

Article

A Comprehensive Review on Residential Demand Side Management Strategies in Smart Grid Environment

Sana Iqbal ¹ , Mohammad Sarfraz ¹ , Mohammad Ayyub ¹, Mohd Tariq ^{1,*} , Ripon K. Chakraborty ² , Michael J. Ryan ² and Basem Alamri ³ 

¹ Department of Electrical Engineering, ZHCET, Aligarh Muslim University, Aligarh 202002, India; sanaiqbal339@yahoo.com (S.I.); msarfraz@zhcet.ac.in (M.S.); mayyub09@gmail.com (M.A.)

² Capability Systems Centre, School of Engineering and Information Technology, University of New South Wales, Canberra, ACT 2612, Australia; r.chakraborty@adfa.edu.au (R.K.C.); mike.ryan@ieee.org (M.J.R.)

³ Department of Electrical Engineering, College of Engineering, Taif University, Taif 21944, Saudi Arabia; b.alamri@tu.edu.sa

* Correspondence: tariq.ee@zhcet.ac.in

Abstract: The ever increasing demand for electricity and the rapid increase in the number of automatic electrical appliances have posed a critical energy management challenge for both utilities and consumers. Substantial work has been reported on the Home Energy Management System (HEMS) but to the best of our knowledge, there is no single review highlighting all recent and past developments on Demand Side Management (DSM) and HEMS altogether. The purpose of each study is to raise user comfort, load scheduling, energy minimization, or economic dispatch problem. Researchers have proposed different soft computing and optimization techniques to address the challenge, but still it seems to be a pressing issue. This paper presents a comprehensive review of research on DSM strategies to identify the challenging perspectives for future study. We have described DSM strategies, their deployment and communication technologies. The application of soft computing techniques such as Fuzzy Logic (FL), Artificial Neural Network (ANN), and Evolutionary Computation (EC) is discussed to deal with energy consumption minimization and scheduling problems. Different optimization-based DSM approaches are also reviewed. We have also reviewed the practical aspects of DSM implementation for smart energy management.

Keywords: demand response; demand-side management; energy consumption optimization; energy efficiency; load scheduling; smart grid; smart home



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1. Introduction

The emerging era of the smart grid not only assists utilities in conserving energy, reducing cost, increasing grid transparency, sustainability and efficiency, but also has captivated consumer attention via Demand Side Management (DSM), which is an important aspect of the smart grid. However, the exponentially increasing demand for electricity at consumer premises is still a pressing issue for both utilities and consumers. According to the forecast by the National Institution for Transforming India (NITI) Ayog, the electricity demand in India for the residential sector is predicted to grow 6–13 times by the year 2047 [1]. Smart energy management refers to planning, monitoring, controlling, and optimizing energy through smart solutions or intelligent means whose ultimate objective is to maximize productivity and comfort on the one hand, and to minimize the energy cost and pollution on the other hand [2]. To achieve these objectives effectively, there is a need for the electric grid to transition from the traditional centralized version to one that uses smart technologies and is known as the smart grid [3]. A smart grid is an electricity network based on digital technology that has the provision for full-duplex communication, as well as bidirectional power flow between utilities and customers [4]. To ensure grid sustainability, the residential customers, as a part of electricity demand, must have a bet-

ter understanding and awareness of the evolving grid's worth. In India, the domestic sector accounts for 24.76% of the total electricity consumption in 2019 [5].

The smart home (utilizing home automation, or domotics), one of the key components of a smart grid, is a dwelling that serves the residents with security, healthcare, comfort, and remote control of the home appliances through smart technology [6,7]. Smart home energy management plays an important role in Demand Side Management (DSM), one of the aspects of the smart grid [8], which deals with controlling and optimizing the various smart home appliances according to the user needs and preferences to reduce the electricity consumption and therefore the cost, enhancing energy efficiency, and maintaining a clean and green environment [9]. Although various researchers have been working in this field for years in achieving said objectives, still there is a need for state-of-the-art technologies and developments to provide optimal solutions in maximizing user comfort levels and assisted living as well as energy consumption and wastage reduction. Figure 1 shows the block diagram of the energy management framework.

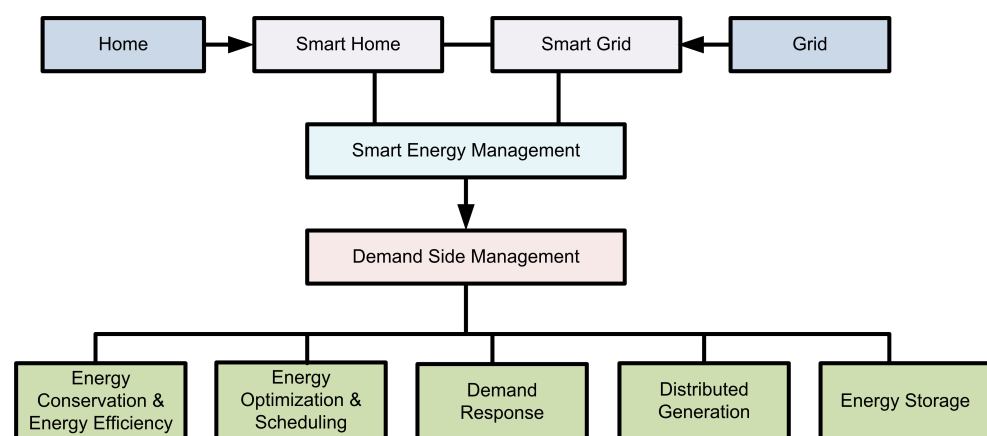


Figure 1. Energy management framework.

The main contributions of this paper are as follows:

1. Description of various DSM strategies.
2. Conduct of a comprehensive review of previous and current research works on DSM through soft computing and optimization techniques.
3. Proposal of new viewpoints and challenges for further research.

The rest of the paper is organized as follows: Section 2 describes DSM strategies. Section 3 addresses the hardware and communication technology in DSM. Section 4 provides the application of soft computing techniques for DSM. Section 5 discusses the optimization-based DSM approaches. Section 6 reviews DSM approaches and their hardware implementation. Section 7 discusses the challenges for future research. The paper is concluded in Section 8.

2. Demand Side Management

Demand Side Management is the planning, controlling, and execution that directly or indirectly influences the user-side demand of the electric meter. The DSM program reduces the energy costs of electricity, which in the long run will restrict the need for more capacity building transmission and distribution networks [10].

