users, while the article [44] proved the efficiency of the control method in reducing the electricity cost of the consumer including the communication technologies. Residential areas in the city of Bath located in the southwest of the UK have been tested with the DR program [86] and it was concluded that the developed DR program offers both reliability and economical benefits for the utility than the consumers. In [87], a graphical user interface model for two cases such as grid-connected mode and islanded mode has been designed. The centralized control with Particle Swarm Optimization (PSO) technique has been provided the flat load profile for both cases with the utilization of switch agent, central coordinator-agent, local controller-agent, and load agent. In [88], the network has three feeders, the first one serves the residential area, the second one serves the industrial area and the last one serves the commercial area. The overall social welfare of the consumers and the utility have been maximized with the implementation of the centralized control.

2.3.2. Decentralized control

In the decentralized controller, the consumers can change their consumption pattern to afford the demand quoted by the utility. Fig. 3 represents the decentralized control of microgrid architecture. Fig. 3 shows that the microgrid has its decentralized control center. The power generation and power demand are scheduled using this control center where the excess power availability should be communicated to decentralized control centers of other microgrids. In [89], the controller received feedback from the stakeholders of the particular area and the control action has been taken accordingly. The residential and commercial consumer in the area of Vijayanagar at Bangalore city to analyze the demand pattern with the decentralized control. The supply–demand gap has been reduced considerably by utilizing the above-mentioned method. In [90], a decentralized controller was suggested for a residential consumer with installed PV and wind power. The Inclined Block Rate (IBR) pricing scheme for DSM implementation has been suggested. Both the decentralized and centralized controller has been critically compared with various performance parameters in [91] for a residential consumer. The decentralized control was proved to be the optimal controller to minimize the electricity cost as compared with a centralized controller.

2.3.3. Distributed control

Distributed control of the microgrid eliminates the few limitations that present in both centralized and decentralized control techniques. It has a wide range of applications in energy management on the generation and consumer end. Fig. 4 represents the distributed control of microgrid architecture. The distributed control center of the microgrid communicates between the grid and among the other microgrids. The distributed control center decides the power flow to the load based on the power generation of the same microgrid, power availability from other microgrids and power taken from the grid . The advantages of distributed control over the centralized and decentralized control techniques have been compared in [92]. The limitations of centralized control include the high cost of centralized control center installation, minimum reliability and stability. On the other hand, decentralized control is cheaper than centralized control, but it is unstable and unreliable due to the lack of communication links and information sharing. The distributed control for the DSM on domestic consumers has been discussed in [93]. The developed control technique has been resulted in reducing the peak demand, transmission losses and the dependency on the grid.

2.4. Business layer

The tariff would be calculated in the business layer and communicate to the utility. This layer controls the DSM operations and decides the investment to be done on additional plant capacity. The two-part pricing scheme has been introduced which is the combination of centralized control center data with RTP and capacity pricing component. The scheme has been proved to be effective in reducing the peak demand [94]. The twelve tariff components and their impacts on the electricity bill for a community of 100 residential consumers has been analyzed in [95] and proved the best choice of billing system as compared with the volumetric billing system. The net purchase and sale for the billing purposes have been implemented. E+ business model has been framed in [96] based on the two agents such as prosumer and aggregated prosumers manager which would be increased both the electric and thermal energy efficiency. Additionally, it can control the energy level of the whole distribution grid. Section 3 deals with the DSM implementations in the microgrid. Also, the different DR programs such as DLC and indirect load control are discussed in Sections 3.1 and 3.2 respectively.

3. Demand side management

The implementation of the load management technique in the electricity suppliers may reduce the cost during the peak power and eliminate the difficulty of increasing the additional capacity on the generation side [58]. The changes in the conventional load management technique denoted as Utility-DSM (U-DSM) in which the demand pattern can be modified to obtain the flat demand curve in the utility itself without considering the consumers [58]. Modern utility DSM programs have been derived from the national energy conservation policy act [97]. Since 1980, DSM has become very popular.

DSM has been utilized to balance the time-varying demand of consumers and generation capacity of the power systems. It has encouraged consumers to actively participate in energy management by providing the incentives. The consumer end energy management deals with the power flow and information exchange between the utility and the consumer [90]. In [98], Minnkota power co-operative supplies 12 rural electric cooperatives in Minnesota and North Dakota. The annual load factor was improved on these electric co-operatives by proper planning on the demand side for effective load management during the severe winter peaks. The manual switching from electricity to oil for space heaters was adopted during the peak-load hours. The load factor was improved from 48% in 1976 to 63% in 1983 without any consumer discomfort [98]. The modern DSM relies on smart switching

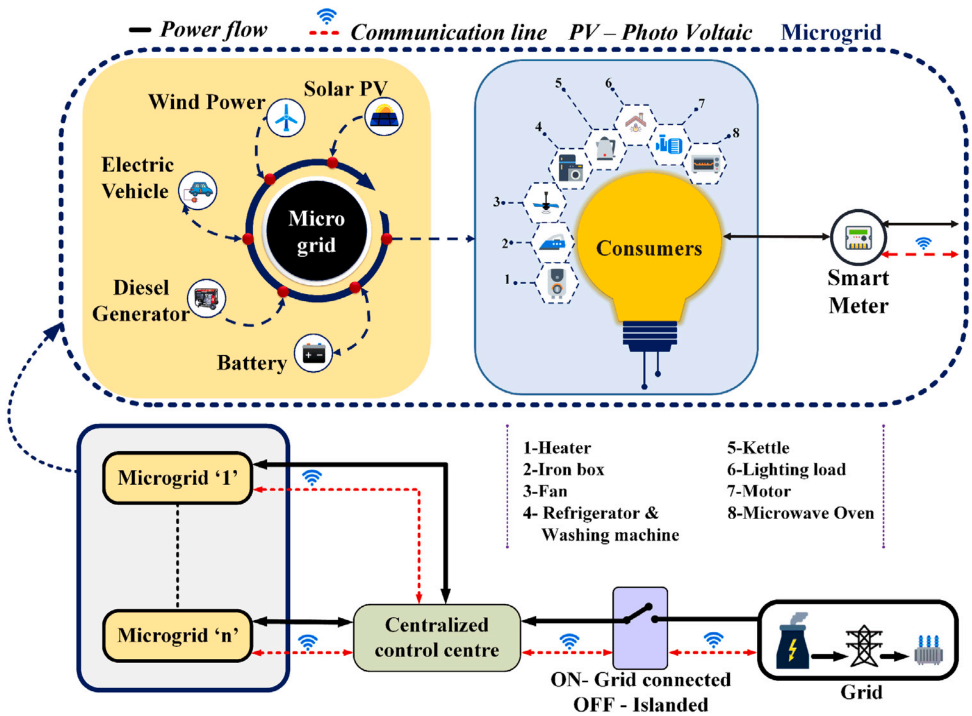

Fig. 2. Centralized control of microgrid.

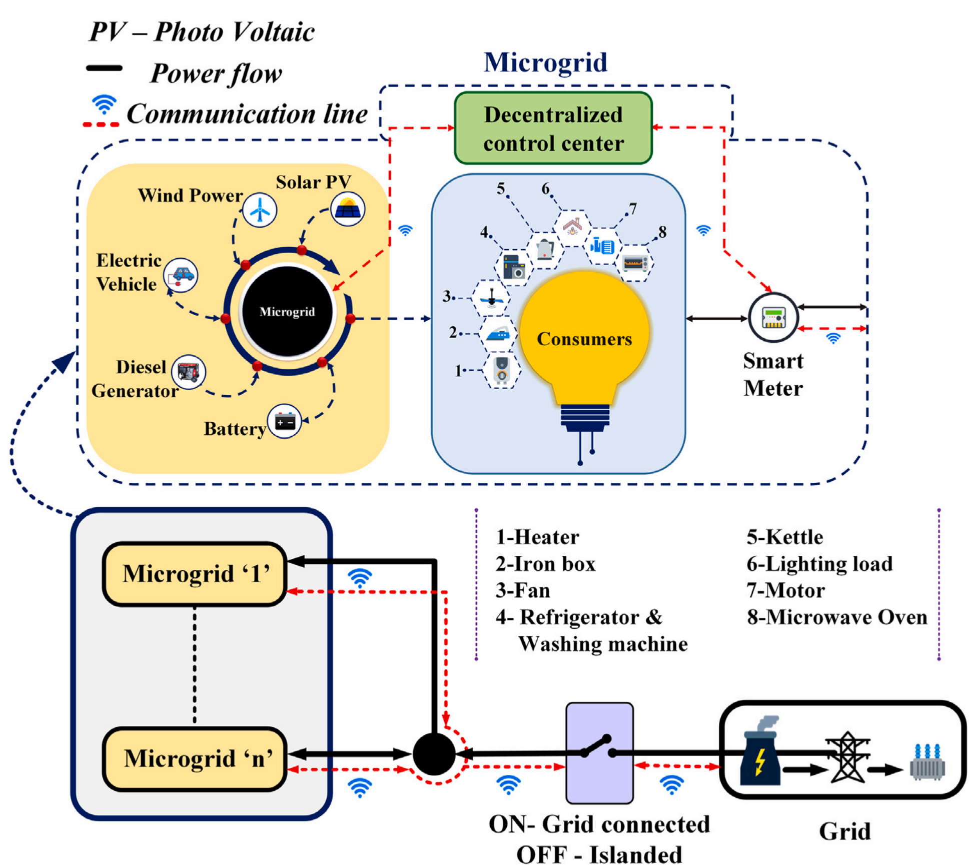

Fig. 3. Decentralized control of microgrid.

according to the demand and supply relationship. DSM has become popular by means of encouraging the consumer side power generation and modifying the electricity tariffs. A flat power demand curve would be obtained by considering both consumer side power generation and electricity tariff. DSM can be implemented by the consumers in three ways [99]:

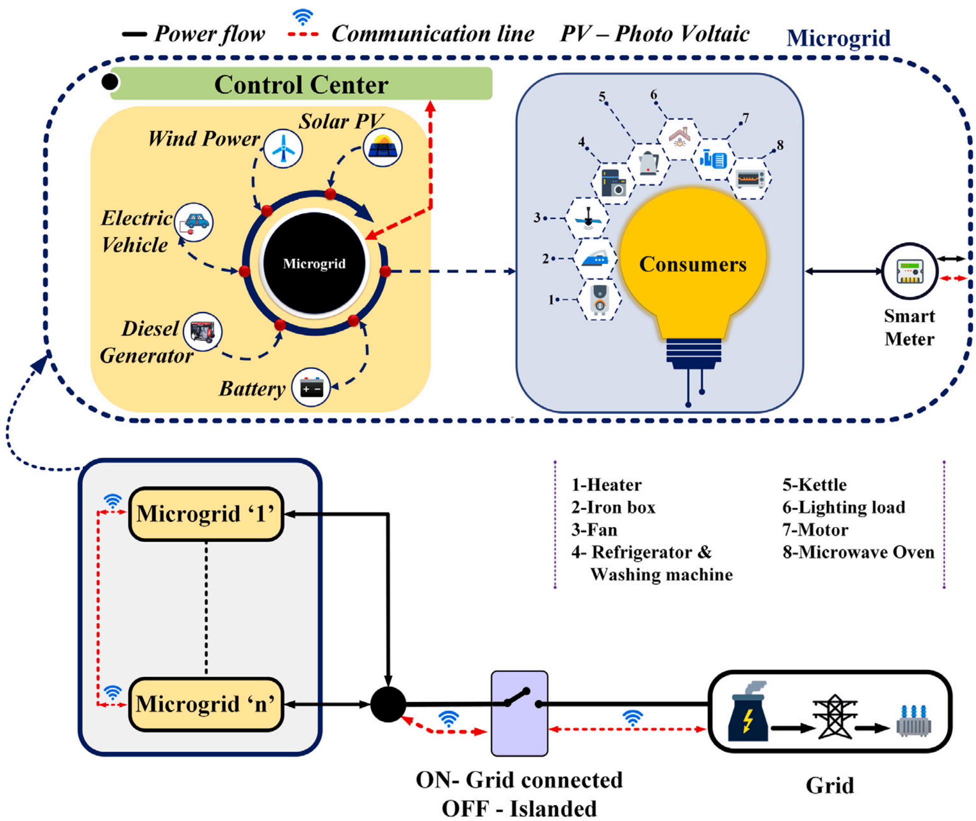

Fig. 4. Distributed control of microgrid.

