


Review

A Survey of Efficient Demand-Side Management Techniques for the Residential Appliance Scheduling Problem in Smart Homes

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Abstract: The residential sector is a major contributor to the global energy demand. The energy demand for the residential sector is expected to increase substantially in the next few decades. As the residential sector is responsible for almost 40% of overall electricity consumption, the demand response solution is considered the most effective and reliable solution to meet the growing energy demands. Home energy management systems (HEMSs) help manage the electricity demand to optimize energy consumption without compromising consumer comfort. HEMSs operate according to multiple criteria, including electricity cost, peak load reduction, consumer comfort, social welfare, environmental factors, etc. The residential appliance scheduling problem (RASP) is defined as the problem of scheduling household appliances in an efficient manner at appropriate periods with respect to dynamic pricing schemes and incentives provided by utilities. The objectives of RASP are to minimize electricity cost and peak load, maximize local energy generation and improve consumer comfort. To increase the effectiveness of demand response programs for smart homes, various demand-side management strategies are used to enable consumers to optimally manage their loads. This study lists out DSM techniques used in the literature for appliance scheduling. Most of these techniques aim at energy management in residential sectors to encourage users to schedule their power consumption in an effective manner. However, the performance of these techniques is rarely analyzed. Additionally, various factors, such as consumer comfort and dynamic pricing constraints, need to be incorporated. This work surveys most recent literature on residential household energy management, especially holistic solutions, and proposes new viewpoints on residential appliance scheduling in smart homes. The paper concludes with key observations and future research directions.

Keywords: optimization; demand response; demand-side management; residential appliance scheduling; smart home



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1. Introduction

An electric grid is a huge complex network designed for providing electricity to consumers to satisfy their growing energy demands. The International Energy Outlook in 2016 projected that there will be a notable increase in the overall energy demand of the world in the next 20 years. This growth in worldwide consumption has led to an immediate change in the conventional grid to meet the increasing demands. The conventional grid is the electricity network used for supplying and distributing the electricity from generation-side to consumer-side. In other terms, it is used for connecting producers of electricity to consumers of electricity. However, the existing electric grid faces few challenges [1]. These challenges vary from country to country based on the energy demands. The main challenges are to fulfill the required demand with the resources available and to provide accessibility of electricity with infrastructure called utilities. The other challenges faced by

the traditional grid are as follows: (a) It is a centralized grid in which the power is generated from a centralized location and carried to consumers. In addition, the conventional grids are powered by non renewable energy sources—natural gas, diesel, etc. (b) One-way communication where the consumer is just a receiver; it cannot provide any user preference, nor can a user state the required energy demand to the utility. (c) It is not well equipped to handle advanced technology and sensors. Thus, it fails to detect the problems and anomalies. (d) Manual monitoring of energy distribution and manual reading of metering infrastructure are required. All the aforementioned problems can lead to increasing grid vulnerability and power outage risks. Thus, it is necessary to overcome these challenges and make huge investments into the existing traditional grids. Additionally, owing to the worldwide rise in energy demand and significant changes in energy infrastructure, there is a need to evaluate/update the conventional grids into smart grids to address future energy demands. The smart grid (SG) represents one such solution that makes an existing grid more responsive and intelligent [2]. It is a relatively new concept with advanced information and communication technologies (ICT) that integrates two-way communication between a utility and its consumers [3]. SG facilitates the customers interacting with the utilities in a bi-directional way to enhance the security, performance, reliability, and sustainability of the generation, transmission, and distribution of electricity. The stakeholders of the smart grid, including utilities, independent system operators, consumers, regulatory authorities, etc., are shown in Figure 1.



Figure 1. Smart grid stakeholders.

The ICT infrastructure in the smart grid facilitates the power and information flow in unidirectional and bi-directional systems. This allows consumers to express their power needs to their service provider, which led to a new concept called demand-side management

(DSM) [4]. Demand-side management refers to the programs implemented by utility companies to encourage the consumers directly or indirectly to reduce their peak load and electricity cost [5]. DSM techniques can maximize the smart grid's efficiency, reliability, and robustness. In the smart grid, the utility manages the household demand and consumption of electricity by a specific set of rules. These rules are termed demand response (DR) [6]. Various incentives are published by the electricity utility companies to encourage consumers to manage their appliances in an effective manner [7]. The utility companies publish dynamic prices, viz., flat rate pricing (FRP), day-ahead pricing (DAP), time of use pricing (ToUP), real time pricing (RTP), critical peak pricing (CPP), and inclined block rate (IBR). Based on these pricing schemes, the consumers can change their consumption patterns and cost-effectively schedule their appliances. Some of the benefits of smart grid are:

- **Efficiency:** Smart grid technology allows consumers to manage their electricity consumption using advanced communication technologies, advanced sensors. Various techniques have been used to manage household consumption such as shifting of the load from on-peak period to off-peak periods, using the direct load techniques, etc.
- **Empowering the customers:** The most important characteristic of SG is two-way communication between consumers and the utility, which allows users to share their electricity demands with the utility, and users can take part in demand response programs to manage their household consumption without compromising their comfort. In addition, SG enables advanced metering infrastructure (AMI), which allows the consumers to receive the dynamic pricing tariffs from utility time to time and respond accordingly.
- **Intelligence:** Smart grid is an intelligent technology that is capable of detecting power failure and outage risks. It works intelligently to identify the overload conditions and respond to them to achieve grid stability. A smart grid also recognizes the system's capability to meet the consumer's power demand.
- **Green energy:** The smart grid leads the path of a clean energy environment. The use of renewable energy sources (RESs) such as hydro, wind, and solar energy can be used in coordination with utilities to increase the stability of the grid and sustainable energy supply. With a smart grid, we have an effective way of reducing carbon emissions and implementing de-carbonized energy generation and distribution. The smart grid is geared towards reducing our need for fossil fuels [8,9].

In recent years, there has been extensive surveying carried out in the area of residential appliance scheduling. Sarker et al. [10] have reviewed the progress of DSM, and they discussed several algorithms to solve DSM optimization problems. Leitão in [11] provided an in-depth survey of home energy management systems with a focus on residential appliance management and its operational goals and strategies. Salameh et al. [12] have presented a review on demand-side management while considering economic, environmental, and operational perspectives. In Zafar et al. [13] have presented a comprehensive survey on HEMSs regarding configurations and enabling technologies. Various optimization techniques on DSM with a focus on peak shaving and load scheduling are comprehensively reviewed in [14]. Iqbal et al. [15] have described various DSM strategies and conducted a comprehensive review of current and previous research works in the field of DSM. A survey on demand response and optimization techniques to solve the appliance scheduling problem is presented in [16]. In [17] is a survey for residential load scheduling in smart homes. Shakeri et al. [18] have presented a review on demand response programs and energy management in buildings. In [19], optimization of demand response techniques for power scheduling is presented.

While all the aforementioned reviews are valuable, however, they are generally narrow in their scopes. They mostly focus on conventional optimization techniques for scheduling and fail to discuss other available optimization approaches. This manuscript provides a deeper and actual analysis of residential appliance scheduling techniques used in the literature related to DSM and also revisits the demand response programs and DSM techniques. We were motivated to present this review to solve the multi-objective residential

appliance scheduling problem in such a way that it can be used in future research in the area of home energy management. As the research and development in the demand response field are evolutionary, this work provides a detailed and summarized survey of the current status of appliance scheduling. Moreover, our survey presents holistic approaches and mechanisms for solving RASP. Moreover, our survey complements the existing surveys by:

- Classification of demand-side management and demand response programs for the residential sector, and critically discussing techniques to schedule home appliances.
- Carrying out a comprehensive review of ongoing and previous research works on residential appliance scheduling through conventional techniques, heuristic and meta-heuristic techniques, soft computing techniques, AI techniques, energy storage based techniques, coordinating and sharing techniques, and incentive-based techniques.
- Encouraging and motivating users to reschedule their appliance use rather than asking them to reduce their consumption.
- Categorization model of smart home appliances.
- Considering the environmental implications of demand response, such as thermal comfort.
- Proposing the key observations and new viewpoints for DR implementation.

The rest of the paper is organized as follows: Section 2 presents demand-side management strategies and demand response programs. In Section 3, the residential appliance scheduling problem is addressed, along with its objectives. Section 4 presents definitions for smart homes, HEMS, its components, and appliance classification. Section 5 describes the scheduling techniques for appliances in a detailed manner with the key observations of the review. Section 6 concludes with possible future directions.

2. Demand-Side Management and Demand Response

2.1. Demand-Side Management

To meet the growing energy demands of the residential sector, every service provider company tries to minimize the extra time and cost by installing new generating units. The optimal solution to this issue is to utilize the existing energy efficiently. Thus, the service provider company deploys DSM programs to manage users' energy consumption [20]. Thus, the primary goal of DSM is to minimize electricity costs by managing household consumption. The term DSM is used to make customers aware of and encouraged by energy management programs. Demand-side management is broadly defined as the set of rules to monitor and implement consumer awareness programs for managing energy efficiency along with peak shaving and encourage the users to be more energy efficient by using energy management algorithms [21]. In general, DSM can be sub-divided into two broad categories, as shown in Figure 2.