The significant objectives of demand-side management [11] are as follows:

1. Reduction in generation margin;
2. Improvement of the economic viability of the grid and its operating efficiency;
3. Improvement of the economic viability of the distribution network;
4. Maintenance of demand-supply balance with renewable;
5. Increasing the efficiency of the overall energy supply system.

Reducing the generation side peak demand is very expensive and according to a study done in [12], at least 10% of supply cost provides only 1% hours per year. To deal with such a challenge, DSM offers a cost-effective opportunity. DSM reduces the overall peak load demand by modifying the energy consumption pattern of the consumer that enhances the grid stability, which in turn reduces the energy consumption cost and carbon footprints [13,14]. Various DSM strategies (as shown in Figure 1) include—Energy Conservation and Energy Efficiency, Energy Consumption Optimization and Scheduling, Demand Response, Distributed Generation, and Energy Storage. Figure 2 illustrates the role of DSM strategies [15]. These roles include peak shaving, valley filling, strategic conservation, load shifting, and time-shifting. Peak shaving and valley filling are the direct load control techniques. Strategic conservation involves direct consumer-side demand reduction. Load shifting and time shifting shift the demand from peak hours to off-peak hours. Peak shaving is carried out through energy efficiency, incentive-based DR, and distributed generation, valley filling through price-based DR, strategic conservation through energy conservation and energy optimization, load shifting, and time-shifting through scheduling and energy storage, respectively.

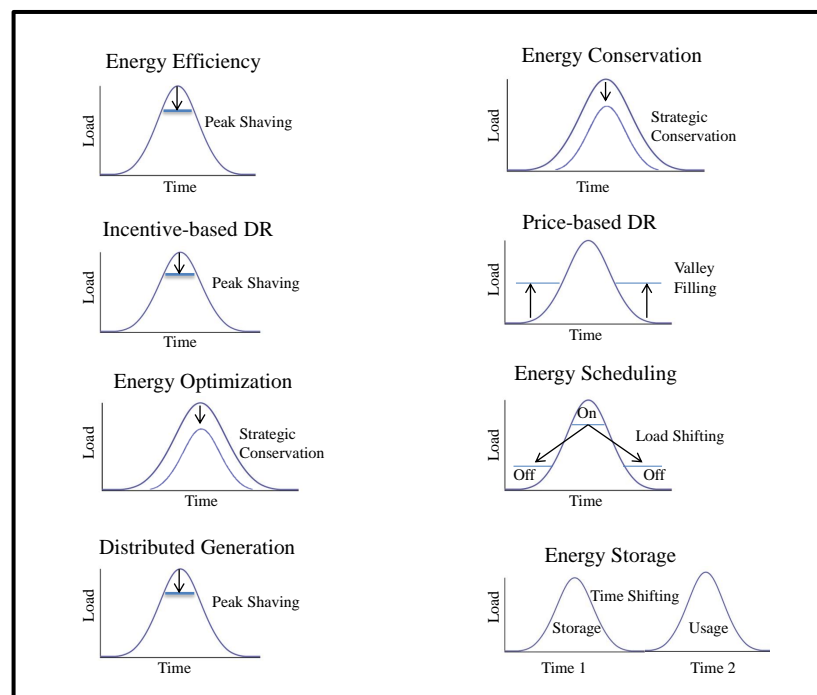


Figure 2. Role of DSM strategies.

2.1. Energy Conservation and Energy Efficiency

Energy conservation is at the heart of energy management that should be considered as a moral, religious, and societal duty. Both energy conservation and energy efficiency aim at saving energy and the environment, but with different methodologies. To clarify the subsequent confusion among consumers, we compared the two with examples in Table 1, which shows the basic differences between energy conservation and energy efficiency.

Table 1. Comparison between energy conservation and energy efficiency.

Attributes	Energy Conservation	Energy Efficiency
Meaning	Changing behavior or habits for using less energy	Using the technology that uses less energy
User-interaction	Yes	May or may not
Type of load	Traditional loads	Digital loads
User comfort	Compromise	Maximum
Examples	<ul style="list-style-type: none"> Switching off lights or fans when leaving the room Using natural day light Walking instead of driving 	<ul style="list-style-type: none"> Replacing incandescent bulbs with LEDs Using Solar panels Using Electric vehicles

The government of India has adopted certain approaches to maintain the consumer demand with the view to minimize carbon dioxide growth rate to protect citizens and environment from its hazardous effects [16]. These approaches include:

- Greater use of renewable energy sources.
- Shifting towards super-critical technologies for conventional power plants.
- Energy efficient innovative measures under the overall realm of the Energy Conservation Act 2001.

The Ministry of Power has implemented many energy efficient programs through the Bureau of Energy Efficiency (BEE) in the fields of household lighting, commercial buildings, standards, and product marketing, and demand-side management.

2.1.1. Energy Conservation and Energy Efficiency Programs

Is bold necessary? If not, we'd like to change them to normal. The following highlighted parts are the same. You can convert them to normal. Bold is not necessary.

- **Standards and Labeling programs**—To provide consumers with a choice regarding the energy-saving potential and thus the cost-saving potential of the related product in the market. These programs aid the vision of energy surplus India with 24 * 7 power to all [1]. Please check if this should be multiplication sign. No this is not the multiplication sign.
- **Energy Conservation Buildings Code**—To set minimum energy standards for large commercial buildings having a connected load of 100 kW or contract demand of 120 KVA and above. For the residential sector, Eco-Niwas Samhita is launched to set various standards for limited heat gain and heat loss and for achieving natural ventilation and daylighting. Figure 3 shows the Eco-Niwas Samhita Scheme in the Residential sector [1].
- **Strengthening Institutional Capacity of States**—To set up State Designated Agencies for initiating the energy conservation activities at the state level.
- **School Education Program**—To promote energy efficiency in schools through the formation of Energy Clubs. BEE is realizing the Students Capacity Building Programme under the Energy Conservation awareness scheme for the XII five year plan.
- **Human Resource Development**—To implement energy-efficient technologies and practices in various sectors, a sound policy is required for the creation, retention, and up-gradation of skills of human resources.
- **National Mission for Enhanced Energy Efficiency**—One of the eight missions under the National Action Plan on Climate Change (NAPCC) is the National Mission for Enhanced Energy Efficiency (NMEEE). The goal of NMEEE is to improve energy efficiency by establishing a favorable regulatory and policy regime for encouraging innovative sustainability in energy efficiency.