1. **Energy Conservation:** Energy conservation reduces energy consumption at peak hours without any alternative solution to the consumers which causes discomfort on the consumer side. Energy conservation measures in the generation, transmission, primary and secondary distribution were discussed in [100]. The combination of energy efficiency and energy conservation was considered to reduce the power consumption. Energy efficiency measures on residential, commercial, industrial and agricultural sectors in India have been analyzed in [101]. The energy shortage in Gujarat could be removed by saving the annual energy (GWh) using energy efficiency technologies. Also, the peak power saved (MW) on the demand-side implies proportionally lower investment than implementing the new power plants.
2. **Peak shifting:** In peak shifting, part of the energy consumption is shifted from peak hour to off-peak hour such that overall consumption remains the same. Peak shifting is one of the most accepted DSM implementations. Much literature has been discussed peak shifting with the different optimization techniques [79,102]. In [79], a two-stage hierarchical energy management for the residential consumers with semi-scenario-based Rolling Horizon Optimization (RHO) algorithm was suggested to reduce the PAR. Data Analytical Demand Response (DADR) in [102] has also a two-stage DR technique such as the consumer-centric and the utility-centric. User comfort and willingness to participate in DR were given importance. Also, the scheduling of appliances could be done by utilizing Consumer-Centric DADR (CC-DADR) based on the consumers' consumption data from smart homes appliance adjustment factor, and appliances priority index. If the CC-DADR failed to reduce the demand up to the threshold level which has declared by the utility, the scheduling would have updated by Utility-Centric DADR (UC-DADR). The penalty will be paid by the utility for the consumer sacrificing [102]. In [91,103,104], peak shifting was done using the distributed algorithm with 'L1' regularization, artificial fish swarm intelligence and hybrid approximate dynamic programming and hybrid big bang-big crunch algorithms respectively.
3. **Use of On-site generation:** DG at the consumer end has advantages such as supports energy management, enhances the reliability of the system and minimize transmission losses. In [105], a grid-connected system consists of a hybrid renewable system with EV has been suggested for the DSM. Five different batteries were compared and a lead–acid battery with a carbon-enhanced electrodes were found to be economical for variable loads [105]. As residential PV penetration is high in Australia, the solar power was utilized for obtaining the flat demand curve in [106]. The capital cost of critical peak availability from gas turbines with the distributed solar in the Australian national electricity market has been compared in [106]. Texas has the largest wind power plant among the other states in the USA which has capable of supplying the power for 71000 MW peak demand [107]. The supply capacity of the wind power plant is greater than its 15 years average value of 64000 MW [107]. In [107], both solar and wind power were preferred as the peak power plants because of zero marginal costs. EVs were also used for supplying the peak demand which operates in charging mode during the off-peak hour (peak shifting) and discharge mode during the peak hour (valley filling) in [108,109]. In [110], it was proved that the real-time decentralized DSM was efficient in reducing the PAR than the centralized scheme of the grid-connected system which consists of the RES such as PV, wind, Energy Storage System (ESS) and EVs. It enabled the consumer to produce a flat load profile and to reduce the electricity cost. The different DSM implementations have been tabulated in Table 2 based on the type of consumers, DG, storage, and application of computing techniques. Section 3.1 discusses the different DLC techniques. Section 3.2 elaborates on the incentive and price-based indirect load control techniques. Section 3.3 explains the soft computing

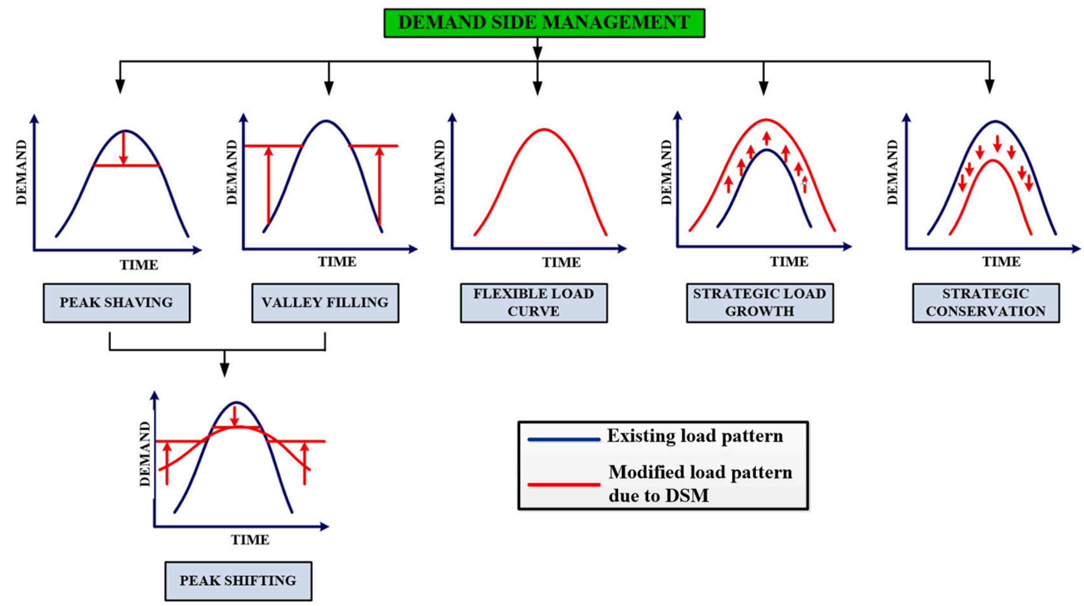

Fig. 5. DSM — Load configurations.

techniques that have been utilized to implement the DSM in the microgrid. Section 3.4 provides information about the scenario on DSM implementation in India.

3.1. Direct load control

Among the three ways of implementing the DSM, the combination of peak shifting and on-site generation to form the current DSM, while energy conservation is not considered. The DSM is categorized into two techniques such as energy efficiency and DR. China invested in the energy efficiency technique by the replacement of Compact Fluorescent Lamps (CFLs) for lighting and decided to modify the electricity tariff in the year 1990 [90]. The state of California had spent 20 billion USD on new power supply contracts during the power crisis in 1999–2000 [111]. It was only able to increase the electricity supply by 2% which is indicated in the case study presented. Whereas, an investment of 1 billion USD on energy efficiency promotion and modification could achieve a 10% reduction in the electricity demand. But the energy efficiency improvement has not sufficient for load management in many cases. In such cases, DR is widely used as a DSM technique that encourages the consumer to modify the consumption pattern and thus alter the configuration of the load curve. Different load pattern changes are portrayed in Fig. 5. Change in load pattern using DSM implementation is obtained by six different methods such as peak clipping, load shifting, valley filling, load growth, strategic conservation and flexible load curve. From Fig. 5, it is evident that six different ways of modification in the actual load curve could be implemented to reduce the peak load. Peak shaving and strategic conservation are the configurations that reduce the electricity consumption without operating the load. On the other hand, valley filling and strategic load growth are the configurations that discuss the increase in load demand. The flexible load curve has unrestricted load variation in all durations. Peak shifting is the most beneficial load configuration which combines both peak shaving and valley filling by shifting the operation of loads from peak hour to off-peak hour.

1. **Peak clipping:** In peak clipping DR programs, the usage of power during the peak-load hour is decreased [112]. In [113], it has been stated that the microgrid can be actively responded to the main grid, the peak-load of the grid tie-line can be clipped with Peak Time Rebate (PTR) programming. Also, it has analyzed the peak-shaving indices such as peak-shaving quantity index and peak-shaving ability index [113]. In [114], PTR along with Incentive-based DR program (IBDR) have obtained the peak clipping by optimal scheduling of controllable appliances. BESS has also used for peak demand reduction. The South-European islanded power system with relatively higher load consumption has been considered in [115] which consists of BESS and renewable energy. The available renewable energy power from the South-European island is very low when compared to its peak demand [115]. Artificial Neural Network (ANN) has been developed for peak clipping during the peak demand hour. Participation of customer side BESS providing the peak-load shaving at distribution feeder with the value of 12.47 kV have been analyzed in [116] for both online and offline optimization. Online optimization has been monitored by Supervisory Control And Data Acquisition (SCADA) and the cost minimization have been observed with ToU based tariff.
2. **Valley filling:** In valley filling, customers are encouraged to use their equipment during off-peak hours. In [117], an online algorithm has been developed for scheduling the EV charging during off-peak hour. IEEE 14 bus system has been considered which has five generator buses and nine buses connected to the EV. By varying the charging rate of EVs during the off-peak hour to fill the valley leads to obtain the flat load curve. For IEEE 30 bus system, Grid to Vehicle (G2V) has been scheduled with the water filling algorithm for charging the battery of the EVs [118].
3. **Load shifting:** In load shifting, the electricity usage is shifted from the peak-load hours to off-peak hours. Load shifting is the combination of peak clipping and valley filling. With the increasing number of EVs usage, the load shifting could be done with the effective interaction between EVs and the power grid [27]. EV charging/discharging model has been developed based on the PSO algorithm to achieve the optimal results through the group-based model in [27]. In [119], the customers have been clustered based on the consumption pattern in which the group with the largest load clipping capability was selected. The load clipping capability was based on the effectiveness of the customer to reduce the supply shortage. Therefore, the load has been shifted to off-peak hour from the peak hour. Peak load shifting in the different applications was tabulated in Table 3.

4. **Load growth:** In load growth, the load-shape changes as an increase in sales by the utility. On the utility side, load growth was linked with the planning for future development and increase in the reserve capacity. For reliable operation of the system, the sequential Monte Carlo simulation method was utilized to forecast the load growth. The optimization model has been tested for the Indian radial distribution system with two scenarios such as DG integration and expansion of reserve capacity. Scenario with DG integration was found to be better than the expansion of reserve capacity [120].
5. **Strategic conservation:** In strategic conservation, total energy consumed over a year is reduced. In [121], illustrates the behavioral changes required for energy conservation. It has also explained the DSM programs in different countries and their objectives. In [115], home automation has been suggested as the energy conservation measure for residential consumers. The demand reductions of 1–5 kW per house during summer and 1–2 kW per house during the winter in the southern region of the USA [115]. Conservation voltage reduction has been suggested for energy savings in [122]. The voltage on the feeders that run from the substations could be reduced while applying the conservation voltage reduction technique in power systems for peak demand shaving and energy consumption reduction. Therefore, it produces considerable energy savings in both utility and consumers.
6. **Flexible load curve:** The electricity usage during different times is redistributed to reduce the PAR in [123]. Interruptible load hopping and constant interruptible load hopping algorithms were applied for hopping and centralized DLC schemes to flatten the load curve leads to reducing the forecasting error. A centralized DLC scheme has been found to produce the flat load profile. In addition to the flat load curve, it has some advantages such as low communication and computation overhead and full consumers privacy [123]. Flexibility in the load shape could be obtained by integration of the grid using dynamic control to schedule the allocation of DG and storage based on the response of the consumer [124]. Different methods of dynamic control are DLC, through independent control agents, using controllable appliances and EMS.

3.2. *Indirect load control*

DR programs are adopted for encouraging consumers to modify their load configuration. DR programs are classified into two programs such as IBDR programs and price-based DR programs. The detailed classification of DR programs is illustrated in Fig. 6.The major classifications are IBDR and price-based DR. The IBDR is further classified into classical programs and market-based programs. Similarly, price-based DR is further classified into RTP, ToU and CPP. IBDR is the most commonly used techniques to modify the load pattern.

3.2.1. *Incentive based DR programs*

IBDR provides incentives to the customers who are willing to reduce/shift their electricity consumption during peak-hours to off-peak hours or a discount in the electricity price is given to these customers for their participation in the program [125]. IBDR or dispatchable programs are classified into two types such as classical-based programs and market-based programs. In classical DR programs, customers receive incentive payments for allowing the utility to control demand by DLC and Interruptible or Curtailable services (I/Cs). In a market-based DR program, consumers receive a discounted electricity rate for reducing the load on request from the utility. Market-based DR programs are classified into four types such as Emergency DR Programs (EDRP), Capacity Market Programs (CMP), Demand Bidding (DB) and ancillary services market programs. In indirect load control, the utility itself reduces the demand of the consumer with an incentive payment to reduce the peak demand [125].

A residential community of 40 smart homes with PV generation and BESS has been taken into account in [43]. It has considered the revenue index and satisfaction cost as the constraints and scheduling have been done with the help of an algorithm based on the Stackelberg equilibrium. It was proved that the outcome of the scheme obtained the flat load profile [43]. Aggregation techniques in this scheme were applied to minimize the loss of welfare of DR resources [91]. On I/Cs, the consumers receive either a discount in electricity bills or bill credits to reduce the load on the occurrence of system contingencies. In EDRP, the utility provides an incentive to the consumers for reducing their loads in case of reliability events. Consumers have an option either to pay the penalty without curtailment of the load or curtailment of the load when the utility notified the customers. The level of the payment is usually notified ahead to the customers from the utility. In CMP, consumers are allowed to commit in providing the load reductions during the system contingencies. If they do not curtail the specified load they have to pay the penalty. The customers may receive a guaranteed payment to curtail the load when it is directed from the utility [91].

In the DB program or the buyback program, consumers bid for a specific load reduction in the day ahead based wholesale electricity market [150]. Consumers have the liberty to choose the value of bidding for the amount of energy reduction. They will be rewarded if the energy saved matches the quoted amount. If it fails to satisfy the requirement, no financial penalty is imposed on the consumer [150]. The last type of IBDR is the ancillary services market programs. It allows the consumer to bid for ancillary services such as storage, operation reserve, reactive power, voltage and frequency control. In [151], the consumer has to bid for acting as reserves by curtailing the load. The consumers were notified by the ISO when the necessity of reserve capacity and they will be paid based on the market price. It disturbs the running load very often. Three cases without DR programs, with RTP and RTP along with IBDR have been compared and it was proved that the IBDR along with RTP provided the flat load profile effectively in [152]. The DSM in the point of retailers have been discussed in [153, 154] and suggested that the IBDR reduced the cost of the customers and maximized the profit of the retailers.

3.2.2. *Price based DR programs*

Price-based DR programs focus on the minimization of PAR by modifying the tariff structure instead of providing incentives to the consumers. In this type of DR program, the electricity charge is higher than the normal charge during the peak-load hour whereas during the off-peak hour the electricity charge is lower than the normal charge [79]. Price-based DR programs are classified into RTP, ToU, CPP. CPP is further divided into two types such as extreme day pricing and extreme day CPP. Also, the PTR technique is explained at the end of this section.