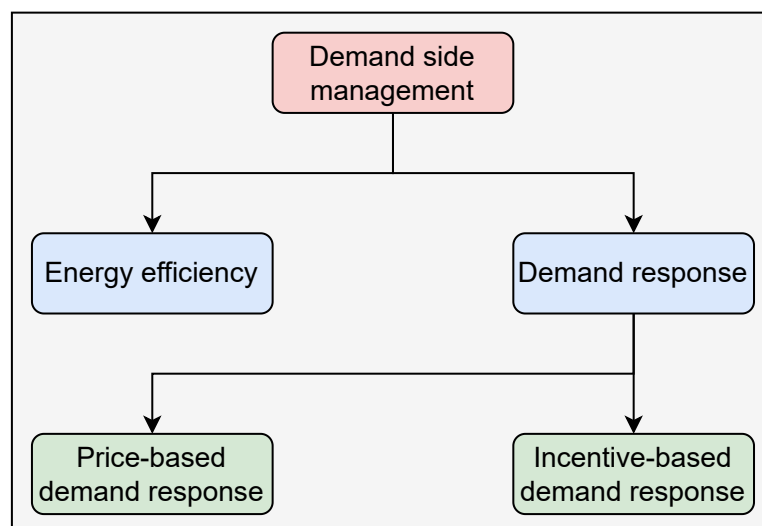


Figure 2. Demand-side management.

Demand-side management includes two categories, energy efficiency and demand response [22–24], which are explained below:

- Energy efficiency: It is achieved by implementing customer-aware programs for consumers who require less energy. As a result of this behavior, lower energy consumption is obtained. Despite the importance of energy efficiency, this approach is not feasible since one cannot force the consumer to lower their electricity consumption.
- Demand response: In this strategy, the service provider aims to minimize the electricity consumption and shift the load from on-peak hours to off-peak hours [25]. In this survey, we focus on demand, and more specifically, residential appliance scheduling. This involves encouraging consumers to change their appliance usage patterns, which could help reducing the peak shaving and electricity cost. The demand response strategy is further divided into two sub-types, namely, price-based demand response and incentive-based demand response, in which the users are charged with different tariffs at different periods of the day and awarded with incentives for changing their consumption patterns. DR is described further in Section 2.2.

For the smooth operation of the grid, there is a need to balance the energy supply and demand. In the traditional energy grid, the balance is achieved by using peak power plants. However, this is not always feasible, as it is difficult to generate new power plants and install new generating units, as that is costly and time-consuming. On the other hand, DSM uses different strategies to meet energy demands, wherein the consumers are encouraged to reduce their consumption or shift consumption from on-peak to off-peak hours. The DSM strategies are shown in Figure 3.

The electricity consumption can be represented in the form of load profile curves which are plotted as load against time. Six different demand-side management techniques shown in Figure 3 are explained below:

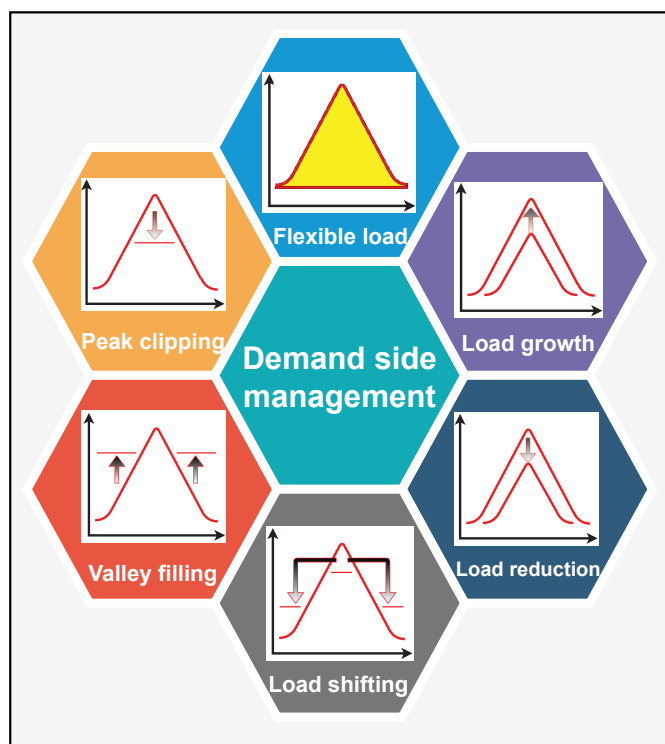


Figure 3. Demand-side management techniques [16].

2.1.1. Peak Clipping

It is defined as total load reduction during high peak duration [24,26]. It can be achieved by direct load control (DLC) or shutting down the unimportant load to maintain

the smooth operation of the grid. This technique is used where new generation plants can not be installed.