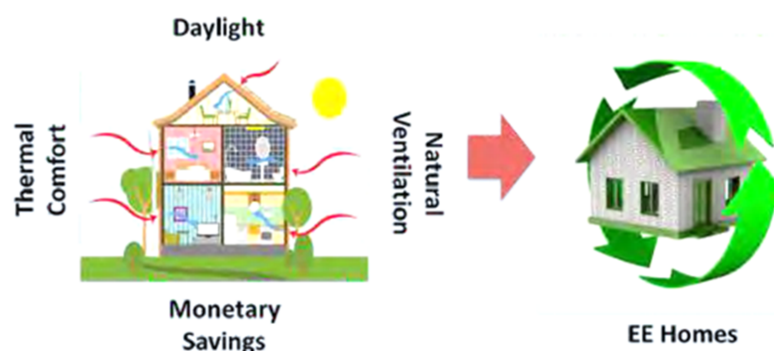


Figure 3. Eco-Niwas Samhita Scheme in the residential sector [1].

2.1.2. Energy Efficiency Projects in India

- **Energy Efficiency in light Bulb:** Domestic Efficient Lighting Program (DELP) scheme (now renamed as Unnat Jeevan by Affordable LEDs and Appliances for All (UJALA)) is designed to monetize energy consumption reduction in the household sector and to attract investments therein. Approximately 45,865 mn kWh of energy were saved per year according to the Ministry of Power, and carbon emissions were reduced by 3, 71, 50, 810 tonnes. For the fiscal year 2019-20, nearly 40 crores of LED bulbs were distributed under UJALA Yojana, resulting in cost savings of Rs 18,341 crores per year [17].
- **Energy Efficiency in Street Lighting:** The inefficient sodium and mercury vapor street lights were replaced by efficient LED street lights in many cities with a payback period of nearly two years. New technologies in LED-based street lights offer noise and pollution sensors, with remote control facilities.
- **Energy Efficiency in Water Pumping:** Five States in the Agricultural sector and 8 States in the Municipal sector replaced the traditional pump with its energy-efficient counterpart. The profound transition towards solar energy is making the water pumping system even smarter and efficient than the previous technologies.

Table 2 shows the international collaboration with India in energy efficiency.

Table 2. International collaboration under energy efficiency programs [1].

S. No.	International Collaboration	Programmes
1	Indo-US	Development of ECBC, Energy Efficient HVAC systems, Capacity Building for Institutional Financing
2	Indo-UK	Industrial Energy Efficiency, DSM Action Plans, Carbon Budgeting Approach
3	Indo-Japan	Energy Conservation Guidelines and Manuals, Waste Heat Recovery Projects, Joint Policy Researchers, Capacity Building and Industrial Energy Efficiency Programmes
4	Indo-German	Energy-Efficient Cooling, Energy Efficiency Standards for Multistorey Buildings, Perform, Achieve, and Trade (PAT) cycle
5	Indo-Switzerland	Smart GHAR Project, Energy Efficient Buildings via Integrated Design Method, Training Programmes

2.2. Demand Response

Demand response (DR) is a process in which the utility may curb the load at customer premises or remotely detach such customer appliances to avoid huge capital investments in generation capacity. DR acts as a resource to deal with a high spike in fuel prices, brownouts, blackouts, and other emergency conditions. DR engages customer participation through various incentives and penalties [10,18]. Scientists and researchers are now showing interest in residential DR programs, which enable a customer to decrease their electricity consumption and manage smart appliances [19–21]. The DR classification as given by the US Department of Energy [22] is shown in Figure 4, and its functional strategy is shown in Figure 5.

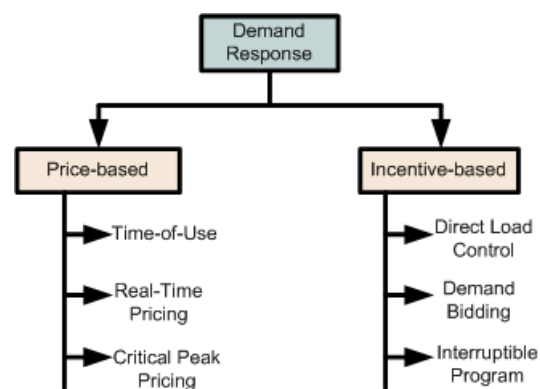


Figure 4. Demand response classification.

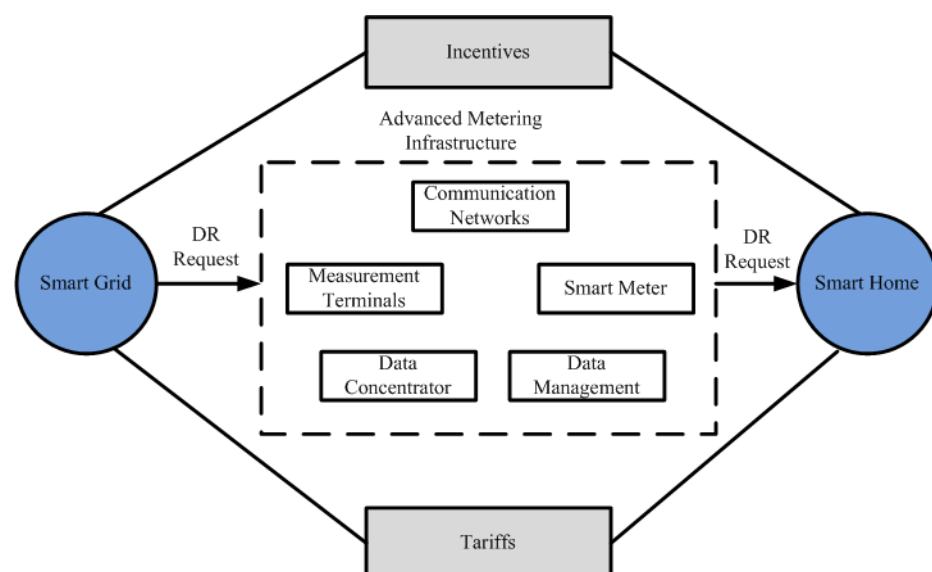


Figure 5. DR functional strategy.