3.2.3. *Real-time pricing*

RTP is the most effective and widely used strategy to reduce the peak-load and PAR. Here, the real-time market electricity price is replaced with respect to the real-time generation cost. The price fluctuates with respect to the time would be informed to the consumers by the retailers based on the day-ahead basis or hour-ahead basis price signals. Therefore, they can participate in retail markets with lower risk so that the RTP becomes more efficient. In [79], semi-scenario-based RHO has been used for the optimization of HEMS to reduce the electricity cost and improve energy efficiency. One supplier, one utility, one ESS and 50 residential consumers have been considered to improve the social welfare with the flexible charge rate depends on the time in [125]. Considering the RTP alone could create the temporary peaks during the off-peak hour [125]. In order to avoid the above-mentioned drawback, the combination of RTP and IBR has been suggested in [90]. Consumers are classified into grid energy consumers, smart energy consumers and

Table 2
Comparison table of different DSM implementations.

Ref No	Objective	Constraints	Type of consumer	Control	DR program	Sources	Storage	Optimization techniques	Result outcome	Inferences
[43]	Minimization of cost including ESS cost	Residential BESS, controllable appliance operation time and operation cycle, non-interruptable controllable appliance operation and interruptible controllable appliance minimum online/ offline time constraints	Residential, commercial and industrial	Centralized	RTP	PV	Battery (Lead acid, Lithium ion), EV	Optimal scheduling algorithm	Performance of lead acid and lithium ion batteries were compared. Efficiency and depth of discharge of lithium ion batteries are proved to be better than the lead acid batteries	Load scheduling not considered along with resource allocation
[79]	Minimization of residential tariff and improvement of energy efficiency	Power flow and limits of DG busbar, load bus, EV aggregator busbar and voltage ramp limits	Residential	Decentralized	RTP	PV	Battery	Semi scenario based RHO	Cost was comparatively low as compared with RHO method and HEMS & absence of semi scenario based RHO	Heating/cooling loads were not and only limited appliances are considered to minimize the cost
[90]	Reduction in PAR and average waiting time, cost minimization with user comfort	Power balance constraints, SoC of energy storage system	Residential	Decentralized	RTP+ IBR	PV and Wind	Battery	Genetic Wind- driven optimization (GWDO)	The developed optimization has been compared with Genetic Algorithm (GA), Binary PSO (BPSO), Wind Driven Optimization (WDO) and it was found to be more suitable for DSM	Consumer comfort was not considered
[125]	Maximization of welfare including supplier, utility and consumer, selection of optimum charge rate	Power balance constraints, SoC of battery, minimum and maximum limits for power generation and consumption	Residential	Centralized	RTP	–	Battery	Distributed load scheduling algorithm with convex optimization method	The presented optimization technique was found better than optimal RTP algorithm. Flexible charge rate have been suggested to afford intermittency	Load shifting was not considered and centralized control affects the privacy of consumer
[126]	Minimization of electricity cost and peak shifting	Power balance constraints, ramp rate of power at time slot	Residential	centralized and decentralized	RTP	–	–	Optimum stopping rule (OSR) based real-time distributed scheduling algorithm	The presented algorithm was utilized for both centralized and decentralized controllers through the central scheduler	Distributed controllers could be implemented which are more suitable than the centralized and decentralized controllers.
[44]	Maximization of cost savings on trading of energy	Power balance constraints, ramp rate of power at time slot, priority index, interruption time constraints	Residential	Centralized	RTP+ feed-in tariff	PV	–	Load scheduling optimization	Dynamic RTP was compared with the feed-in tariff and proved to be effective in the prosumer based DSM	Load scheduling was not considered. Resource allocation alone could not be efficient in trading of excess power
[127]	Minimization of PAR and dissatisfaction level at user end	Amount of load shaving in each time step, dissatisfaction level, temperature variation	University of Connecticut campus, USA	Centralized and decentralized	DLC	Combined Heat & Power (CHP)	Fuel cell	Alternating direction method of multipliers based DR algorithm	SCADA with minimum communication requirement have been considered. Decentralized controller was compared with the centralized controller	CHP are not environmental friendly and economical than DGs such as solar PV and wind
[45]	Minimization of electricity bill and PAR	Power balance and appliance operational time constraints	Residential	Decentralized	TOU	PV	–	Cuckoo, GA, BPSO with and without RES	GA-RES was found suitable for reduction in PAR, cuckoo search method with RES have been suggested for cost minimization and PAR reduction	Storage devices were not considered that has the limitation of intermittency and uncertainity of solar PV
[91]	Reduction in cost of energy consumption, daily peak demand and minimization of PAR	Power balance, standby power level, appliance operation time	Residential	centralized and decentralized	RTP+ ToU			Nikaido-Isoda function based relaxation algorithm, Newton method toward centralized coordination	Customers discomfort have been decreased with sparse pattern. A super linear convergence rate has been obtained using l_1 regularization compared with traditional models and algorithms.	On-site generation, battery and EV were not considered
[46]	Reduction in PAR and improvement in energy sharing among neighbors	Power balance, operation time constraints, appliance operation duration, SoC, Charge\discharge efficiency	Residential	Decentralized	ToU	PV	ESS	GA	Group-based and turn-based co-ordination models were compared with the baseline algorithm	Distributed controllers could be more suitable than the decentralized controllers

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Table 2 (*continued*).

Ref No	Objective	Constraints	Type of consumer	Control	DR program	Sources	Storage	Optimization techniques	Result outcome	Inferences
[128]	Minimization of electricity bills and reduce peak demand by controlling the shiftable loads.	Power constraints, operational time constraints, ramp rate limits	Residential	Centralized and decentralized	RTP	–	–	OSR based opportunistic Scheduling Algorithms	Framed algorithm have been implemented in centralized and decentralized schemes and the savings were 35.6% and 35.2% respectively	On-site generation, battery and EV were not considered
[129]	Minimization of electricity bill including the battery system cost	Power balance constraints, charge and discharge rates, SoC, power conversion losses	Residential	Agent based control	ToU	–	Flywheel, Superconducting magnetic energy storage, nickel cadmium,lithium ion, metal air, lead acid, sodium sulfur, Super capacitor, Compressed Air Energy Storage (CAES) and pumped hydroelectric storage	Peak shaving simulator model	Performance of different storage devices were compared. Pumped hydroelectric storage was proved to be the most suitable ESS. Among the batteries, zinc manganese dioxide has provided the maximum profit considering the seasonal variation.	On-site generation and load shifting were not considered
[48]	Minimization of peak load	Charging rate, discharge rate, time constraints, power balance	Residential	–	DG	PV	Battery, EV	Improved decision-tree based algorithm	The algorithm was compared with ANN and proved to be most economical. The two different types of EVs considered in this work were Nissan leaf and Tesla. The peak load reduction of 25% and 68.5% have been obtained with Nissan leaf and Tesla respectively.	Lead acid batteries were harmful to environment and load shifting did not include in the appliance scheduling
[130]	Maximization of profit of residential consumer	Power constraints, time constraints, charge and discharge constraints, Response Fatigue Index	Residential	Decentralized	ToU, CPP, Interruptible or Curtailable services (I/Cs), RTP, Emergency DR Programs	PV, Wind	Battery, EV	RWM for scenario generation	Price-based DR schemes were compared with deterministic and stochastic models. As a result, ToU has provided the maximum profit	Distributed controllers were not included which are more suitable for DSM than both centralized and decentralized
[131]	Maximization of profit with minimum investment	Power balance, Power generation and limits	Commercial and industrial	Decentralized	RTP	–	–	Gaseous diffusion model	EMS operates in coordination with the AMI and communication system to reduce the load and to manage the generation and load	On-site generation, battery and EV were not considered
[132]	Maximization of consumer welfare	Power constraints, ramp limit for consumer budget, consumption pattern	Residential	Decentralized	ToU	–	–	Case1: Fixed daily non-base load budget algorithm, Case2:Fixed daily non-base load consumption algorithm	Case 1 was found to the best in improving the social welfare	Distributed controller with RTP was not considered
[47]	Maximization of shared energy storage provider's revenue and minimization of the user-level social cost	Revenue index and satisfaction cost	Residential	Centralized	IBDR	PV	BESS	Algorithm with Stackelberg equilibrium	The algorithm suggested in this work to achieve the flat load profile	Forecast errors, maintenance of secure grid voltage levels fluctuations, and benefits for participating consumers were not considered
[133]	Minimization of peak-load and energy loss	Substation feeder active power limit, operational time constraint, bus voltage limits, feeder current limits, and LTC and SC operating limits	Residential	Centralized	IBDR	PV, Wind	Battery	GA	Three cases were framed based on β and T_{max} values. As a result, $\beta = 1$ and $T_{max} = 12$ hours, provides the optimal solution	EV was not considered, centralized controllers have privacy issues

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Table 2 (*continued*).

Ref No	Objective	Constraints	Type of consumer	Control	DR program	Sources	Storage	Optimization techniques	Result outcome	Inferences
[134]	PAR and energy cost minimization	Power generation, voltage magnitude, line flow and power balance constraints	Residential	Decentralized	IBDR		PHEV	Distributed algorithm with Nash equilibrium	The PAR was 2.1 and the energy cost was \$44.77 without the scheduler whereas the PAR reduced to 1.8 (i.e., 17% less) and the energy cost reduced to \$37.90 (i.e., 18% less), when the scheduler is enabled	Load shifting with appliance scheduling was not considered
[114]	Minimization of the impact on customers being affected by load shedding	Strategy enrollment, load clipping and load shifting, daily consumption, system load variation, system reserve, hourly supply shortage relieving, daily total electricity usage, peak and valley periods load variation	Residential, commercial and industrial	Decentralized	ToU	–	–	Mixed Integer Linear Programming (MILP)	Clusters were formed by selecting the participating customers based on their capability of load clipping, shifting. it is proved that customers who efficiently clip its load could manage the supply shortage.	Impact of DGs and storage devices in load shifting were not considered
[135]	Optimization of the peak rate and rebate	Average electricity price, Customer's satisfactory constraint, peak–valley difference constraint, critical price and discount constraint	–	–	CPP	–	EV	PSO	Electricity bill and maximum peak to valley difference have been compared with different number of CPP and the suggested optimization technique was proved to obtain the optimal result even for higher number of CPP	The model is not consumer centric and impact of DGs were not considered
[136]	Minimization of energy consumption and maximization of residential consumer satisfaction	Peak and valley energy price and demand, satisfaction of residents, price elasticity,	Residential	–	ToU, ladder pricing	–	–	GA	With ladder pricing, the energy saving have been improved from 502.378 kWh to 745.999 kWh and the customer satisfaction have been improved from 0.997 to 0.998	On-site generation, battery and EV were not considered
[137]	Reduction in electricity bills, reduction in the power dissipated through the dump load	Load idle constraint, computational interval constraint, pre-emptive constraint, power demand constraint, battery operation constraint, battery boundary constraint, power export constraint	Residential	Decentralized	RTP	PV and small scale wind	PHEV	GA	The annual electricity bill without IRES was \$2337 whereas, the annual electricity bill with the IRES was \$1159	Distributed controllers could be better than the decentralized controllers
[138]	Minimization of the electricity cost and PAR.	Energy consumption constraint, operation timeslots constraint, power balance constraint	Residential, commercial and industrial	Centralized	RTP+ IBR	PV	ESS	GWDO	Reduced electricity cost and PAR was 22.5% and 29.1% in scenario 1, 47.7% and 30% in scenario 2, and 49.2% and 35.4% in scenario 3	Distributed controllers were not considered and impact of EVs in load shifting was not included
[139]	Minimization of electricity cost and PAR, Maximization of user comfort	Energy consumption constraint, lower and upper limit of scheduling horizon, storage limit	Residential	Decentralized	RTP	PV, wind	ESS	WD-GA, WD- Grey Wolf Optimization (GWO) and WBPSO	The electricity cost was reduced by 35.02%, 35.60% and 53.39% on implementing WDGA, WDGWO and WBPSO, respectively and the PAR minimized was 61.30%, 61.43% and 18.89% by considered the same	Distributed controllers could be more suitable for residential DSM than the decentralized controllers

Table 3
Comparison table of peak-load shifting in different application.

Ref No	DG	Storage device	DR technique	Methodology	Environmental/PQ impacts	Application	Outcome	Inference
[140]	PV	Battery	Dynamic pricing	Metaheuristic solver based on rolling time horizon		Home	The performance have been proved to be best as it includes both day-ahead scheduling and real-time control for optimization.	Appliance scheduling was not considered
[141]		PHEV	DLC	Approximate dynamic programming with heuristic priority scheme		Home	A multi-agent based DR have been suggested for utilization of PHEV in peak-load reduction.	Impact of DGs in peak load reduction was not considered
[142]	–	–	ToU	PSO		Home	Non scheduled and scheduled with PSO results were compared. Peak load and cost reduction could be obtained when scheduled with PSO	DGs and storage devices were not considered
[143]	–	–	RTP	Heuristic based evolutionary algorithm	–	Home, commercial, industrial	DSM has been proved to be effective in all type of consumers.	DGs and storage devices were not considered
[144]	PV, DG, Wind	Battery	Dynamic pricing	MIL problem by CPLEX solver	Reduce emission rate	IEEE 33 bus system	The optimal day-ahead scheduling have been analyzed with and without DR implementation. It was insisted that DR techniques can reduce the cost and peak-load.	Impact of forecasting errors and uncertainities were not considered
[145]	PV, Wind	EV	ToU, Capacity Market Programs (CMP), RTP, DLC, IC, EDRP, CPP	Monte Carlo simulation and k-means clustering algorithm		IEEE 39 bus system	DLC and CMP have been proved comparatively effective in peak load reduction along with congestion management	Battery was not considered. EV could not be used as an alternative instead of battery in this case due to its limited availability time.
[146]	PV	Battery	RTP	Uncertainty-aware microgridbased DR		Commercial Building	Kalman filters have been used to reduce the forecasting error. The model has provided the visible reduction in peak-load and cost for seasonal variation.	Short term load scheduling was not considered. Thermal loads has only considered
[147]	PV	Battery	Dynamic pricing	Monte Carlo simulation	Nearly Zero Emission	Nearly zero energy building)	Nearly zero energy building have been upgraded to Km zero energy building in which the cost reduction was achieved without reducing user comfort.	Peak shifting due to appliances other than thermal loads were not considered.
[148]	–	–	DLC	Queuing theory model		Inelastic Home appliances	Dish washer and laundry machines have been scheduled with the electric plugs. It was controlled by the central controller through internet	DGs and storage devices not considered.
[149]	–	EV	RTP	GA	–	Home	Energy virtual network operator have been suggested for peak-load reduction and better utilization of EVs. It has acted as a virtual battery pool.	DGs and battery not considered. EV could not be an alternative for battery as it is only available during non-driving durations

traditional energy consumers based on the generation and consumption of energy. Appliances were classified into traditional and smart appliances. Smart appliances were classified into power elastic, time elastic and essential appliances. The optimal scheduling has been made by Genetic Wind-driven optimization (GWDO) to minimize the electricity cost, PAR and increase the user comfort. As a result, when the demand is increased beyond the pre-specified threshold, a penalty function will be included in the cost equation which avoids peak formation [90]. Day-ahead RTP have been applied with 32 node radial distribution network in Ontario which provides the maximum profit of both supply provider and customer [155].