2.1.2. Valley Filling

It is a process of filling valleys (periods of low demand) [27]. It focuses on consumption during off-peak hours. Consumers are encouraged to use electricity during the off-peak period by providing a relatively lower pricing rate during that time. It can also be achieved by improving system load factors during the off-peak duration.

2.1.3. Load Shifting

In demand-side management, this strategy is frequently utilized and highly effective [24]. It entails both a reduction in peak load and a shift in demand from on-peak to off-peak hours. Consumers are encouraged to do so by lower rates offered during off-peak periods.

2.1.4. Load Reduction

Load conservation is another name for this technique [26]. It involves utilizing energy-efficient appliances and focusing on reducing the overall electricity consumption.

2.1.5. Strategic Load Growth

Load building is the term for this approach [24,26,27]. It refers to an increase in load as a result of increased energy consumption generally. It boosts users' power consumption to a certain level and promotes them to do so to keep the power system running smoothly.

2.1.6. Flexible Load Shape

This technique involves specific tariffs and contracts with the possibility of flexible control of consumers' equipment [24,26,27]. Users with a flexible load are identified as those who are willing to limit their consumption in exchange for rewards.

Different DSM techniques can be used in the consumption of electricity to reduce the peak load and increase the off-peak load. The peak load can be reduced directly by controlling the load from utility using the direct load technique. However, if the utility company applies this technique to a residential sector, there is always a concern for consumers' privacy. This acts as an obstacle in the implementation of this technique [28–32]. A few of the other limitations in the way of implementing DSM programs are listed in [33]. These limitations can be overcome by using the alternative method for load control. In this method, the service provider company does not force consumers to shut down the load. Instead, it gives them options to reduce their electricity consumption by managing their demand at different times of the day [34–36]. The utility uses dynamic-price-approach-based demand variation. It periodically notifies the pricing tariff information to consumers via smart components of the home energy management system and the consumer manages their demand in response to the price. DSM helps in energy conservation by ensuring efficient use of electricity at the distribution end [37–41]. This approach is referred to as demand response. We discuss the demand response programs in detail in the next subsection.

2.2. Demand Response

Consumers in the wholesale energy market respond to different prices by shifting their consumption patterns from on-peak to off-peak to earn monetary incentives, resulting in decreased electricity use during high-price periods, which is called demand response [8,42,43].

2.2.1. Main Objectives of Demand Response

The main objectives of demand response are as follows:

- To reduce the power consumption in such a way that both consumers and the utility companies get the mutual profit. It also involves reducing transmission and distribution loss and consumer power demands [44].
- The main effect of the aforementioned goal is to reduce the amount of needed electricity generation. As a result, there is no need to turn on expensive-to-run power plants to satisfy peak demand. It also allows electricity companies to achieve their pollution targets [42].
- The goal is to limit the number of overloads in the distribution system. This goal is achieved through the use of a distribution management system (DMS), which monitors the distribution system's performance and makes near-real-time decisions to improve the system's reliability [45].
- To maximize overall system's stability and to balance available supply, particularly in areas where renewable energy sources such as solar panels and wind turbines are frequently used [46].
- To enhance the use of local power generation means, such as PV panels. The local generation enables customers with the opportunity to supply the electricity back to the grid. This will help with reducing the overall electricity costs for residential households.

In smart home energy management, various demand-response-based techniques have been used [47–54]. These techniques mainly focus on residential appliance scheduling using price-based DR programs. The optimization-based techniques are designed and embedded into the energy consumption scheduler to achieve the assigned objectives. These techniques work automatically based on given inputs, which can be listed as:

- The electricity demand of the households.
- User preferences to schedule the appliances.
- Environmental parameters—temperature, weather, etc.
- Electricity pricing signals.

One of the most essential aspects in the residential appliance scheduling domain is the power pricing signal, which is one of the above inputs. ToUP and DAP signals are employed in most energy management strategies, since these pricing schemes are widely adopted by many retailers and are simple to apply in the residential sector. The different types of demand response programs are depicted in Figure 4.