Utility sends the DR request to the consumer via Advanced Metering Infrastructure (AMI), which is an integration of smart meters, communication networks, measurement terminals, data concentrators, and data management systems [23]. AMI replaces the conventional meters with smart meters to promote two-way communication for remote monitoring and control applications. Table 3 highlights the basic differences between the aforesaid DR programs. Price-based DR programs are time-dependent programs that require price design and involve voluntary participation. On the other hand Incentive-based DR programs are time-independent programs that require baseline estimation and involve voluntary, mandatory, or market-based participation.

Table 3. Difference between price-based and incentive-based DR programs.

Attributes	Price-Based DR	Incentive-Based DR
Price-variation Requirement	Time-dependent Price-design	Time-independent Baseline estimation
Discounts offered	Time-varying	Fixed or Time-varying
Consumer participation	Voluntary	Voluntary, mandatory, or market-based
Applicability	Mostly addressed to have a propensity for less electricity use during peak hours	Mostly addressed during overload periods or emergencies

2.2.1. Price-Based DR Program

In a price-based DR program or indirect load control, consumers modify their energy consumption patterns at peak demand times in response to different time-based pricing schemes called tariffs. This in turn offers financial benefits to users. The various pricing schemes include Time-Of-Use pricing (TOU), Critical Peak Pricing (CPP), and Real-Time Pricing (RTP). TOU is a widely used tariff in which usage charges are divided into different time slots for different seasons of the year or hours of the day [24]. Generally, prices are higher during peak hours and lower during off-peak hours, so consumers may respond through scheduling. CPP is quite similar to TOU, but here the prices change periodically often during the summer when the system is overloaded. The participants are notified of the new price a day ahead [25,26]. RTP or dynamic pricing is the one where the hourly prices fluctuate and participants are notified about the time beforehand. RTP implementation requires real-time communication between utilities and customers and an energy management controller for modifying the energy consumption pattern resulting in overall price reduction [21].

2.2.2. Incentive-Based DR Program

In incentive-based DR programs, participants reduce their energy consumption during overload periods, and they avail financial incentives in return. Incentive-based DR programs include Direct Load Control (DLC), demand bidding, and interruptible programs. In DLC, as the name signifies, the utility can directly switch on or off the customer's air conditioner or water heater based on the mutual contract [19,27,28]. Demand bidding is also known as negawatt or buyback program, is a market-based program where customers bid for the load they are willing to reduce [29]. Once the bid is accepted and customers commit according to the requirement, and is paid for that. Interruptible programs allow customers to shift their load to off-peak hours or shut down especially during emergencies. Enrolled customers may get penalties if they fail to respond during the event [30].

2.3. Energy Optimization and Scheduling

Optimization refers to the selection of the best possible element from several alternatives to achieve a target. Mathematically, it deals with finding the maxima or minima of a function that is subjected to some constraints [31]. Energy consumption optimization is used to find the optimal parameters needed for smart energy management [32]. Two important parameters include current indoor parameters and user-desired parameters [33]. The difference between the two produces the error, which is minimized using optimization to minimize energy consumption. Traditional energy management that is based on load forecasting and machine learning where the data is taken from traditional meters fails to predict hourly consumption [34]. The issue is overcome either by replacing these meters with digital ones or by using DR-based load forecasting [26]. Energy prediction is a prerequisite for energy consumption optimization [35]. The user comfort level is a prime factor in considering the optimization problem. Many researchers have proposed various optimization techniques for controlling energy consumption without jeopardizing user comfort.

As the conventional grid is transforming into a decentralized grid, load scheduling is now replacing load shedding. Demand-side management involves scheduling of home appliances by modifying their energy consumption pattern. Scheduling is a load management technique wherein the smart home appliances are shifted from on-peak hours to off-peak hours (during DR programs) [36], thereby shaving the peaks and filling the valleys resulting in load factor improvement.

2.4. Distributed Generation

Distributed Generation or Decentralized Generation (DG) is an electricity source directly connected to the distribution level or on the user-end side [37]. DG serves as a backup plan to the demand side, which not only mitigates the transmission losses, but also improves well-being, as no one wants the high transmission lines to pass over their residence. DG technologies provide economic benefits for cogeneration, peak-shaving, and standby power applications [38]. The DG technologies in smart homes include renewables (solar and wind), gas turbines, microturbines, and fuel cells [39].

With the rapid sustainable development and the need for emission-free generation, renewable energy penetration seems to be the largest among the DG technologies. These are some of the sources of cost-effective, clean, and green energy. In the solar energy domain, photovoltaic technology is the most prevailing among smart homes. Another renewable technology is wind power, which is also growing worldwide after solar. Wind power is generated by wind turbines, which include a fan, generator, gearbox, tower, and safety mechanisms [40]. Biomass is also used in smart homes, especially for cooking and heating. Biomass technologies include combustion, gasification, and biogas [41,42]. According to the annual report of the Ministry of New and Renewable Energy (MNRE), nearly 86 GW of renewable power capacity has been set up by December 2019 in India, and the target is to extend it further to 175 GW by the year 2022 [43].

Now, in the era of renewable energy sources coupled with information and communication technology, the devices are becoming smart. The LED light bulb, LED street light, and energy-efficient water pump are enriched with smart technology and get power from solar photovoltaic systems and are now called smart home lights, smart street lights, and smart water pumps. In India, the present solar energy contribution includes 1,721,343 smart home lights, 679,772 smart street lights, and 246,074 smart water pumps, respectively, [43]. Please confirm the number format. I confirm.

2.5. Energy Storage

Energy storage is the ultimate solution to overcome the intermittency challenges associated with renewable power [44]. Storing renewable power will abort the dependency on the grid power supply. With intelligent energy management, customers are engaged to buy and store electricity when it is available in plenty or when prices are low. With smart metering, customers can reduce their consumption and therefore cost during peak load hours (or high price periods). Energy storage technologies in the smart home include batteries, ultracapacitors, and electric vehicles [45,46]. Commonly used batteries are lead-acid, lithium-ion, zinc-bromine, zinc-iron, etc. [10]. Electric Vehicle (EV) or portable energy storage replacing the conventional vehicles are one of the promising green energy technologies that will turn the entire energy scenario shortly. EV technology comprises a battery, hybrid, plug-in hybrid, and fuel cell. In India, Faster Adoption and Manufacturing of Electric Vehicles (FAME-II) provides inputs on different aspects of electric mobility. Renewable energy-based charging infrastructure is in progress [43].