3.2.4. Time-of-use rates

ToU is the modified form of RTP. In ToU, the rates of electricity price per unit consumption must differ for different time blocks [91]. The rate during peak-hours is higher than the rate during off-peak

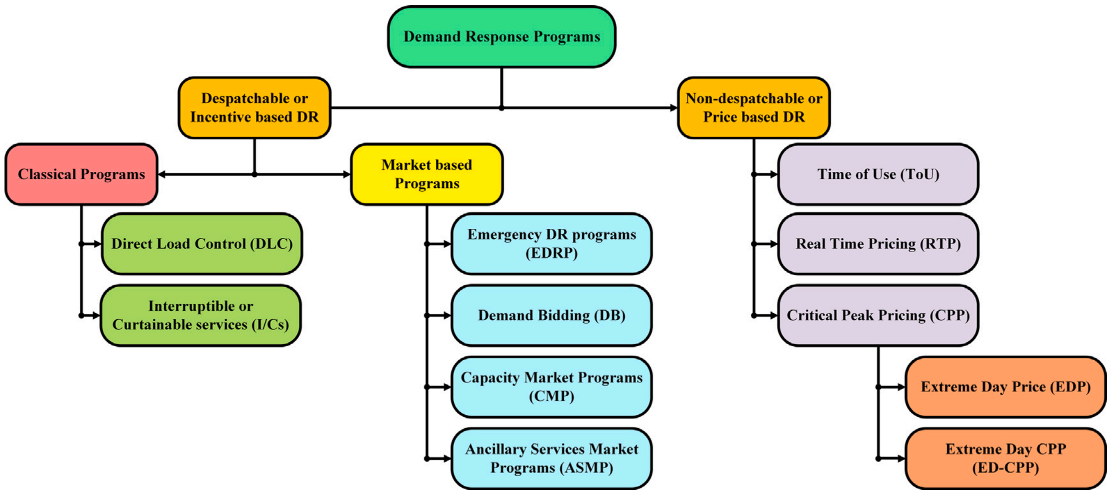

Fig. 6. Classification of DR programs.

hours. The simplest ToU rate must contain the two-time blocks namely peak and off-peak. The three-time blocks such as peak, mid-peak and shoulder-peak were framed with sparse patterns in [91]. It focused on reducing the waiting time, number of interruptions and PAR. Consumers were clustered based on the consumption pattern and the centralized control has been adopted with the proper communication. Smart home management systems developed on a multi-agent system platform with four-time blocks such as peak, shoulder, off-peak and low peak hours were considered in [156]. It was implemented with IoT in the Singapore energy system for efficient information exchange and control.

3.2.5. *Critical peak pricing*

CPP is the DR program in which the customers are imposed with very high prices during the critical peak time [157]. CPP is higher than the peak price but occurs for a very short duration. CPP has four schemes such as fixed-period CPP (CPP-F), variable-period CPP (CPP-V), variable peak pricing and critical peak rebates. The two constraints considered to implement CPP were the number of critical peak times implemented by the energy service provider within a certain period and the minimum interval (e.g. 24 h) between two different critical peak times. When the energy demand significantly increases, the participating customers would be notified about the price increment [157]. In [158], the CPP was implemented in the U.S. New England electricity and the system performance was analyzed. To achieve the performance, the two different schemes adopted based on the real-time basis such as CPP-F scheme has preset critical peak time with days and CPP-V scheme has the duration of the critical peak time for different days. In [159], an appropriate peak pricing window has been designed for Great Britain to implement the CPP. The energy cost savings from CPP have been observed by peak demand reduction. The peak rate was set based on the peak-hours to reduce the peak demand and improve the stability of the system. EV batteries were used to supply the power to the consumer during critical peak time in [135]. As the number of participating EVs increases, the peak–valley difference and the electricity bill have been reduced. The results of the model were verified with the PSO algorithm. CPP with the different base prices was tabulated in Table 4.

3.2.6. *Peak time rebate pricing*

PTR programs provide monetary rebates to the customers who have reduced the electricity consumption during periods of high-cost electricity (peak times) [163]. The customers who do not reduce the usage of electricity during peak events are simply charged by the normal rate. In [164], the low consumption, off-peak periods and peak periods have been considered as the load profile with the implementation of RTP and PTR. Two cases of PTR have been considered with revenue loss minimization and without loss minimization. It was concluded that the performance of PTR is better than RTP without considering loss minimization whereas RTP is a preferable one with loss minimization [164]. In [165], when the incentive is greater than the retail electricity price, the consumer utilizes more energy during the base-load period which affects the system reliability. It was found that most of the consumers shift/ increase their demand during peak/off-peak hours to maximize their profits. But only the consumers with a high level of uncertainty could reduce their energy consumption. Therefore, it was found that a PTR program may not suitable for a system where the net consumption needs to be reduced [165].

3.3. *Load forecasting*

Load forecasting is the prediction of future load demand in advance. Load forecasting has been utilized to implement in the day-ahead and hour-ahead DSM programs. Various methods for load forecasting with the implementation of price-based DR programs such as RTP, ToU and CPP have been discussed in [166]. Lacks in the availability of historical data, AMI and communication technologies have been considered as the challenges of load forecasting. The implementation of artificial intelligence techniques in load forecasting has been suggested to handle the historic data [166]. A clustering-based approach has been developed for the analysis of smart meter data to improve load forecast accuracy [167]. The developed forecasting method has been provided the data with minimum errors and reduced the data size.

Load forecasting has been beneficial for load scheduling on both utility [168] and consumer end [169]. In [168], the fast forecast algorithm based on double seasonal exponential smoothing has been suggested to forecast the substation load data in short-term planning. Power outages and fluctuations have not been considered which are the major concern in [168]. In [169], time-series image encoding techniques and convolutional neural network have been utilized to forecast RTP and power demand. The effectiveness of the forecasting has been proved based on the different parameters such as mean absolute error, root mean square error and mean absolute percentage error [169].

The application of Deep Reinforcement Learning (DRL) has minimized the forecasting error by utilizing Q-network [170]. The peak shifting has been achieved based on the demand and generation forecast obtained from the DRL [171]. The impacts of EV in peak shifting have been implemented based on the load forecasted from the RL technique [172]. But the major limitation with the load forecasting is the uncertainties in load forecasting and forecasting errors were not considered while discussing the impact of EV.

Table 4
Critical Peak Pricing with different base price.

Ref no	Base price	Objective	Optimization technique	Description	Inference
[157]	RTP	Maximization of incentive and profit of energy service provider	Backward dynamic programming	Swing option methodology have been used in the utility to decide the time of optimal critical peak points.	The developed peak pricing has not considered the profit of consumer
[158]	TOU	Reducing the customer electricity bills and electricity purchase cost of utility	Monte Carlo simulation method	In CPP-F scheme, the duration of critical peak period, critical peak rate and maximum number of critical peak hours per year were predetermined	In CPP-F scheme was not flexible where only critical days can be selected
[159]	TOU	Reducing the demand during critical peak time and the electricity cost	Statistical model	The peak/off-peak rate have been calculated based on the market volume and market price data. It follows the CPP-F	Transmission cost, operation cost and distribution cost were not considered
[160]	TOU	Maximization of social welfare	Quadratic programming	CPP of 6.3504 Baht/kWh was proved to be optimal for Thailand Power system	Forecasting error and uncertainity were not considered for tariff prediction
[161]	TOU	Minimization of electricity cost and optimize the load curve	Non-sorting GA -II	In commercial building of Taijan, 15% expense was reduced, 20% peak-load was curtailed, 35% peak–valley gap was filled with the developed method. The method has also provided expense saving of 8% and 30% of peak-load shed when executed the strategy in peak days.	The developed CPP was not suitable for non-peak days
[162]	RTP	Minimization of generation cost and emission rate	Modified ϵ-constraint method	For a 10 generating unit test system with centralized control at ISO the efficiency, of the CPP load control have been proved effectively.	Impact of uncertain sources such as PV and wind were not considered while setting the tariff

3.4. Energy management

Energy management in the consumer end has been achieved by DSM implementation. ToU-based DR has been implemented in a microgrid with combined heat and power (CHP) plants [173]. Robust optimization has been utilized for scheduling the CHP plants to minimize the electricity cost. The results have been proved that the efficiency of the developed framework in minimizing the electricity cost for different cases in [173]. The CHP plants have supported the thermal demand of the consumers which indirectly reduces the electrical demand. The intra-day DR has been implemented for Hybrid Power Plant (HPP) with storage devices in [174]. The HPP consists of wind, PV, compressed air energy storage (CAES), BESS, and thermal units. Hence, the electrical demand due to the heating loads has been supported by thermal units and the remaining electrical demand has been supported by the PV, wind and storage devices. The scheduling of HPP has been framed into a multi-objective optimization to maximize the profit of HPP and conditional value at risk. The risk-based DR framework has been suggested to schedule the reserve capacity of the Virtual Power Plants (VPP) in [175]. The VPP consists of DGs, BESS and flexible loads. The developed bidding-based electricity market model has been achieved the maximization of VPP profit in [175]. The reliability of VPP has been improved by handling the uncertainty of the DGs in it. The risk assessment-based DR has been implemented in the microgrid with CHP, CAES, RES and thermal energy storage [176]. The multi-objective optimization has been modeled to minimize the electricity cost and carbon emission rate of microgrids.

3.4.1. Residential consumers

Different methods of implementing the DSM on HEMS have been discussed in [177]. It has been insisted that space heating should be considered for peak load reduction. Scheduling of thermal loads alone has been considered in [177]. RTP-based DR program has been considered as the most suitable. The RTP-based DR program has been considered to minimize the electricity cost and peak load of residential consumers in [45,126]. HEMS with RTP-based DSM has been utilized to minimize electricity cost and improve energy efficiency [178].

3.4.2. Industrial consumers

DSM could be implemented in industries where it contains time-insensitive processes. In [179], peak load has been decreased by 19% and the electricity cost has been reduced by 4% due to the shifting of spinning process in the cotton mill from 08:00 to 09:00 h. In [180], the air separation plant has been implemented with a ToU-based tariff. The peak load of the plant has been reduced which in turn reduced the electricity cost of the plant [180]. In [181], the food and plastic sector have been considered as the smart consumers where the electricity cost has been reduced by scheduling the heating, cooling and air conditioning loads.

3.4.3. Commercial consumers

Energy management in the commercial sector has been limited to thermal storage scheduling in [182]. In [183], peak load reduction and CO_2 emission reduction have been obtained by scheduling the thermal storage and thermal loads. Capital cost has been insisted as a barrier to implement the DSM in commercial buildings [184]. In [185], the energy trading between two prosumers has been achieved a cost savings of 4.9%. The detailed literature survey based on energy management with different kinds of consumers has been critically discussed in Table 2.

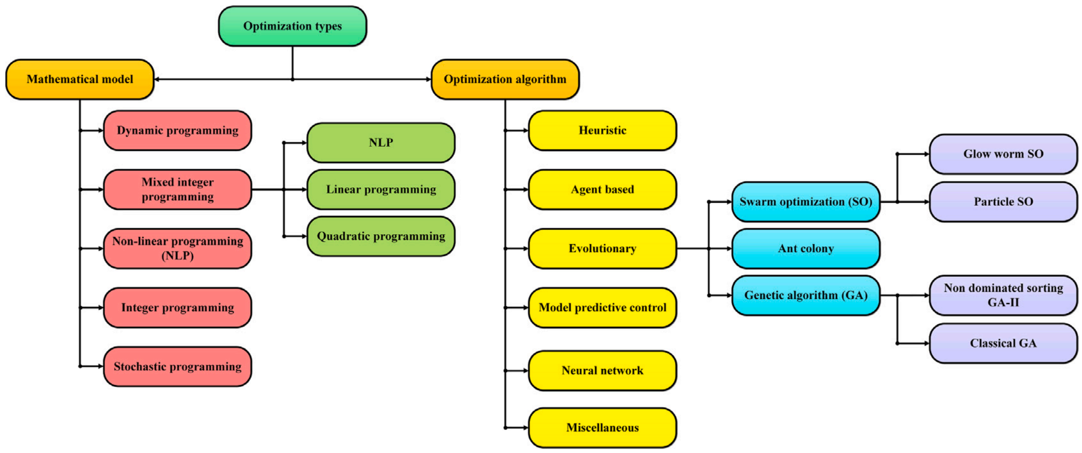

Fig. 7. Classification of optimization techniques.