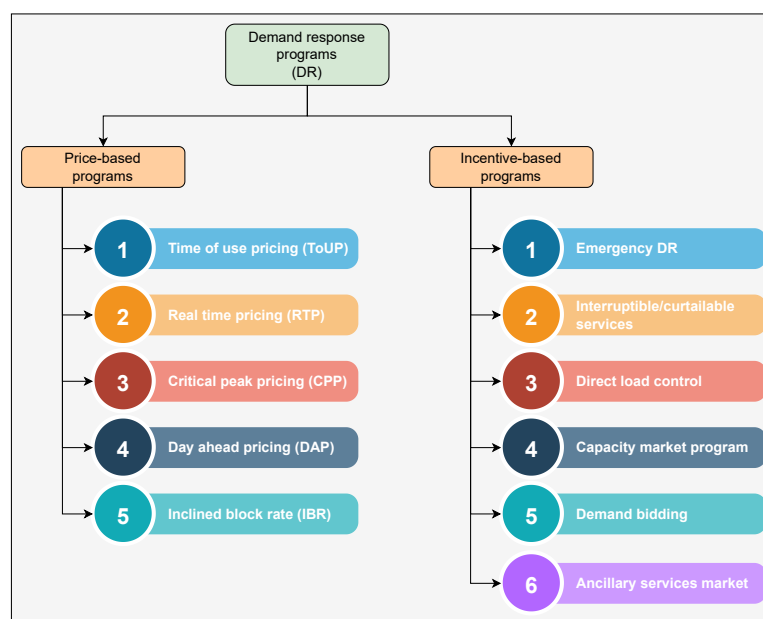


Figure 4. Types of demand response programs.

2.2.2. Price-Based Demand Response

In price-based demand response programs, the electricity cost fluctuates between a certain limit concerning variation in power demand. These programs include ToUP, RTP, CPP, DAP, and IBR. The pricing schemes are divided into multiple rates because the utility companies have to maintain a balance between demand and supply. The rate of electricity is higher when there is high energy demand. The consumers get the benefits of these programs by properly responding to the utility. Generally, the consumers' responses are driven by the adjustments in their consumption and load modification.

2.2.3. Incentive-Based Demand Response

These programs are specially designed by utilities, retailers, policymakers, grid operators, energy producers, etc. They refer to contractual arrangements to draw out the energy demands from consumers during certain hours. The participating users are given monetary incentives prices through these programs which are other than regular fixed prices. Participation is open to every consumer. However, customers violating the programs are given penalties. Table 1 represents a detailed explanation of all the DR programs.

2.2.4. Demand Response Applicability for Residential Appliance Scheduling

Typically, there are four sectors for electricity consumers, which are residential, industrial, commercial, and transportation [55]. Considering the sectors to which it is applied, the effectiveness of DR can be improved. However, these programs are mostly applicable to residential, industrial, and commercial consumers. In this work, we have focused on the residential sector. Thus, we consider the appliance scheduling problem in residential households only. The residential users can be divided into the following types [56]:

- Short-range users: These users are concerned about the electricity price at the current time.
- Postponing users: These users focus on current and future prices.
- Advancing users: These users focus on current and past prices.
- Mixed users: These users are a mix of both advancing and postponing users.
- Long-range users: These users can shift their consumption patterns over a long duration of time.
- Residential household users

Since residential households involve multiple appliances running simultaneously and the consumption patterns are random, the implementation of demand response is more complicated for residential users than industrial users. To address this problem, residential appliance scheduling management programs are deployed which either shift consumption or reduce it [25]. However, it should not be assumed that all the households have the same power-consuming patterns. The electricity consumption is minimized by encouraging energy-aware consumption patterns or building energy-efficient homes [57]. However, it is observed that by shifting the power consumption from on-peak hours to off-peak, a significant reduction in the PAR can be achieved. In the next section, we will discuss the residential appliance scheduling problem statement in detail.

Table 1. Summarized demand response programs.

Price-Based Demand Response	Incentive-Based Demand Response
<p>1. ToUP: Splits a day into equal periods. The electricity is billed at a fixed price rate for each period. The periods vary depending on underlying billing tariffs and the time of the day. The periods and tariffs depend on the season, day of the week, etc. A day of 24 h is divided into equal time slots. The electricity rates vary according to the time of day.</p> <p>2. RTP: The utility publishes the rate of electricity in real-time usually on an hourly or daily basis. It is dynamic pricing where the participants are notified beforehand. RTP implementation requires real-time communication between consumers and utilities. Additionally, in energy management the controller is required to change the energy consumption pattern resulting in overall price reduction.</p> <p>3. CPP: defines the higher price rates for critically overloaded periods. These critical periods are decided by utilities based on a threshold of the total electricity consumption of the user. This tariff scheme is similar to ToUP except for the critical period. This type of pricing scheme is often required in summer when the prices change periodically and the system is overloaded.</p> <p>4. DAP: The utility company publishes the tariff rate a day advance. Thus, the electricity prices are updated one day beforehand so that the consumer can plan their consumption well in advance.</p> <p>5. IBR: Considers unit electricity price rate and which increases incrementally with the blocks of hundreds of kWh.</p>	<p>1. Emergency DR: In this program, the participating consumers who are involved in the load reduction during fault conditions are eligible for incentives from the utility companies. The consumers violating the the agreement may/may not attract the penalties.</p> <p>2. Interruptible/curtailable services: These services are generally integrated with the consumer’s ongoing tariff. Similar to the above DR program, the consumers participating in this program can get the incentives for load reduction but those not participating in the program during fault conditions are charged high electricity bills or could be removed from the system for that particular period. These programs are mostly used for large commercial sectors.</p> <p>3. Direct load control: It is a DR program in which the utility shuts down a few residential loads to address reliability issues. The utility companies are directly given full access to partial loads such as air conditioners, water heaters. The involved customers can get the benefits of incentives from the utility providers. However, if the participation agreement is violated, users are accountable for the penalties. The DLC program is best suited for the residential sector and small industries.</p> <p>4. Capacity market programs: These programs are implemented for the users who are ready to reduce/curtail their specified load in the given period.</p> <p>5. Demand bidding: In this program, the consumers offer a certain price to the utilities at which they agree to curtail their load and encourage the end-users how much load they would curtail on the given utility pricing.</p> <p>6. Ancillary services market (ASM): The consumers following this program can bid on curtailment of load. However, the bids refer to ASM. The participating consumers get the incentives for committing to the program if bids are accepted.</p>