3. Hardware and Communication Technology

Home Energy Management System (HEMS) uses smart sensors to collect information and communicate with the smart appliances to perform the specific action. Various research projects have been carried out in the framework of intelligent HEMS, leveraging smart technologies to build HEMS hardware and control algorithms. In [47], authors presented

a hardware demonstration for DR management comprising of home energy management unit, load controllers, PC, communication module, and a smart meter. A hardware HEMS is developed for controlling domestic loads in response to pricing signals in the department of Electrical Power Systems of Politehnica University of Bucharest [48]. The system employed a smart meter, bipolar fuses, relays, Raspberry PI, and wireless router. The work in [49] proposed an intelligent HEMS for DR management. The hardware setup consists of wireless modules, controllers, and smart plugs. The study in [50] provided the architecture and practical implementation of an IoT and cloud computing-based HEMS on a project circuit board. The hardware components used are the WeMos D1 Mini microcontroller with a built-in Wi-Fi module, current and voltage sensors, power module, multiplexer, and relay.

To apply appropriate appliance scheduling and energy management measures, smart HEMS needs communication technology. A smart home uses wireless sensor networks to connect home appliances with HEMS. Most widely used communication technologies include BACnet [51], Digital Addressable Lighting Interface (DALI) [52], Zigbee [53], Bluetooth [54], Wi-Fi [55], and Power Line Communication (PLC) [56]. BACnet was developed by Ashrae for controlling HVAC systems. The authors in [57] introduced the building automation and communication requirement using BACnet. The DALI protocol is used to provide communication between the fuzzy controller and LED luminaires [58]. Zigbee, Bluetooth, and Wi-Fi are wireless communication technologies. Zigbee is mostly preferred for communication in smart homes due to its low power requirement, simplicity, reasonable range, low cost, and support to a large number of network nodes [59]. An intelligent HEMS is designed for demand response and load management via Zigbee based on IEEE 802.15.4 standard [60]. A Zigbee-based protection system is constructed for building safety against fire [61]. An intelligent cloud home energy management system is proposed using the Zigbee protocol to overcome the intermittency challenges associated with renewable power [62]. HEMS based on Zigbee technology is developed that is capable of monitoring energy usage with accuracy, and thus is well suited to energy conservation and planning [63]. The hardware demonstrations for DR management using the Zigbee protocol are presented [47,64].

The use of Bluetooth is limited as it provides short-range communication (up to 10 m) and requires more power consumption than Zigbee. Researchers introduced a novel Bluetooth-based HEMS capable of reducing the peak load demand and electricity cost while maintaining user comfort [65]. Wi-Fi on the other hand provides a communication range of more than 100 m with high speed, but it requires more power consumption and additional components than Zigbee. The hardware demonstration of DSM for controlling air conditioners through Wi-Fi technology and DR programs is discussed [66]. A Wi-Fi smart plug is designed for monitoring and controlling smart home appliances. This inexpensive solution enables a user to remotely switch on/off the devices [67]. PLC provides high security at low cost, but it offers low speed and low data transmission quality. The study in [56] described HEMS that used power line communication to provide real-time information on energy consumption patterns.

4. Soft Computing Based DSM

Owing to the myriads of applications, soft computing techniques have been successfully applied to solve complex problems (imprecise or uncertain) of intelligent building control [68]. Based on the type of soft computing techniques, the DSM can be classified as Fuzzy Logic (FL) based DSM, Artificial Neural Network (ANN) based DSM, and Evolutionary Computation (EC) based DSM.

4.1. FL Based DSM

Fuzzy logic has been extensively used for controlling and monitoring home appliances for many years due to its simplicity, adaptability, flexibility, and outstanding capability in dealing with uncertainties and nonlinearities [69,70]. D. Kolokotsa et al. [71] designed fuzzy PD, fuzzy PID, and adaptive fuzzy PD controllers. They proved that the adaptive controller

gives optimum performance and results in effective energy saving (25–30% more than ON-OFF controller) when user preferences are critical and suggested to use fuzzy PD for visual control and adaptive fuzzy PD for thermal and air quality control. A genetic algorithm (GA) tuned fuzzy controller is proposed in [72] for controlling the indoor building parameters and energy consumption minimization. The study in [73] showed that the fuzzy P controller yields an annual energy saving of 76% for electric lighting as compared to the fuzzy PD, fuzzy PI, fuzzy PID, and adaptive fuzzy PD controllers. These three works focused on providing thermal, visual, and air quality comfort via a smart card. An adaptive fuzzy controller is developed for ensuring the thermal comfort of the Heating Ventilation and Air-Conditioning (HVAC) system [74]. A fuzzy-based automatic roller blind [75] was designed for luminance control on account of the availability of solar radiation. The aim is to utilize the maximum daylight illumination effectively [75]. Improved adaptive fuzzy controllers are developed for controlling the air handling unit of the HVAC system in real-time where the GA is used for rule matrix and membership adjustment [76,77]. Authors in [78] presented an intelligent coordinator control with five fuzzy controllers for thermal, visual, and air quality control.

A scheduling problem for air conditioner temperature control based on day-ahead pricing is modeled using FL, and the temperature forecasting is done through immune clonal selection programming [79]. The concept of adaptive actively spheres integration with FL [80] is proposed, where the system learns and adapts to the changing human behavior and artifacts. As the era of the smart grid is emerging, various technologies like smart sensors, communication, and smart home appliance commitment are becoming a topic of interest to many researchers. The work in [81] applied fuzzy logic for scheduling smart home appliances based on the day-ahead pricing scheme and user comfort. Novel agent-based energy optimization of the HVAC system for higher education building is proposed [82]. Intelligent agents are used for prediction, control, sensing, and data processing. The experimental results showed 3% energy saving while maintaining user thermal comfort [82]. Authors used the synergy of wireless sensor networks, fuzzy logic, and smart grid incentives to design a smart thermostat for the HVAC system using a programmable communicating thermostat [83]. Then an adaptive model is developed to adjust the user's changing preferences [84]. The results are compared with the existing thermostat and it is observed that developed systems automatically respond to DR programs and resulted in a significant reduction in load demand without user discomfort [83,84]. Researchers in [85] proposed a fuzzy logic-based behavioral controller for HEMS.