3.5. Soft computing techniques for DSM

The optimal solution of DSM can be achieved effectively by implementing the soft computing techniques. The mathematical models for selecting the objectives based on the appropriate application have been discussed [186]. Also, the different algorithms with mathematical and behavioral modeling have been examined for various applications in [186]. The different types of optimization techniques used for solving the objective function as shown in Fig. 7. Optimization problems are classified into mathematical modeling and application of optimization algorithm. The mathematical modeling is categorized based on the type of objective function whereas optimization algorithms are classified based on the inspiration from the environment to explore and exploit. The objective of the DSM mainly focuses on the minimization of PAR, minimization of cost, maximization of social-welfare, minimization of emissions and minimization of losses [187]. In [187], optimization-based residential energy management has been compared with in-HEMS. The different DR programs and the application of artificial intelligence, neural network and ML in the DR techniques have been reviewed in [188]. The DSM was implemented with artificial intelligence-based elitist non-dominated sorting GA II resulted in a cost-saving of 51.4% when including the DG and battery in [189].

Based on the application, constraints and complexity of the microgrid, a suitable mathematical model can be selected. The major classification of the model includes linear and non-linear programming [190]. The minimization of electricity bills and consumer discomfort have been focussed in [190]. Linear programming can be further divided into Integer Linear Programming (ILP) and MILP. ILP for efficient energy management of the integrated operation of microgrid networks [190, 191]. In [192], a two-phase planning model was framed with MILP for optimal operation of DG. The DSM for a grid-connected residential consumer having the own PV energy generation has been presented in [193]. The scheduling for cost minimization has been done with the help of dynamic programming.

Heuristic algorithms are widely employed where the approximate solutions required whereas the finding of exact solutions requires more time and computationally expensive [194]. Meta-heuristics have been utilized to overcome the drawback of the heuristic approach like to attain the difficulty of local optima. The most commonly used meta-heuristic algorithm for DSM is the Genetic Algorithm (GA) that solves the problem through the concept of chromosomes. GA has been utilized to obtain optimal economic operation of the system in two stages. Gujranwala electric power company located in the hub of an industrial and commercial zone that suffers from a huge supply–demand gap have been considered in [195] with neural network for scheduling. The objectives were framed to reduce the supply–demand gap, minimize the black-outs, increasing efficiency, increasing revenue, enhanced reliability and consumer trust/satisfaction without huge investment and wastage of time [195]. Model predictive control implementation on building owners, energy managers or energy-saving companies has been increased both energy savings and occupant's comfort [196]. Also, the developed method reduces the user‘s complaints and energy bills. In [142], a test system with six household appliances with the PSO technique has been utilized for demand shifting from peak-hour to off-peak hour. The recently developed nature-inspired optimization algorithms for DSM implementation have been critically discussed in Table 5.

A two-stage DR scheduling was developed in [207] for increasing the cost savings and improving the system performance. The developed real-time framework was proved efficient for improving the performance where customers can participate in different DR schemes. It has also predicted and secured the system from dishonest entities using ML. The ML methods such as Q-learning, DL, RL and DRL have been widely suggested for DSM implementation in microgrid. Table 6 critically discussed the application of different ML techniques in DSM implementation.

3.6. DSM in India

In India, the DSM initiative was taken by implementing the energy efficiency measures in residential consumers under control of the Bureau of Energy Efficiency (BEE). BEE has framed the plans and policies to implement the utility-driven DSM. In [215], the DSM programs in India have been critically reviewed and compared with the DSM programs in UK and USA. Also, the barriers to the implementation of DSM have been discussed and the necessity for institutional frameworks in DSM implementation was insisted in [215]. The DSM is further extended by implementing the Time of Day (ToD) tariffs for industrial consumers by State Electricity Regulatory Commission (SERC) [216]. Each state in India follows its own tariff. Table 7 provides the ToD tariff implemented in different states of India. In 2016, the Government of India amended the tariff policy to promote DSM by providing the initiatives to the consumers. In 2017, the SERCs has initiated to implement/install smart meters for consumers having consumption of greater than 500 kWh and consumers with greater than 200 kWh consumption at the end of 2019 [216]. Also, the Government of India encourages the SERCs to consider the renewable energy plants installation at the consumer end.

India's first large-scale DSM program was initiated in southern and western Delhi by Bombay suburban Electric supply Rajdhani power limited and oracle utilities (Opower) with the support of United States trade and development agency. For this program, 2.6 lakh consumers were selected from 10 different districts where the overloaded occur in

Table 5
Optimization algorithms used for the implementation of DSM.

Ref No	Optimization algorithm used	Objective	DR program	Description	Inference
[197]	GA	Minimize the electricity cost and peak load	RTP	Appliances scheduled using GA to minimize the electricity cost to 29% and peak load reduction of 36.2% as compared with loop search algorithm	Thermostatically controllable loads were not included in the scheduling
[198]	Real coded GA	Minimize the peak load, maximize the profit of power producer	RTP	Power demand has reduced and profit of power producer & load factor has increased which tends to flatten the load profile	Consumer preference and response were not considered
[199]	Grasshopper optimization algorithm	Minimize the generating and operational costs of microgrid	Dynamic pricing	The profit of the microgrid has been improved by scheduling the resources. The algorithm has been proved to be comparatively effective than whale optimization and cuttlefish algorithm	Load shifting was not considered which may further improve the cost savings
[200]	Bat genetic algorithm	Minimize the electricity cost, PAR and appliance delay time	ToU	The Bat GA has been proved to be efficient than GA and Bat algorithm	Minimization of cost but increased the delay time. Suggested DSM model was not achieved both minimization of cost and delay time at the same time
[201]	Hybrid genetic and pigeon inspired optimization algorithm	Minimize the peak load, PAR and electricity cost	RTP	The hybrid genetic and pigeon inspired algorithm has achieved the most optimal cost for different operational time intervals than GA and pigeon inspired algorithm	Minimization of cost but increased the waiting time which in turn affects the user comfort
[202]	Hybrid elephant and firefly optimization	Minimize the electricity cost and maximize the user comfort	RTP, ToU and CPP	Developed hybrid algorithm has achieved the optimal electricity cost and waiting time than the elephant herding algorithm and firefly optimization algorithm. In particular, RTP was proved to be best in minimizing the cost whereas CPP was proved to minimize the waiting time	Limited appliances were considered and consumer comfort was sacrificed
[203]	Bacterial foraging and Flower pollination algorithm	Minimize the electricity cost and PAR	CPP	This work has achieved with minimum waiting time by utilizing the hybrid bacterial foraging and flower pollination algorithm	Limited number of appliances were considered as schedulable while most of the appliances were categorized as non-interruptible and unschedulable
[204]	Adaptive moth flame optimization	Minimize the peak load and operational cost	DLC	The developed DSM program has achieved the cost minimization and peak load reduction in residential, industrial and commercial consumers where the residential consumers has benefited more than other two consumers	Moth flame algorithm has not achieved the cost minimization as compared with PSO algorithm
[205]	Hybrid genetic ant colony optimization algorithm	Minimize electricity cost, carbon emission, and peak load	RTP	The efficacy of the developed DSM model has been proved by comparing the results with GA, WDO, teaching learning based algorithm, teaching learning genetic algorithm.	Appliances were very limited and centralized controller could be replaced with distributed controller
[206]	Modified grey wolf optimization algorithm	Minimize the electricity cost	ToU	Uncertainty on cooling, heating, wind speed, solar irradiation and the energy carriers prices has been included	Appliances other than thermal loads were not considered

Table 6
Application of machine learning in DSM implementation.

Ref No	Data science methods	Application	Consumer	Objectives	Optimization model	Description	Outcome	Inference
[208]	Supervised ML	Load shifting	Residential	Minimize the electricity cost	Predictive optimization model	Thermal energy storage has been scheduled to minimize the electrical energy consumption. The efficacy of developed model has been proved with mean absolute error and root mean square error	Achieved 40% of cost minimization and 39% of carbon emission reduction	Appliances other heating/cooling loads not considered
[209]	Resilient ML	Energy conservation with improved security to prevent dishonest entities	Residential	Minimize the electricity consumption	Predictive model with Naïve Bayes algorithms	The developed IoT has enabled ML provided the secure communication with resilient agent	Predicted secure communication correctly — 96%, Predicted insecure communication correctly — 93%, Wrongly predicted as secure communication — 4% and wrongly predicted as insecure — 7%	Limited appliances has considered (only four)
[210]	Supervised ML	Load forecasting	High-rise office building	Minimize the peak load	Data-driven learning algorithm	The accuracy of demand prediction performance has achieved with minimum historical data	Peak load has reduced by 21.9%, normalized mean bias error >10% and root mean square error >30%	Thermal loads of the building were alone considered. Appliances load pattern was not considered
[211]	RL	Peak shifting	Residential	Minimize the peak load and electricity cost	Q-learning with Markov decisive process	The EV SoC has been maintained along with the load shifting	Total electricity cost has reduced by 20% and peak load has reduced by 24%	Limited appliances were considered as controllable loads and data dimensionality is a major drawback of RL
[172]	RL	Load forecasting	Residential	Minimize the peak demand	W-learning	RL has been utilized to forecast the load pattern and EV usage to implement peak shifting	EV peak charging has reduced by 33%	Forecasting errors and uncertainities were not considered
[212]	RL with time delay	Energy conservation	Isolated microgrid	Minimize the load consumption	ANN	RL has been utilized to minimize the power consumed by electric water heaters in microgrid	Average energy consumption by electric water heaters has reduced by 8.91%	Appliances other than water heater were not considered
[213]	DL	Load and generation forecasting	Pennsylvania-New Jersey-Maryland microgrid	Minimize the forecasting errors	Recurrent neural network	Solar PV & wind power generation and load pattern has been forecasted with stacked long short-term memory to implement DSM	Mean absolute error, root mean square error and mean absolute percentage error are obtained as 0.021, 0.36 and 0.95 respectively	Load shifting was not considered. Performance has to be improved with implementation of energy trading
[170]	DRL	Load and generation forecasting	Distribution network	Minimize the forecasting errors	Deep neural network	Deep Q-network has been utilized to improve the privacy	Error distributions for 2%, 4%, 6%, 8% & 10% are obtained as 0, 0, 0.61%, 0.98%, & 1.28% respectively.	Impact of interaction between distribution companies and DR aggregators on privacy was not analyzed

(continued on next page)

Table 6 (*continued*).

Ref No	Data science methods	Application	Consumer	Objectives	Optimization model	Description	Outcome	Inference
[171]	DRL	Peak shifting	Residential	Minimize the peak load and maximize the cost savings	ANN	DRL algorithm has been utilized to reduce energy consumption by optimizing the usage of PV energy production	Cost savings has achieved by 16% and 10.2% of peak load shifting has done	Thermal loads were alone considered. Privacy issues were not addressed
[214]	DRL	Peak shifting	Residential	Minimize the peak load	Deep deterministic policy gradient	DRL with disappoint coefficient and penalty coefficient has been considered to improve the performance in load shifting.	Disappoint coefficient was obtained as 0.62 which is the loss due to failure of task. Penalty coefficient has zero which indicates no penalty for DSM violation	Impact of security and privacy issues were not addressed

Delhi [217]. They were randomly divided into two groups based on the information exchange. Two lakh consumers receiving the home energy report from the first group whereas the second group of sixty thousand consumers did not receive the home energy report [217]. Based on the communication mode, the consumers with home energy reports were further classified into three groups such as a paper-based report, web/communication and email-based communication. The program encourages the SERCs of remaining states in India to implement the same kind of programs in their own states. Section 4 includes the contribution of ESS in the DSM implementation. Section 4.1 explains the part of EV as a storage device in DSM. Section 4.2 discusses the necessity of BESS in the implementation of DSM in the microgrid.

4. Peak shifting based on Electric Vehicles and Battery energy storage system

4.1. Electric Vehicles

International energy agency in [218] stated that "Electric vehicles can save more energy than they use". It has indicated the various benefits of EV in both economical and environmental aspects [218]. The different types of fuel cells and their features, storage elements (batteries or fuel cells), configurations, energy management and scheduling have been critically reviewed analyzed in [219]. The Fuel cell-based EV has been suggested as a future EV that controls the emission rate and considerably long driving range [219]. The components and controls associated with the EV have been discussed in [220]. It has also stated that the performance of EV could be better by focusing on the streamlined maintenance management [220]. By optimizing the charging cycles of an electric car using DSM the peak shifting could be obtained. The EV with its charging flexibility has been used for DSM in [221]. Sliding mode control has been used to balance the supply–demand gap despite the uncertainties. The limitations of the EVs have been addressed in [222] and provided the solution to slow down the battery degradation using the efficient charging method. It has also discussed the impact of EVs in high renewable energy penetration regions on supporting the grid.

EVs have been effectively used with RES to achieve various factors such as financial savings, reduction in the demand of thermal generation plant, peak-load reduction and increasing the demand on the renewable sources in [223]. From the results, it was evident that significant gains can be achieved without any further technological advents [223]. An optimization-based model has been presented in [224] to perform the load shifting and congestion management in smart grids during peak hours. Agents called EV aggregators have been suggested to control the charging/discharging of EVs based on the analysis of the Vehicle to Grid (V2G) capabilities [224]. The above conditions have been implemented in a test system based on the IEEE 37-bus distribution grid and the results were proved the effectiveness of the approach on flattening the load curve [224]. In [225], the power interaction between EV and the grid has been presented. A framework for V2G has been suggested to support the bidirectional power flow. It has also discussed the role of plugged-in EV aggregators, different modes of interconnection and the intelligent communication link.