3. Residential Appliance Scheduling Problem

This section describes the proposed residential appliance scheduling problem. Here, the major emphasis is given to finding more optimized appliance schedules based on user preferences. It is assumed that the consumers have set the operating times for the appliances before their scheduling so that the algorithm finds the best optimal schedule without violating constraints. While considering the residential appliance scheduling problem, the following criteria/objectives are commonly considered.

3.1. Electricity Cost

The objective of minimizing the electricity cost is given by (1):

$$\text{minimize } \beta \times \sum_{n=1}^N \sum_{t=1}^T (P_{avg,n} \times S_{n,t}) \quad (1)$$

where β is the average electricity price taken from Nord pool cost data, $P_{avg,n}$ is the average power rating of the n th appliance, as shown in Table 2. t is the time-varying from 1 to T ; $T = 24$, n denotes the number of appliances varies from 1 to N . In the current dataset, 14 appliances are considered. $S_{n,t}$ denotes the status of the appliance whether it is on or off.

Table 2. Power ratings of appliances.

Appliances	Average Power Rating
Dishwasher	1.3
Laptop	0.35
Air conditioner	2.8
Television	0.5
Washing Machine	0.5
Water Heater	4.5
Refrigerator	0.5
Microwave Oven	0.25
Light	0.3
Fan	0.5
Electric iron	1.2
Vacuum cleaner	1.5
Clothes dryer	4.8
Electric Kettle	1.0

3.2. Peak Load

The peak load is a period when the power requirement on the electric grid is at its highest. The utility companies encourage the consumers to minimize the peak load to achieve balance between supply and demand. It is represented in terms of PAR, i.e., peak-to-average ratio. Reducing the peak load enables PAR to be minimized. The lower the PAR is to 1, the flatter the load profile curve is over a day.

3.3. Consumer Comfort

The solutions for residential appliance scheduling problems are provided by considering consumer comfort and preferences. Usually, consumer comfort is expressed as waiting time for scheduling the appliances. The waiting time and consumer comfort are inversely proportional to each other. The closer the waiting time to 0, the higher is the consumer comfort. Newer works in the field of appliance scheduling also consider thermal comfort as a part of consumer comfort. The consumer comfort in terms of appliance scheduling can be assessed/evaluated based on the following constraints:

- Timing: Consumer comfort is affected if the appliances are scheduled outside of their preferred time windows.
- Use of appliances: Consumer comfort is affected if the appliance functioning stops prematurely or the appliance does not perform at all.
- Appliance priorities: While scheduling the appliances, the order in which the appliances are scheduled is very important. Thus, consumer comfort is affected if the precedence or priority of a certain appliance over the other is changed.

3.4. Social Welfare

It is a factor to denote the balance between consumers' grid benefits and their associated costs. The home energy management system uses this factor to improve the overall social welfare of the group of consumers at a global level.

3.5. Environmental Criteria

Renewable energy sources are critical in maintaining the sustainability of energy. Thus, it is important to propose an appliance scheduling method which reduces toxic and harmful emissions by installing reliable RESs.

4. Home Energy Management System (HEMS)

A smart home is a key component of the smart grid which comprises a dwelling that provides consumers with comfort, home automation, security, and remote control of household appliances via smart technology [58,59]. Lutolf in [60] has defined a smart home as:

“The smart home concept is the integration of different services within a home by using a common communication system. It assures economic, secure and comfortable operation of the home and includes a high degree of intelligent functionality and flexibility.”