A fuzzy logic-based smart LED lighting system is designed to provide visual comfort. The experimentation encompasses the DALI protocol for communication, daylight, user movement, and preferences [58]. The HVAC system is controlled using FL concepts and the performance is compared with the conventional on-off controller. The study implemented the simulation using the Building Control Virtual Test Bed platform [86]. The thermal comfort provided by the fuzzy controller is found superior to the on-off controller. A fuzzy logic-based smart HEMS for battery and load management was proposed in [87], which used Wi-Fi communication technology and IoT based monitoring. An additional humidity parameter is introduced in the fuzzy system and the rules are generated automatically using the combinatorial method [88]. Additionally, the study also utilized IoT-based sensors and a feedback loop. It is concluded that the proposed method can reduce energy consumption by up to 50%. The study in [8] classified the appliances based on their energy consumption pattern [89] and accordingly designed fuzzy controllers to control the HVAC and the illumination system.

4.2. ANN Based DSM

ANN is a machine learning approach that is flooded with numerous applications due to its simplicity, adaptability, real-time fast solution, and self-organization. An ANN-based predictive and adaptive control logic is developed for providing thermal comfort. The proposed logic used two predicted models and a hardware framework that resulted

in accurate prediction and better thermal comfort than the conventional logic [90]. They also considered the humidity factor. Then a discrete model predictive approach is developed for an HVAC system. ANN is used for model prediction and branch and bound approach for optimization [91]. Simulations showed an energy saving of 50%.

An ANN-based HEMS is proposed with the DR program to maintain the energy consumption below the demand limit, and the system is trained using a Levenberg–Marquardt and feed-forward network [92]. An hourly energy consumption predictor [93] is developed using a multilayer perceptron. Recently, ANN was used for forecasting DR signals and energy consumption patterns for maintaining an energy-efficient smart home [94–96]. A hybrid Lighting Search algorithm (LSA)-ANN-based HEMS was developed [97]. For optimal scheduling, the LSA selects the appropriate neurons and learning rate. Deep Extreme Learning Machine (DELIM) based energy consumption predictors were proposed and subsequently compared with other machine learning methods [98,99]. The DELIM predictor outperformed the other methods. A hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) controller [100] was proposed to control the temperature and air quality concerning changing demands [101].

4.3. EC Based DSM

Evolutionary computation is well known for its highly optimized solutions, and therefore is widely used to solve complex nonlinear, nonconvex, and constrained optimization problems. An efficient energy management reset scheme using evolutionary programming was proposed [102] with 7% energy-saving potential. Authors used Binary Particle Swarm Optimization (BPSO) for scheduling interruptible loads for cost and interruption minimization [103]. They divided the swarms into subswarms for significant scheduling improvement. A day-ahead load scheduling method capable of handling a variety of loads was developed using a heuristic evolutionary algorithm [13].

The authors in [104] proposed an energy management system for micro-grids equipped with wind-turbines. The economic dispatch problem is solved by Ant Colony Optimization (ACO). The study in [105] used the dual pricing model RTP with Inclined Block Rate (IBR) for efficient load scheduling. The optimization of the operational time of the appliances is performed using GA [106]. GA was compared with ACO [107] and also with Particle Swarm Optimization (PSO) [108,109] for maximizing user comfort. Multi-objective optimization problems were solved using a non-dominated sorting GA [110,111] and PSO [112]. The works in [113,114] used Artificial Bee Colony for appliance scheduling for energy management considering renewables as well. The algorithm yields a cost reduction of about 47%. Different heuristic algorithms GA, ACO, BPSO, Wind-Driven Optimization, Bacterial Foraging Optimization, and Hybrid GA-PSO were compared, wherein the GA based controllers outperformed the other methods [115–117]. They also considered TOU and IBR dual models.

A multi-agent control system [118] with hybrid multi-objective GA is developed for energy-efficient buildings. The developed method resulted in 31.6% energy efficiency. A real-time appliance scheduling is performed by Binary Backtracking Search Algorithm for energy management [119]. For electricity cost and peak load reduction, HEMS comprising of GA, Cuckoo Search Algorithm, BPSO, and Crow Search Algorithm [120] were designed with RTP and TOU pricing models, respectively, [121,122]. The studies also considered energy storage and renewable energy options. An optimal energy scheduler for load reliability was investigated and the optimization problem was solved using PSO [123]. A real-time electricity scheduler was developed for smart home energy management, considering renewables and energy storage resources [124]. GA was used to solve the multiobjective optimization problem. A day-ahead load forecasting was assumed before scheduling, and a hybrid Harmony Search-PSO algorithm was used for optimal scheduling via a human–machine interface, central controller, and different loads [125].

The study in [126] introduced and implemented the Lightlearn controller based on reinforcement learning. Due to its adaptive nature, it learned the user's behavior and adapted to controlling actions accordingly. Recent research presented a bi-level deep reinforcement learning approach for appliance scheduling. Besides, it incorporated charge

and discharge schedules of energy storage and EV [127]. In [128], a load scheduling problem was solved via the Dijkstra algorithm, and the simulation results are compared with GA, Optimal Pattern Recognition Algorithm, and BPSO. The results showed a cost reduction of about 51%. Renewable generation and storage systems were also considered. Table 4 summarizes the soft computing based DSM.

Table 4. Soft computing based DSM.