Charging/discharging strategy to control the scheduling of driving pattern has been presented in [226]. EVs at the same bus of a radial distribution system were allowed to charge or discharge at the workplace or home during off-peak hours and peak hours respectively. A multi-objective multiverse optimization algorithm has been applied to decide the number of EVs and the bus at which they must be connected. It was observed that the impact of charging/discharging of EVs was reduced, the cost of electricity was minimum for the users and PAR reduced on the utility side [226]. G2V and vehicle to building have utilized a battery of the EV to supply the required local load in [227]. It has considered two different EVs: Chevy Volt a plugged-in EV model and Nissan Leaf a battery EV model. The performance has been analyzed for six different drive cycles. The load shifting and peak load shaving reduced the peak-load and total energy consumption which reduce the electricity purchase cost for the customer and vehicle owner [227]. A battery swapping station has been presented as an alternative solution for the charging station in [228]. It has been used to manage both high penetration of variable RES and real-time EV charging using the flexible energy storage with DR [228]. Battery swapping station has been used for the smart community microgrid and proved to be more economical.

4.2. Battery energy storage system

In electricity storage technologies, batteries have been widely used at small and medium scales due to their relatively high energy density, lack of geographic constraints, low noise levels, and low maintenance requirements [229]. It is used for obtaining the DSM of peak shifting. Various literature has presented that batteries as effective DR technology. Considering the secondary substation level of the UK electricity distribution, the storage installed at the scale of 1 kWh per house [229] provides the maximum peak demand reduction at a scale of 0.5 kW. Self-consumption of the residential PV, storage units has been presented to compensate for the peak demand in [230]. It is suggested to utilize a community energy storage unit instead of separate storage units in houses [230]. The increment in profit by changing from individual to shared electricity meter in the community obtained was 23% [230].

Table 7
ToD tariff in different states of India.

States	Peak		Off-peak	
	Duration	Tariff	Duration	Tariff
Tamilnadu	6 h to 9 h and 18 h to 21 h	120% of normal charge	22 h to 5 h	95% of normal charge
Andhra pradesh	10 h to 14 h	(Normal charge + 0.75) Rs /kwh	22 h to 6 h	(Normal charge - 1) in Rs /kwh
	18 h to 22 h	(Normal charge + 1) Rs /kwh		
Delhi	14 h to 17 h and 22 h to 1 h	120% of normal charge	4 h to 10 h	80% from normal charge
Karnataka	6 h to 10 h and 18 h to 22 h	(Normal charge + 1) Rs /kwh	22 h to 6 h	(Normal charge - 1) in Rs /kwh
Gujarat	12 h to 17 h and 18.30 h to 21.30 hrs (April to october)	(Normal charge + 0.8) Rs /kwh (up to 300 kW (Normal charge+1) Rs/ kwh (above 300 kW)	22 h to 6 h	(Normal charge −0.3) in Rs /kwh
	8 h to 12 h and 18 h to 22 hrs (November to march)			
Jharkhand	6 h to 10 h and 18 h to 22 h	120% of normal charge	22 h to 6 h	85% from normal charge
Haryana	5.30 h to 8 h and 17.30 h to 22 h	(Normal charge+2) Rs./kwh (up to 30% average consumption) (Normal charge+4) Rs./kwh (above 30% of average daily load)	22 h to 5.30 h	75% of normal charge for 20% of average daily consumption
Maharashtra	9 h to 12 h	(Normal charge+0.8) Rs./kwh (Maharashtra State Electricity Distribution Company Limited (MSEDL))	22 h to 6 h	(Normal charge-1) in Rs./kwh (MSEDL)
		(Normal charge+0.5) Rs./kwh (Other DIStribution COMpanies (DISCOM))		
	18 h to 22 h	(Normal charge+1.1) Rs./kwh (MSEDL)		(Normal charge+0.75) in Rs./kwh (Other DISCOM)
		(Normal charge+1) Rs./kwh (Other DISCOM)		

For different regions of Canada, the battery sizing have been done to obtain the peak demand reduction in [231]. Peak demand reductions between 42% and 49% have been achieved for all Canadian regions except Quebec [231]. These reductions have been achieved when a BESS was installed with an energy capacity of 5 kWh in the Atlantic, Prairies, and BC regions, and an 8 kWh capacity in Ontario [231]. But the peak reduction in Quebec was only 28% because the house in Quebec requires a BESS capacity of 22 kWh [231]. Hence the peak demand reduction in this region is ineffective with BESS .

Grey Wolf Optimization (GWO) has been used for optimally locating the energy storage in [232]. It has considered a 34 bus test system with wind power generation and battery [232]. As a result of implementing the GWO, the minimum battery size required has been calculated and the loss minimization has been improved when compared to the GA by peak shaving at the optimal locations [232]. Optimal charging/discharging regime significantly reduced the electricity bill of the home installed with BESS and PV system [233]. The annual electricity bill has been decreased by 58.65% [233]. Linear programming based optimal sizing of the BESS have been modeled based on the local demand and billing scheme in [234]. It was described that the peak shaving technique could reduce the payback period, return of investment and battery aging of the system in industrial customers [234].

The concept of mobile BESS has been presented in [235] and its performance has been compared with static BESS. The mobile BESS has been improved the economic and reliability efficiency of the system. During the peak season, a mobile BESS can be connected to a peak demand area to balance the demand and renewable energy whereas during the off-peak season the mobile BESS could be moved to another area where the peak-load exist [235]. The scheduling has been made with ANN and proved that the cost savings is maximum. The different ESS such as batteries, fuel cells, electrochemical capacitors or supercapacitors including their advantages, disadvantages and limitations have been discussed in [236]. As a consequence, the different types of EVs could be combined to achieve high efficiency and sustainability [236]. This approach could be effective and more appropriate to reduce energy losses, costs, environmental impacts and health concerns. Section 5 elaborates the advancement in communication, metering and data handling for DSM implementation in the microgrid.

5. Application of Advanced Metering Infrastructure (AMI) and communication technologies in DSM

5.1. Communication and data handling

The advanced technologies in communication, data handling and metering reduces the complexity of DSM implementation in microgrids. IoT and google firebase cloud had developed for the implementation of DSM in residential consumers [237]. The load pattern data had uploaded to the web portal in terms of voltage, current, power and energy that could be downloaded and used for DSM implementation. Open access of the load pattern data is insecure and often possess intrusions. In order to make the DSM more secure and flexible, the ML for the IoT enabled home area network has been suggested in [209]. The real-time problems on data handling have been critically reviewed in [238]. Fog and edge computing has been suggested as the energy efficient methods with the minimum number of data transmissions in [238]. The ToU tariff-based DSM has been implemented using IoT technology with Wi-Fi network connectivity [239]. IBR tariff has been included along with ToU for peak shifting to minimize the electricity cost in both summer and non-summer seasons. Cloud storage-based edge analytics has been utilized for IoT-enabled smart homes to minimize the electricity cost [240].

The energy sector handles a bulk quantity of data such as consumer energy consumption, weather and data from the geographic information center [241]. For DSM implementation in the microgrid, the data storage and handling has been done by big data analysis in [241]. Big data analysis implemented in a building automation system of Hong kong achieved balanced load scheduling despite the huge load dynamics in [242]. It has been utilized an unsupervised data mining technique to perform the operation by automatic knowledge recovery. In [243], big data has been implemented for commercial and residential energy building in the United States. The data collected from the consumers have been recorded and utilized for DSM implementation.

Blockchain is the most emerging technology for data handling in DSM implementation [244]. It has been proved that the real-time application of blockchain in DSM resulted in energy savings and load scheduling without manual operation. The blockchain has been utilized for peer-to-peer energy trading among the prosumers in [245]. The developed blockchain-based trading could encourage passive prosumers to involve in energy trading. Permissioned blockchain-based residential energy trading system has been implemented for a community with 8 homes in a Canadian microgrid [246]. Based on the test system result, it was evident that the peak demand has been reduced and the energy trading has provided the minimum electricity cost. In [247], the contribution of blockchain and artificial intelligence in different energy management processes has been analyzed. Secure data analytics, privacy, smart contracts, development cost and lack of standards & professionals have been given as a future scope for the researchers who works in the blockchain-based DSM implementation [247]. Ethereum-based blockchain has been utilized to implement the DR programs in [248]. Also, a distributed ledger has been recommended as the data storage for secure energy trading in [248]. The contribution of bigdata and blockchain in DSM implementation has been elaborately discussed in Table 8.

5.2. Advanced metering infrastructure

One of the major challenges in DSM implementation is the lack of metering infrastructure [279]. The necessity of smart meters and their privacy issues have been explained in detail [280]. The key issues were lack of data management facilities, lack of prioritizing the privacy for billing & other value-added services and lack of consideration of privacy in economic models. In [281], the lack of privacy-preserving schemes has been analyzed for secure communication between the consumer and utility. Based on the survey results, privacy has to be given importance in both data management and trading of electricity. Also, the cost of smart meters is a major concern. The implementation of smart meters in the consumer premises enhances the implementation of DSM to monitor the key performance indicators such as consumption pattern, savings target and power consumption. In [282], AMI protocol has been developed for improving the performance in terms of computation and communication. The features of AMI are monitoring and recording of energy usage that has been used for DSM implementation in [283].

In [284], the adaptive compression mechanism has been implemented in the smart meter to minimize the communicated data with the grid. It also facilitates the consumers to modify the load pattern using the load shifting technique. The adaptive compressing mechanism in the IoT-based DSM minimizes the burden on grid by compressing the data flow [284]. Smart Compact Energy Meter (SCEM) has been developed to implement DSM in commercial building energy management [285]. The developed SCEM has synchronized with IoT to communicate the demand & tariff, to monitor and control voltage, current, power factor, frequency & power. Also, SCEM notifies the power quality issues to the consumer by text messages. In [286], AMI has been utilized to implement price-based DSM. AMI has connected with the DISCOM & consumers to provide the necessary data to the energy management controller. The energy management controller has been implemented with hybrid bacterial foraging and PSO algorithm to minimize the electricity cost, PAR, CO_2 emissions and user discomfort [286]. The prepaid meters have been suggested to implement the DSM by utilizing the IoT in [287]. Advancements in smart meters and their application in DSM implementation have been elaborately discussed in Table 9. Section 6 deals with the impact of DSM implementation in the microgrid due to PQ issues.

6. PQ issues related to DSM

The major PQ issues on the DSM are voltage deviation, harmonic distortion and phase unbalance [305]. A test microgrid with American voltage levels has been considered and simulated to handle the PQ indices (voltage deviation, harmonic distortion, phase unbalance) along with the peak-load electricity cost reduction. The PQ improvement indices have been included in the optimization-based EMS algorithm as the constraints. This algorithm has been included the regulation loop between MILP optimization and harmonic load flows. The active and reactive powers have been included to show the changes in the magnitude of PQ-related parameters in MILP optimization [305]. The IEEE 1547-2003 standard recommends that a microgrid should not deviate voltage variations greater than ±5% around the nominal value [306]. The IEEE 1547.4.11 recommends that at least one DER should be responsible for regulating voltage and frequency in islanded mode while connecting in coordination with other loads and DERs. Also, the voltage unbalance factor is the measure of phase unbalance which must be lower than 3% at every node. Different standards on the %Total Harmonic Distortion(THD) of current and voltage have been addressed in [307]. In, the PQ parameters such as %THD of voltage and current, long-time flicker severity and power frequency have been discussed. A multilayer neural network as a tool for forecasting has been used in [308]. The PQ issues in DSM is illustrated in Fig. 8. From Fig. 8, it is evident that the voltage sag and swell are caused by the intermittent nature of DGs and the switching of loads. Switching on bulk loads at the same duration causes voltage sag whereas switching off bulk loads causes voltage swell. Similarly, bulk switching ON/OFF of similar kinds of loads at the same duration causes the PQ issues such as harmonics and power factor.

The utilization of CFL for improving energy efficiency leads to an increase in PQ problems [309]. The capacitive nature of CFLs has reduced the overall reactive power demand of the load and increased the system voltage. The implementation of plenty of CFLs in the system may reduce the %THD value which is closer to the 5% limit as per the IEEE 1459-2010 standard. Therefore, the performance is found to be better when compared to incandescent lamps. The true power factor of the aggregated load can reduce slightly which leads to reduce the power transfer. The PQ issues like voltage unbalance and harmonics have been created in the plug-in EVs where the EVs were not equally distributed to the phases during the charging period [310]. Therefore, the limit of negative voltage unbalance may exceed the rated value. It was suggested that only a three-phase charging can be used to avoid the above-mentioned drawback [310]. Also, the fifth-order harmonic voltage was slightly reduced by the EVs, but the penetration of EVs dominates the third-order harmonic emission [310]. The different PQ issues in microgrids and their causes have been examined in [311]. Table 10 represents the DSM impact on PQ. The PQ issues in the microgrid are mainly due to the switching of loads and DER [311]. The reconnection of loads creates both voltage variation (sag) and

Table 8
Contribution of big data and blockchain in DSM implementation.