A home energy management system plays an important role in demand-side management, which deals with controlling and optimizing the home appliances on the basis of user preferences to enhance the energy efficiency. HEMS is a device that acts as a bridge between utility and smart home appliances to minimize or to shift the electricity consumption of the user. The main application of HEMS is smart dispatching between the utility company and the smart homes. It helps the utilities to deploy demand response programs to smart homes and the electricity pricing tariff is notified to the consumer. HEMS also helps to avoid blackouts or power outages by sending signals to the controller to either shift or curtail the appliances' load. Figure 5 shows the schematic block diagram of HEMS.

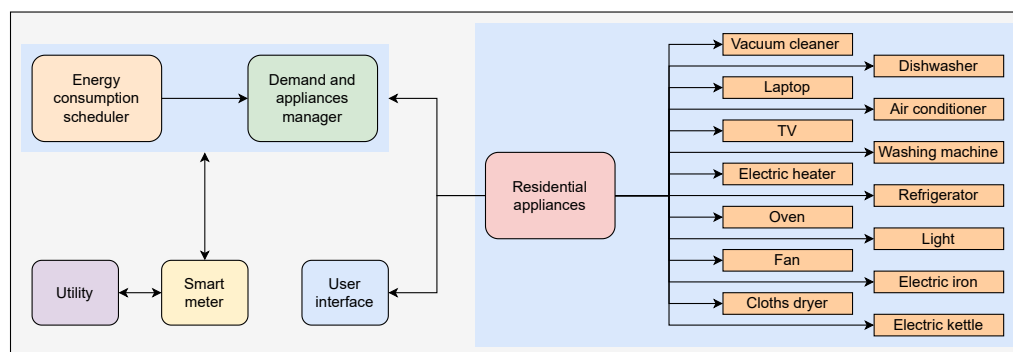


Figure 5. Block diagram for a home energy management system.

An energy consumption scheduler (ECS) is a core component of HEMS. It is an intelligent electronic device that monitors the residential consumer's consumption pattern. It makes sure that the aggregate demand does not exceed the predefined limit. The ECS contains scheduling algorithms that generate the final appliance schedules. The ECS is capable of communicating information among the HEMS and its components. The demand and appliances manager decides the priority and preferences of the appliances to be scheduled. The installation of smart meter in households allows the implementation of dynamic pricing mechanisms for utilities and consumers. A smart meter is a device that collects and monitors consumption data of households. It is a tool which facilitates bi-directional communication between the consumers and the utility. The smart meter analyzes and monitors the data received from the appliances. The users are informed about the dynamic tariff schemes published by the utility via a smart meter. The appliances

mentioned in Figure 5 are managed and monitored by the smart meter. Normally, the appliances used in the literature are vacuum cleaners, laptops, TVs, electric heaters, ovens, fans, clothes dryers, dishwashers, air conditioners, washing machines, refrigerators, lights, electric irons, and kettles. These appliances can be classified based on users' clarity on their classification and their operating mechanisms. The user interface is utilized by a smart meter to exchange the control information and readings between the utility and users.

4.1. Categorization of Household Appliances

In this work, we have assumed a smart home with loads concerning household appliances only. In the literature, smart home appliances are classified into different categories on the basis of comfort of consumers. Barbato et al. [61] classified home appliances into fixed, shiftable, and elastic types. The authors of [62] classified household loads into thermal loads, electrical loads, heat pump, etc. A few of the recent articles classified the appliances into controllable comfort based loads, controllable energy based loads, and non-controllable loads. In [63], the authors classified appliances into base, interruptible and non-interruptible appliances. Raza et al. [64] used the appliance classification as fixed, shiftable, and interruptible. In our study, we categorized smart home appliances into shiftable and manually operated appliances (MOA) for better energy management and scheduling. We consider a home where N is number of smart appliances used, having different lengths of operational time (LOT). The categorization of appliances is shown in Table 3.

Table 3. Classification of appliances.

Shiftable Interruptible (SI)	Shiftable Non Interruptible (SNI)	Manually Operated (MO)
Vacuum Cleaner	Washing machine	Television
Dishwasher	Water Heater	Light
Clothes dryer	Electric Kettle	Fan
Microwave oven	Electric iron	Laptop
		Air conditioner
		Refrigerator

4.1.1. Shiftable Appliances

This type of appliance can be shifted from a one-time slot to another time slot within a particular time duration where the pricing rate is minimum. These appliances can be further classified into two sub-categories: (i) shiftable interruptible appliances and (ii) shiftable non-interruptible appliances.

a. Shiftable interruptible appliances (SI): This type of appliance can be shifted from one slot to another and can be interrupted during its operation. However, they can be scheduled at any time within their stipulated time horizon. Interruptible appliances can suspend their operations during functioning and restart again to continue the operation, e.g., vacuum cleaners, dishwashers, and clothes dryers.

b. Shiftable non-interruptible appliances (SNI): This type of appliance can be shifted but is non-interruptible. They work in a cycle and cannot be interrupted once started and must keep running until they finish their tasks, e.g., washing machines, water heaters, and electric kettles.