References	Method	Objective	Contribution
[71–73]	FL	thermal, visual, and air quality comfort	Fuzzy P, Fuzzy PD, Fuzzy PID, Adaptive fuzzy PD controller, and GA tuned Fuzzy controller
[74]	FL	thermal comfort	An adaptive fuzzy controller
[75]	FL	visual comfort	fuzzy-based automatic roller blind
[76,77]	FL	air quality comfort	Improved adaptive fuzzy controllers in real-time
[78]	FL	thermal, visual, and air quality comfort	intelligent coordinator control with five fuzzy controllers
[79,81]	FL	thermal comfort	A scheduling problem for air conditioner temperature control based on day-ahead pricing is modeled smart thermostat for the HVAC system using a programmable communicating thermostat and an adaptive model to adjust the user's changing preferences
[83,84]	FL	thermal comfort	A fuzzy logic-based smart LED lighting system
[58]	FL	visual comfort	Fuzzy based controller for HVAC system using the Building Control Virtual Test Bed platform
[86]	FL	thermal comfort	A fuzzy logic-based smart HEMS for battery and load management
[87]	FL	-	fuzzy controllers to control the HVAC and illumination system
[8]	FL	thermal, visual and air quality comfort	ANN-based predictive and adaptive control logic
[90]	ANN	thermal comfort	discrete model predictive approach is developed for an HVAC system
[91]	ANN	thermal and air quality comfort	forecasting DR signals and energy consumption patterns for maintaining an energy-efficient smart home
[94–96]	ANN	thermal comfort	hybrid Lightning Search algorithm LSA-ANN-based HEMS
[97]	ANN	visual comfort	hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) controller
[100,101]	ANN	thermal and air quality comfort	Binary Particle Swarm Optimization (BPSO) for scheduling interruptible loads for cost and interruption minimization
[103]	EC	load scheduling	A day-ahead scheduling method using a heuristic evolutionary algorithm
[13]	EC	load scheduling	an energy management system for micro-grids equipped with wind-turbines using ACO
[104]	EC	economoc dispatch problem	dual pricing model RTP with Inclined Block Rate (IBR)
[105]	EC	load scheduling	GA is compared with ACO and PSO
[107–109]	EC	user comfort	used Artificial Bee Colony for energy management considering renewables as well
[113,114]	EC	load scheduling	Different heuristic algorithms GA, ACO, BPSO, Wind-Driven Optimization, Bacterial Foraging Optimization, and Hybrid GA-PSO are compared
[115–117]	EC	energy cost reduction	A real-time appliance scheduling is performed by Binary Backtracking Search Algorithm
[119]	EC	energy management	home energy management schemes comprising of GA, Cuckoo Search Algorithm, BPSO, and Crow Search Algorithm
[120–122]	EC	electricity cost and peak load reduction	An optimal energy scheduler for load reliability using PSO
[123]	EC	load scheduling	A real-time electricity scheduler considering renewables and energy storage resources
[124]	EC	load scheduling	A hybrid Harmony Search-PSO algorithm
[125]	EC	load scheduling	Lightlearn controller based on reinforcement learning
[126]	EC	visual comfort	a bi-level deep reinforcement learning approach
[127]	EC	load scheduling	Dijkstra algorithm compared with GA, Optimal Pattern Recognition Algorithm, and BPSO
[128]	EC	load scheduling	

5. Optimization Based DSM

Game Theory is one of the most powerful and widely used optimization techniques. Autonomous Game-Theory-based DSM is presented in [129,130]. The players act as users and their strategies as daily home appliances schedules [131]. There is only interaction among participating users rather than utilities, and a single energy source is shared by the users. Their ultimate objective was to minimize energy costs and Peak to Average Ratio (PAR). Then, Game Theory was also used for load scheduling considering renewable sources [132], EV [133], and for realizing user-aware DSM considering user preferences [134].

Researchers in [135] used two optimization methods for RTP-based DSM. Stochastic optimization was used for price minimization and controlling associated financial risks. On the other hand, robust optimization deals with the price uncertainty intervals [136]. A mixed-integer programming optimization was used for smart home appliance scheduling [137–139], with EV and energy storage in [140]. Reference [141] transformed the Mixed-Integer Linear Programming (MILP) problem into a convex programming optimization one for flexible and efficient performance. To deal with the uncertainties such as price-elasticities of demand, [24] proposed a TOU tariff design using stochastic optimization based on quadratically constrained quadratic programming and RTP design in [142]. Simulated Annealing was used for DSM [143], which uses white tariff, an extension of TOU tariff. Researchers introduced a cost-efficient scheduling approach using fractional programming while considering service fees and renewables [144].

To implement an incentive-based DR program [145] proposed a practical load scheduling optimization algorithm for user satisfied energy management. A comparative study among Linear programming, PSO, Extended PSO, adaptive dynamic programming, and self-learning procedures was made for smart load scheduling while considering data uncertainties [146]. In a study, a multiobjective mixed-integer non-linear programming optimization was used for energy saving and maintaining thermal comfort [147]. The scheduling problem was solved by interval number optimization in [148]. At first, the uncertain parameters were transformed into interval numbers and then successively solved by BPSO coupled with Integer linear programming. A metaheuristic optimization method that is a hybrid bacterial foraging-GA is proposed to handle multiple constraints and improve search efficiency [149]. Dynamic programming is used for real-time appliance scheduling. A heuristic optimization based appliance scheduling and energy management system was developed, which considered both renewable sources as well as user preferences [150].

A recent study [151] used MILP with normalized weighted sum and compromise programming for solving scheduling problems considering the TOU pricing scheme. The work in [8] scheduled the appliances using the Bat algorithm [152], Flower pollination, and hybrid Bat Flower pollination optimization techniques, respectively. A novel appliance scheduling optimization for a flexible and comfortable environment contributed to peak load reduction while considering socio-technical factors [153]. Table 5 summarizes optimization-based DSM.

Table 5. Optimization based DSM.

References	Optimization Method	Objective	Contribution
[129,130]	Game Theory	minimize energy costs and Peak to Average Ratio (PAR)	Autonomous Game-Theory-based DSM
[132–134]	Game Theory	load scheduling	realizing user-aware DSM considering user preferences and renewable sources
[135]	Stochastic-Robust	price minimization	RTP-based DSM
[137–140]	Mixed-integer programming	load scheduling	smart home appliance scheduling
[143]	Simulated Annealing	energy optimization	DSM using white tariff
[146]	Linear programming	load scheduling	A comparative study among Linear programming, PSO, Extended PSO, Adaptive dynamic programming, and Self-learning procedures
[148]	Interval number optimization	load scheduling	BPSO coupled with Integer linear programming
[150]	Dynamic programming	load scheduling	A heuristic optimization based energy management system considering both renewable sources as well as user preferences
[151]	MILP	load scheduling	normalized weighted sum and compromise programming for solving scheduling problems considering the TOU pricing scheme
[152]	Bat algorithm, Flower pollination, and hybrid Bat Flower pollination	load scheduling	Energy management scheduler for smart home

Table 6 shows the comparison between the soft computing DSM and optimization DSM.

Table 6. Comparison between the soft computing DSM and optimization DSM.

S. No.	Soft Computing Based DSM	Optimization-Based DSM
1.	Set of computational techniques and algorithms that are used to deal with complex problems [154].	Selection of the best possible element from several alternatives to achieve a target [31]
2.	Does not require a mathematical model	Requires mathematical model
3.	Approximate solutions	Accurate solutions
4.	Fast	Time-consuming
5.	May use heuristics or learning methods	Require iterative methods
6.	Simplicity, adaptability, and flexibility	Robustness, stochastic, and optimality
7.	Best suited for real-world problems	It may be difficult to solve real-world problems
8.	Examples- Fuzzy logic [8], Artificial neural network [101], Genetic algorithm [124], Particle swarm optimization [125], Ant colony optimization [104], Cuckoo search algorithm [120], etc.	Examples- Game theory [129], Mixed-integer linear programming [151], Dynamic programming [150], Simulated annealing [143], Interval number optimization [148], Stochastic and Robust optimization [135], etc.