Ref no	Objective	Consumers	Technology used	Contribution of technology	Data	Privacy issues	Inference
[249]	Improve the thermal comfort of consumer, minimize the energy consumption, PAR and carbon dioxide	Residential	Blockchain	Probability of the next hour	Load pattern, initial values and boundary conditions	Privacy settings can be modified by individual consumers through permissioned private blockchain	Limited number of appliances were considered and DGs were not considered
[250]	Flatten the load curve	EV charging network	Blockchain	Peer-to-peer energy trading	Availability of sustainable energy, load pattern, incentives for load shifting	Permissioned blockchain enhances the privacy of the network	Modeling based on uncertainities were not considered
[251]	Eliminate the third party-based system operator	–	Ethereum based blockchain	Energytrading	DG and load power data, storage devices availability	Due to the elimination of third party interference, the privacy is enhanced	Modeling has not been done for consumer specific
[252]	Minimize electricity cost, emission cost and PAR	Smart microgrid	IoT	ToU based DR	Availability of DGs, battery & EV and load pattern	–	Privacy issues with data sharing and handling has not been addressed
[253]	Maximize the welfare of EVs	Plug-in hybrid EV	Consortium blockchain	Double auction mechanism based trading	Battery data, cost for accessing charging lots, Welfare due to V2G and electricity consumption pattern	Consortium blockchain enhances the privacy and security of data	Execution time is large
[254]	Minimize PAR, flatten the load profile and maximize the welfare of consumer & system	Residential, industrial and commercial	Blockchain	Decentralized DSM for peer-to-peer energy trading	Solar, wind, battery & EV powers, Demand profile and tariff details	Privacy against the end users data accessibility	Limited privacy due to the sharing of data only with central control center
[255]	Improve bidding efficiency and social welfare	Buyers and sellers of energy market	Decentralized blockchain	Maintaining the energy contract based on the request from buyers and sellers	Historical data of load pattern and power generation	Using historical data for real-time transactions enhance privacy of the network	Existence of forecasting errors
[256]	Prevent electricity theft and mitigate false data injection attacks	Prosumers	Electron volt exchange blockchain	Implementation of hyper ledger fabric	Bidding value and data from grid sensors	Distributed protocol of electron volt exchange has improved the privacy of the energy market	Contract on energy market was not considered
[257]	Increase the efficiency and security of energy market	Buyers and sellers of energy market	Decentralized blockchain on consortium ethereum network	Implementation of double auction with reduced blockchain overhead cost	Quantity, price and market identification number of consumption bid and generation bid	–	Competitive market based on prosumers has not considered
[258]	Minimize the electricity cost and flatten the load pattern	Residential, industrial and commercial	Blockchain	Decentralized identifier has been utilized as a digital identity for accessing blockchain	Availability of DG power and load profile, battery & fuelcell data of consumers	Digital identity has enhanced the system to identify the suspicious data	Real-time implementation requires the cloud computing and large system with huge number of participants
[259]	Minimize electrical energy consumption and maintain supply–demand balance	Smartgrid	Blockchain, IoT	Blockchain based distributed DSM	Data from smart meters, rewards or penalties and smart contract data	Privacy and anonymity has been improved with distributed environment	Prosumers have not been considered
[260]	Minimize the peak load and peak time stress on grid	Residential	Big data, and ML	ToU based DR	Tariff and electricity consumption data and the data collected from questionnaires	–	Impact of DGs and storage devices have not been considered
[261]	Minimize the sent data to electric power company with adaptive data compression	Residential	Big data, IoT with wireless sensor networks	Automatic energy management at consumer premises	Compressed data of demand and DG power availability as coefficients of cost function	–	Privacy and security issues on data compression and extraction have not been considered
[262]	Minimize the peak load	Residential, industrial and commercial consumers in DC microgrid	Blockchain	Implement power sharing between energy storage devices and consumers through bidirectional converters with fuzzy logic controller	Load demand, availability of power from energy storage device, tariffs and incentives	–	Privacy issues have not been considered and impact of uncertainites on demand have not considered
[263]	Minimize the electricity cost by scheduling the demand on most economical generating unit	Community microgrid	Blockchain	Blockchain allows the autonomous monitoring and billing through smart contracts	Historical data of demand and DG power for forecasting	–	Controllable appliances are much limited
[264]	Minimize the non-technical losses	Distribution system	Data mining	Data mining has been utilized to detect the non-technical losses	Power consumption data of individual consumers connected in the distribution network	–	Consumers with large range of consumption alone were considered which affects the accuracy of developed model
[265]	Minimize the energy consumption, cost & peak load and improve power quality	Residential consumers of islanded village with solar microgrid	Data logger	Data logger records the data and communicated it to the laptop or personal computer	Load pattern, PV power availability and battery data	–	The increasing the village size and its total consumption creates major impact in the reliability of the system

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Table 8 (*continued*).

Ref no	Objective	Consumers	Technology used	Contribution of technology	Data	Privacy issues	Inference
[266]	Minimize the load shedding or blockout by load shifting	Nanogrid	Cloud storage	The undervoltage and overvoltage relays have sent the load shedding signal to the consumers incase of extremely high peak loads. The consumers shift the loads to off-peak hour to avoid blackout	Voltage, frequency, power generation and load demand	The developed model affects the privacy of consumer as the information on the load pattern has been shared in cloud storage	Privacy and user comfort has been neglected
[267]	Maximize the profitability & consumer satisfaction and minimize the environmental impacts	Residential consumers	Blockchain	Public blockchain allows the consumers to verify or add the data which are validated by public key cryptography.	Dynamic pricing, DR signal, Energy profile, new schedule	Public blockchain with distributed control has provided limited privacy on data access to registered participants	Appliance scheduling not considered. Also DGs on consumer premises not included. Accessibility of data editing affects the security
[268]	Improve the accuracy of big data in DR	Residential consumers	Big data	DR has been implemented based on time and price	Population, appliances, living habits, income distribution and point of view on energy conservation of household	Privacy issues has existed due to sharing of huge information of household	The privacy and security issues have not been addressed
[269]	Minimize the peak load	Smartgrid	Big data	National virtual power plant platform enhanced with big data monitor and record the energy consumption data for automated DR	Power availability, demand, energy loss	–	The developed model has not been application specific and privacy & security issues has not been discussed
[270]	Minimize the peak load and improve the cost savings	Both small and large scale consumers	Big data	It has been utilized to minimize the peak load than forecasted peak load	Smart meter data and utility data	–	Privacy and security on data have not been considered. Computational complexity increases with increase in the size of system
[271]	Maximize the social welfare	Residential, commercial and industrial	Blockchain	Energy trading has been scheduled based on iterative double auction	Electricity consumption, solar power generation and trading cost	–	Privacy issues not addressed. Also, the scheduling of appliances not included
[272]	Minimize the cost and peak load	Small and medium range of consumers	Ethereum private blockchain	Private blockchain carried out the double auction without minimum data transfer through public blockchain	Power generation, demand, bidding values, final market price	Restricted data to the public blockchain has enhanced private blockchain	Transmission capacity and voltage constraints were not considered
[273]	Minimize the processing speed of big data	–	Big data	Fuzzy C-mean clustering has been used in power big data to fasten the DSM in daily load curve	Load pattern of consumers, Peak & off-peak durations, ToU tariff	–	Application specific issues has not been addressed
[274]	Forecast the load and generation using ML prediction model for DSM	Residential	Data mining	Based on the historical data from data mining, the load and generation has been forecasted with minimum mean squared error	Historical data of load pattern and power generation	–	Privacy issues were not addressed. HVAC loads alone were considered
[275]	Improve the security of DSM implementation in industrial IoT	Industrial and residential	Big data with IoT	Payload authentication framework with constrained application protocol improved the security and reliability of datafile	Load pattern	–	Third party tool known as Apache Spark has been used for data processing which affects the privacy of the consumer
[276]	Minimize the PAR	Consumers with EV	Big data and cloud computing	Data collection and processing for the implementation of DSM	Peak, off-peak durations & tariff and EV charging/discharging schedule	–	Load scheduling has not considered.
[277]	Minimize the electricity cost by remote monitoring and control of smart appliances	Smart home	Edge analytics	Embedded flexible edge analytics has been utilized to monitor and shift the electrical appliances operation from peak hour to off-peak hour	Data from sensors in the appliances, load pattern, status of actuators and controllers, power availability and battery status	–	Impact of DG in smart home were not considered. Complete load profile has been recorded but the privacy and security issues has not been addressed
[278]	Improve the preventive maintenance of DSM	Industrial, commercial and residential	Cloud analytics	Load shedding during peak duration has been efficiently prevented with historical data	Load pattern and peak load duration	–	Uncertainities and forecasting has not been considered.

Table 9
Advanced metering infrastructure for DSM implementation.

Ref No	Objective	Description	Technology/model	Communication	Advantages	Limitations
[288]	Reducing the deployment cost and prolonging network lifetime	Third generation partnership project technology has been utilized for communication with AMI which has reduced the cost and increase the lifetime	Narrow band IoT	Low power wide area network	With the existing communication networks, it is more robust and covered larger areas without high investment	Narrow band IoT utilizes cellular communication which is prone to natural and man-made disasters. It requires skilled personnel
[289]	Protection of information from cyber attacks	Light weight security solution has been suggested to communicate finger-print signal along with actual data	Blockchain	Low power wireless network	Secure and privacy enhanced data transfer and handling with no additional hardware requirement	Data provenance have tracked the origin of data rather than in between modifications. Therefore, data lineage might be a good alternate for Data provenance which tracks the flow of data from origin to the destination
[290]	Maximization of sum-rate to improve the communication efficiency	Cellular assisted device-to-device communication has been utilized for smart meters to cluster head. Wired communication has been used between cluster heads and meter data management unit	-	Cellular assisted device-to-device communication	The sum-rate has been improved by 25.3% than random algorithm.	The sum-rate has been reduced by 12.3% than linear random search
[28]	Improving the anonymity and untraceability of security in data transfer of AMI	Secure communication protocol has been developed based on random oracle model for data transfer between smart meters, AMI head end system and trusted authority	IoT	–	The security, anonymity, untraceability and performance of communication for AMI has been improved by random oracle model	Bits required for participant's identity, public/private keys, shared private keys, for hash values and time stamps have been assumed. Hence, the error due to the mismatch of assumed bit size and actual requirement affects the efficiency and performance of the model
[291]	Minimization of network traffic and improving the network performance	PLC has been utilized for the data transfer between the data concentrator and data storage	-	PLC	PLC has minimized the traffic on the network by 285.26 bits per second with negligible installation cost for communication link	Transmission lines for communication purpose injects noise signals on the data to be transferred. Therefore, it requires additional noise suppression devices.
[292]	Minimum cost of investment for AMI communication network	Cellular network has been utilized for the communication in AMI. The traffic on cellular network due to smart meters have been reduced by optimal choice of cellular base station with low traffic.	Scalable route map for wireless heterogeneous networks	Long term evolution cellular communication	Smart meters has communicated with the universal data aggregation points using existing cellular network	Utilization of the same network for mobile phone and smart meter is a short term planning. For long term usage, it requires the installation of additional base stations for network communication.
[293]	Detecting the fraudulent electricity access	Tunable fraud detection system has been utilized in AMI for detecting the ongoing fraud with short lived patterns. The optimization model have included the true or false alarms as a constraint. It has also included the maximization of revenue as an objective.	Short lived pattern model using fuzzy	–	The performance of short lived pattern has been proved to be efficient in detecting the fraud activities within short duration of time	Short lived patterns have designed the consumption pattern based on fewer sets of recent consumption data which may involve forecasting errors. Therefore, fault detection is a major limitation
[294]	Preventing the voltage collapse in the power system	When the SCADA detects any contingency activities in the power system, the event driven emergency DR program is initialized. The DR program is modeled as multi-objective optimization which controls the change in load pattern	SCADA	–	SCADA has centralized monitoring and control abilities which makes the process to implement in simple.	The centralized DR program implementation has a limitation that the process of optimal scheduling is complex due to the large network
[295]	Preventing the inference of privacy issues in sensitive loads	Privacy-utility trade-off algorithm has been developed for the secure data transfer between the smart meters and electrical utility companies			The developed algorithm has improved the privacy of smart meter data and insecure operation of sensitive appliances and permit the utility to track the load pattern of the smart home periodically.	The secure communication link has a major impact on the privacy of data transfer.
[296]	Improving the reliability and performance of communication in AMI	Grid topological routing has been utilized to select the optimal path for the data transfer between the smart meters and cluster heads	Grid topological router	–	The fault tolerance of developed routing model has been proved to be better than routing model for low-power & lousy networks and Ad-hoc networks	The response of grid topological routing during the uncertainities in network are less fault tolerant
[297]	Improving the computational efficiency and secure communication	The identity document-based authentication has been utilized for secure communication and access of power consumption data.	Identity document-based authentication	Neighborhood area network and wide area network	The developed model has enhanced the privacy on data between AMI and distributed system operator from cyber attacks.	The complexity of the model increases the size of the network

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Table 9 (*continued*).