6. Miscellaneous

In addition to the soft computing and optimization based DSM, there are some other approaches, and this very section summarizes those works in the literature. Two of the major features of a smart grid are the integration of renewable energies [155] and storage resources and increased customer participation. For integration, [156] designed and tested an embedded system in which a microcontroller switches between the various power sources. The energy peaks are managed by the home gateway and utility server via the GSM modem. A net energy saving of about 33% is achieved. Since these integrations may also cause power supply uncertainty. To overcome the issue, [157] developed TOU-based DSM schemes for both prosumers and consumers. The latter is achieved by presenting a schedul-

ing algorithm that takes into account the customer preferences and RTP using Analytical Hierarchy Process and Piecewise Cubic Hermite Interpolating Polynomial [158].

In DLC, it is quite difficult to decide which appliance to turn on or off while maintaining user comfort [159]. Researchers proposed a naïve control method for controlling an electric water heater without a temperature parameter. Instead, a time-varied weight matrix and heating durations are used to generate a customer satisfaction prediction index, which in turn selects the appropriate heater for DLC [160]. Asha Radhakrishnan and M.P. Selvan proposed a DR based off-line scheduling algorithm considering renewable sources [36]. The method comprises load classification, load prioritization, and application of tariff plans.

The hardware implementation of DR programs and cloud computing methods considering customer's preferences and load priority for energy management are presented [62,161]. A smart residential energy management system is designed for appliances and battery scheduling [162]. Graph theory and the Fast greedy approach [163] were used for efficient load scheduling implementation of thermostatic devices [164]. Then model predictive controllers [165] were used for scheduling both thermostatic [166–169] as well as non-thermostatic appliances [170]. An energy-saving smart LED lighting system is developed using sensors and microcontrollers. The experimental results achieved 55% and 65% energy saving in continuous and discrete pattern environment [171]. The work in [172] discussed DR management through practical implementation. The required algorithm is designed based on user indices and engagement plans. The authors proposed an energy management algorithm considering renewable power, battery state of charge level, grid availability, and different tariffs [173]. From the simulation, it is shown that energy-saving with the proposed algorithm with renewable energy is about 28% whereas it is 25% without renewable energy.

Recently researchers developed a residential load simulator using MATLAB-Simulink graphical user interface [174], which cannot only model the smart appliances, but also the local generation resources for extracting the power profiles. In [47] and [64], authors presented a hardware demonstration for DR management using the Zigbee protocol, considering load priority [175] and user preferences. The performance analysis of global model based anticipated building energy management system was developed for energy management [176]. A real-time rule-based DR controller with load shifting and curtailment mechanisms was proposed in [177]. The study in [178] conducted a quality of experience perception analysis and based on user profile proposed a smart HEMS considering the degree of annoyance and renewable energy resources. The hardware demonstration of DSM for controlling air conditioners through Wi-Fi technology and DR programs was discussed [66]. The control methodology in [64] used the combination of fuzzy controller, rolling optimization, and real-time control strategy for appliance scheduling in a DR environment. For efficient utilization of energy storage systems [179] developed a nonhomogenous hidden Markov model that formulates the energy storage management problem and used piecewise linear approximation for further solving. Table 7 summarizes the miscellaneous DSM approaches.

Table 7. Miscellaneous DSM approaches.

References	Contribution
[156]	Integration of renewable energies through microcontroller based embedded system
[157]	TOU-based DSM schemes for both prosumers and consumers and a scheduling algorithm that takes into account the customer preferences
[160]	A naïve control method for controlling an electric water heater without a temperature parameter
[36]	DR based off-line scheduling algorithm considering renewable sources
[62,161]	The hardware implementation of DR programs and cloud computing methods considering customer's preferences and load priority
[162]	A smart residential energy management system for appliances and battery scheduling
[163]	Efficient load scheduling implementation of thermostatic devices using Graph theory and the Fast greedy approach
[165–169]	Model predictive controllers for scheduling thermostatic appliances
[172]	DR management through practical implementation
[173]	Energy management algorithm considering renewable power, battery state of charge level, grid availability, and different tariffs
[174]	Residential load simulator using MATLAB-Simulink graphical user interface
[47,64]	Hardware demonstration for DR management using Zigbee protocol
[177]	Real-time rule-based DR controller with load shifting and curtailment mechanisms
[66]	Hardware demonstration of DSM for controlling air conditioners through Wi-Fi technology and DR programs
[64]	Appliance scheduling in a DR environment using the combination of fuzzy controller, rolling optimization, and real-time control strategy

7. Discussion and Future Works

From a technical point of view, the most challenging proposals are as follows:

1. As the number of HVAC systems is increasing, heat dissipation from the condensing coil is also increasing, thereby causing environmental issues indirectly affecting human comfort. To overcome the challenge there is a need for the development of a DSM scheme that can accommodate this heat which can either be used for space heating or in kitchen applications.
2. The majority of the research focused on thermal, visual, and air quality comfort, but did not consider humidity, social comfort, and assisted living in their experiments.
3. Design and real-time implementation of hybrid DR controllers considering both technical and economic aspects of the grid to provide enough knowledge of the system (experience) concerning decentralized control and to maintain the reliability of the grid (to control the peaks at off-peak hours).
4. Integration of Fuzzy Logic with metaheuristic algorithms capable of energy prediction, optimization, and scheduling in real-time could give the best results for energy consumption minimization without affecting the degree of comfort.
5. The system should also include renewable energy resources, energy storage devices, and an IoT based protocol to maintain the flexibility and security within the smart home.

8. Conclusions

This paper provides a review of the previous and ongoing research on DSM. DSM strategies are described and a comparison is made between energy conservation and energy efficiency, price-based and incentive-based DR programs, energy optimization and scheduling, and distributed generation and energy storage. We addressed soft computing techniques namely FL, ANN, EC, and different optimization techniques for energy management and scheduling using renewables and storage devices and finally compared them. From a sustainable point of view, DSM is economically viable, provides grid stability,

improves the demand and supply-side efficiency, and is environmentally friendly. It is still a developing and promising area of the smart grid. We hope that this review can help new researchers and readers gain insights into various terminologies and methodologies adopted in DSM implementation.

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