Ref No	Objective	Description	Technology/model	Communication	Advantages	Limitations
[298]	Capacity estimation of network for resource allocation	Consumers having similar consumption pattern has formed into clusters and the consumption pattern for each cluster has optimally scheduled and communicated to the supplier	Data mining	–	The overall consumption at any time slot or peak load of the cluster has been reduced based on the developed model	The effectiveness of the developed model on load reduction is very minimum which requires additional load shifting action
[299]	Minimization of electricity cost, PAR, user discomfort and carbon dioxide emission	Hybrid bacterial foraging and particle swarm optimization (HBFPSO) algorithm has been utilized in energy management controller to achieve the objectives. It has implemented ToU tariff.	-	Wireless local area network	The developed model could be applied for residential, industrial and commercial sectors	RTP tariff has not been considered. Temperature dependent loads in all three sectors has not been scheduled by considering temperature as a constraint
[300]	Minimization of outage duration	The outage management system follows the steps of fault identification, fault location, consumer notification and service restoration	-	Narrow band and broad band PLC	Additional investment on communication lines has been avoided. Notification of outages to the consumer could enhance the energy management of consumers	PLC requires noise suppression to avoid the false alarm of outage to consumer and it has utilized 597 bytes for communication of data which is very large
[301]	Minimize the electricity cost	Collaborative filtering algorithm has been utilized for determining the most suitable tariff to minimize the cost	Cloud storage	Wide area network and home area network	Individual user has the choice of selecting the tariff	Optimal scheduling of load demand has not been considered
[284]	Monitor the electricity consumption and power quality	Adaptive data compression has been used to reduce the data size	IoT	Local area network	It supports the implementation of DSM and DSM could enhance the power quality	The DGs and storage devices has not been included. Also, dynamic pricing based DR has not been considered
[302]	Monitoring the DG power, building and home energy management	Solar PV and wind power data has been transferred and stored through Zigbee for DSM implementation	Zigbee	Wireless service network	Zigbee devices has been proved to be sufficient for high rise buildings and several urban homes. The developed energy management model has allocated the most economical source	Appliance scheduling has not been considered
[303]	Maximize energy savings and user comfort	Appliances, smart sensors and energy technologies have been monitored and controlled through Zigbee	Zigbee	Wireless service network	Ubiquitous home networks with zigbee devices are flexible, easy to implement and requires minimum cost	Limited number of appliances were considered and impact of DGs have not been included. Air conditioners should be modeled based on temperature
[304]	Minimization of peak load and distribution losses	The developed DSM model has evident to provide uninterruptible power supply to residential consumer during peak hour		Local area network and wide area network	The reliability of the system has improved	The developed model has concentrated on resource allocation than load pattern change

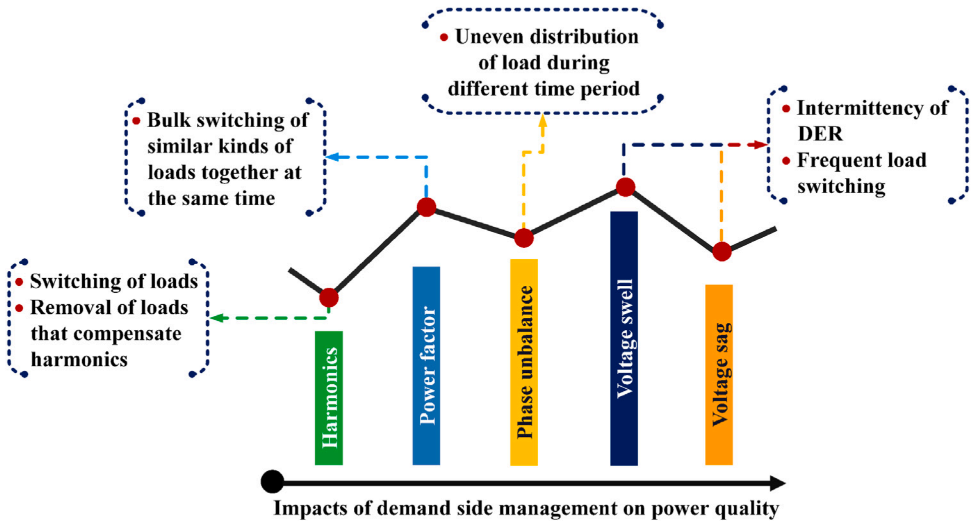

Fig. 8. Impacts of DSM on PQ.

harmonics. If the large resistive electric heating loads have disconnected, it would have reduced the damping which provides higher distortion levels. The damping can be increased by adding either the resistive part of passive filters or by means of the active filters. The impacts of micro-generation and the DSM on PQ (voltage fluctuation and unbalance) have been analyzed in [312] with a case study in a low voltage radial distribution network. It was proved that the voltage variations could not reach beyond the threshold values when the DSM strategy implemented in the system. Section 7 provides the research gap of the DSM implementation in the microgrid for future research. The DSM implementation could be utilized for improving the stability and reliability of the microgrid. The DSM has been achieved voltage control, frequency and the peak load reduction in [313]. In [314], reliability and voltage stability has been suggested to include while implementing the DSM programs. The different PQ issues such as voltage and frequency variations, reliability, stability and their improvement have been critically discussed in Table 10.

7. Future scope

DSM implementation in the microgrid has become popular in the last two decades but a few areas like energy storage, PQ issues, environmental issues, forecasting error, implementation of the latest technologies should be focused on for further development. The utilization of a hybrid storage system (both battery and EV) for the enhancement of BESS whereas the installation of a distributed ESS in the microgrid could be the best solution for the effective utilization of BESS. Fuel cell-based EVs could be utilized as an emission-free transport and also a storage device for DSM. Mobile BESS could be considered as common storage for microgrids that having different usage patterns instead of using a static BESS. Also, it could be incorporated in microgrids where the battery was kept idle for a longer duration. The impact of uncertainties of DGs could be considered for the resource allocation. The forecasting errors could be minimized by analyzing the mean absolute percent error of the on-site generation. The most commonly used on-site generations were PV and wind. Other DGs without uncertainty issues such as CHP and biomass-based power plants need to be considered for efficient resource allocation and load shifting.

Frequent switching of loads in DSM causes some PQ issues such as harmonics, power factor, voltage deviation in the microgrid. Such parameters could be added as a constraint of the optimization problem along with the power balance, storage and other constraints in order to overcome the above-said drawbacks. The voltage spring concept could be included in the implementation of DSM to avoid the voltage unbalance caused by the frequent switching of loads. Load shifting in industrial consumers and commercial consumers is much limited than residential consumers. Hence, industrial consumers and shiftable commercial appliances could be scheduled to reduce the peak load of the utility.

Online energy management controllers could be used for load forecasting and sizing of BESS. Real-time implementation of load shifting in residential consumer needs further advancements such as secure data storage with privacy enhanced data transfer. The implementation of advanced metering infrastructure is required for effective DSM implementation. Internet of Energy, blockchain technology, ML and big data analytics could be used for the real-time implementation of DSM. Market-based analysis should be done to improve the tariff structure. The real-time implementation of the price-based DR program requires certain modifications such as the inclusion of power factor and harmonic contribution of the consumer. Peer-to-peer energy trading could be implemented for a microgrid with prosumers to achieve economic energy sharing among the prosumers with minimum transmission losses. Privacy and security issues related to the data transfer, storage and handling requirements should be increased attention in real-time DSM implementation.

8. Conclusion

The review article has been discussed the different types of microgrid layers with different DSM implementations, economic and environmental behaviors of the microgrid while the implementation of DSM. Also, the article has been critically discussed with the recent trends in the different types of DR programs such as the IBDR program and price-based DR program. A detailed comparison has been made to select the appropriate DR technique for different applications, storage devices and DGs that are used in the microgrid. The overview of soft computing techniques has been discussed based on the mathematical model and optimization algorithms. The DSM implementation in India has been discussed with the ToD tariff for different states. The recent advancements in DSM and the impact of DSM in different PQ issues have been examined. As a result, this review article provides the useful insights to the future researchers who are seeking the DSM implementation in various aspects such as data science, energy storage and EV.

Table 10
Impact of DSM on PQ, stability and power flow issues.

Ref No	Key issues	Causes	DSM	Contribution	Benefits	Inference
[315]	PQ (Harmonics,Voltage unbalance, electromagnetic interference)	Electronic Adjustable Speed Drives (ASD)	Energy efficiency, peak demand reduction	Improvement in efficiency, minimizes the electricity consumption and cost	ASD with energy efficient motor have been used to obtain the cost savings in residential, commercial and industrial sectors	Investment on energy efficient motor is high and the respective cost minimization is very minimum
[316]	Voltage sag, harmonics	Insufficient var support, high short circuit currents, arc furnaces, ASD, PE devices	Energy conservation	Energy conservation measures reduce the total energy consumed during peak duration	Integration of power electronic controllers and communication with distribution automation to reduce the distribution and customer losses.	Energy conservation measures the consumer comfort and it is suitable only for industrial consumers
[317]	Voltage distortion, power factor, harmonics	Electronic ballast, ASD	Energy efficiency	Replacement of fluorescent lamp by CFL increases the energy savings	Impact of using CFLs for minimum energy consumption has achieved the harmonics mitigation and reduced the voltage distortion	It is not beneficial for consumers. Only utility get benefits in fuel savings
[318]	Voltage swell, harmonics	Grid integration of DG	On-site generation, DLC	On-site DG reduces the peak load	On-site generation has reduced the cost of transmission and distribution in addition to peak load reduction	Co-ordinated control is required to avoid the technical issues and strategies for implementing the DSM
[319]	Harmonics, power factor	Electronic ballast of fluorescent lamps	Energy efficiency	Replacement of conventional ballast with electronic ballast has reduced the energy consumption. The electronic ballast is modeled with high frequency resonant inverter	Power factor has improved and radio interference has reduced	High electromagnetic interference, high switching losses, large size and heavy weight
[320]	Reliability and uncertainty	Intermittency and uncertainity of DG	RTP	Optimal sizing of energy storage system with implementation of RTP-based DR has reduced the peak load and electricity cost	Microgrid with DG, DSM and sizing of ESS reduces the cost, improve the reliability by reducing the outages	Only reliability and uncertainty issues has addressed. Stability of the microgrid due to the renewable energy penetration was not considered
[321]	Reliability	Poor load pattern with high peaks and deep valleys	Peak shifting	Impact of DSM on the system reliability with operating consideration model.	Included the duty cycle, operating reserve policy, outage postponability and unit commitment policy as the constraints which enhanced reliability of the system	Energy recovery and load diversity was not considered
[322]	Power flow (reactive power)	Power shortage during peak duration	Load shedding	DSM quality index and DSM appreciation index has been utilized for analyzing the techno-economical benefits of peak shifting	DSM quality index monitor the existence of reactive power whereas DSM appreciation index monitor the cost savings due to the implementation of DSM which has enabled the control of both power quality and cost minimization	The developed model is only applicable for industrial consumers.
[323]	Reliability	Load forecast uncertainity	Peak shifting	Impact of load forecast uncertainity on peak shifting has reduced by improving the reliability indices such as loss of load expectation and loss of energy expectation	Implementation of load shifting with reliability analysis has reduced the peak load	Generation forecasting uncertainity was not considered

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Table 10 (*continued*).

Ref No	Key issues	Causes	DSM	Contribution	Benefits	Inference
[324]	Reliability	Power fluctuation of renewable energy generation	Peak shaving and valley filling	Flat load pattern has obtained by implementing DR programs based on availability of DG power and ESS	Reliability indices such as loss of load probability, loss of load expectation and expected energy not supplied has proved the effectiveness of DR program in achieving the flat load curve	Impact of DGs and their uncertainties were not considered
[313]	Stability	Load uncertainity	Frequency linked pricing	Storage devices at consumers premises has utilized to provide both active and reactive power support to distribution utility by paying the frequency linked pricing which improve the voltage stability	Real and reactive power support has improved the voltage stability and reduced the load shedding in the distribution network	Initial cost of investment is high (infrastructure cost). Success depends on the willingness of the consumer to participate in DSM program.
[325]	Power flow (Voltage and frequency control)	Uncertainity and intermittency of solar PV	Electric spring	Frequency and voltage control has achieved by injecting active power. d-q transformation has utilized for independent control of voltage & frequency at the distribution end.	Electric spring has enhanced the voltage and frequency control of microgrid to restore it to nominal rating within a short duration of time	Selectivity, zone of protection of relay affects the operation of electric spring were not considered
[326]	Stability	Uncertainity and intermittency of DG	On-site generation	PI controller with atom search optimization algorithm has utilized to maintain the stable with DSM implementation	BESS along with solar dish-stirling arrangement has reduced the peak load that consumed from utility and maintained the voltage stability	Computationally complex for larger microgrids
[327]	Power flow control	Fluctuations in frequency, voltage and power due to penetration of PV energy	On-site generation	On-site generation has reduced the peak demand and power fluctuations while including the battery and super capacitor bank	Droop control has been utilized for power flow control with grid integration of PV system and storage device	Transient performance with dynamic loads were not considered
[328]	Stability	Power shortage during peak duration	Adaptive load shedding and EDRP	Adaptive load shedding and EDRP has used to improve the stability of the system and minimize the frequency drop	Reduced power interruption and probability of failure in 39-bus distribution system has obtained by minimizing the convergence time and frequency drop	Load shedding affects the consumer comfort
[329]	Power flow control	Voltage instability due to high peak load	EDRP	Droop control with non sorting GA II has used for optimal power flow control with EDRP	Load factor has improved and Peak to valley difference has reduced	Transient performance with load dynamics were not considered. Flexibility of the optimal power flow with other DR programs were not addressed
[330]	Power flow control	Forecasting error of RES	RTP	Model predictive control has utilized to reduce the forecast errors.	Peak to valley difference, load fluctuation and total cost has reduced but the utilization of RES is increased to 100%	Impact of storage devices in uncertainity was not considered
[331]	Power flow control	Impact of load on radial and meshed distribution networks	Load shifting	Demand-responsive loads has used to maximize the network benefits by optimizing upstream network constraints and operating reserve	Minimized the electricity cost by maintaining the real and reactive power flow through load shifting from peak to off-peak hour	Operational constraints of load were not considered

Declaration of competing interest

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

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