4.1.2. Manually Operated Appliances (MOA)/Non-Shiftable Appliances (NS)

The appliances with fixed energy usage, such as TV, and music player, are in this category. In these appliances, the energy consumption is manually controlled by the real-time demands of the consumers and is uncertain compared to other shiftable appliances. These are manually operated, and users must be available to operate them. These appliances have fixed operation patterns, and user convenience depends on real-time demands. Exam-

ples are TVs, lights, fans, laptops, and air conditioners. The average power rating of the appliances is recorded from Nord pool cost data shown in Table 2.

5. Optimization Techniques for Residential Appliance Scheduling

Home energy management system (HEMS) keeps track of household energy usage and controls appliance schedules and operations. It can be accomplished through demand-side management, which assists consumers in shifting their appliance consumption from peak to off-peak hours, lowering household electricity costs. To adjust the appliance usage pattern, it's crucial to schedule them in such a way that they meet all of the RASP's optimization goals. Researchers have been working on providing local energy (RES) that is easy to generate, less expensive, and environmentally beneficial for several decades. According to several studies, integrating renewable energy sources into the residential sector provides the most cost-effective alternatives. The residential appliance scheduling is formulated as an optimization problem which schedules the smart home appliances in such a way that electricity cost is minimized, peak-to-average ratio is minimized, and consumer comfort is maximized. The aforementioned objectives are optimization objectives. Thus, to solve this problem, the methodologies employed to survey the scheduling techniques involve optimization techniques. The optimization techniques used in the literature are addressed using classical techniques with mathematical optimization, heuristic techniques, meta-heuristic techniques, hybrid-heuristic techniques, soft computing techniques based on artificial neural networks and fuzzy logic, artificial-intelligence-based techniques, reinforcement-learning-based techniques, and storage-system-based techniques. In this paper, we have surveyed the above mentioned techniques for appliance scheduling in residential sector.

In the literature, a significant amount of work exists on in-home energy management related to appliance scheduling, electricity cost, PAR, and consumer comfort. In the last few years, numerous optimization methods have been proposed to achieve the cost reduction objective. Some related work is cited below and summarized in Table 4. Similarly to previous sections, the approaches are classified based on optimization techniques for appliance scheduling, as shown in Figure 6.

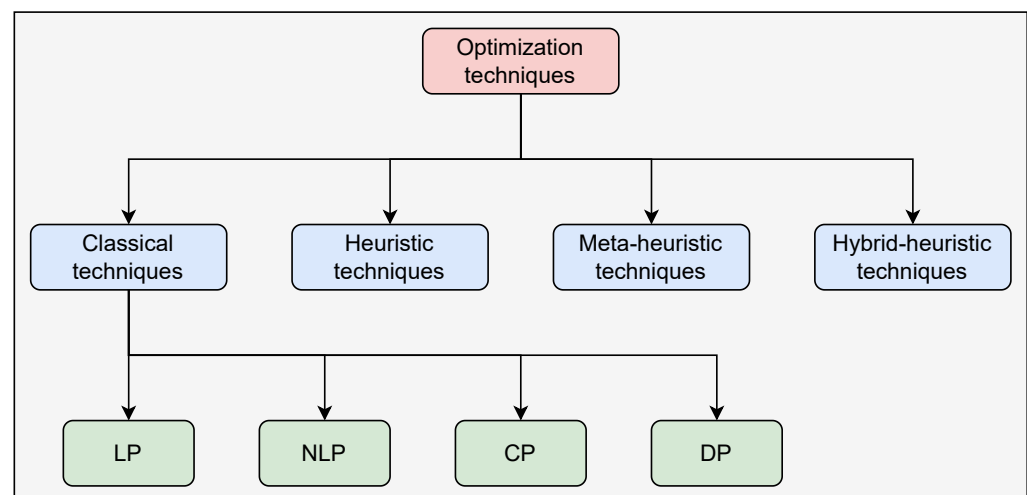


Figure 6. Classification of optimization techniques.

Table 4. Conventional techniques based on LP and NLP.

Demand Response Program	Objective	Optimization Algorithm	Consumer
Demand response program using load shifting and load curtailment [65]	To payoff demand response aggregator	MILP	Residential/commercial/industrial
RTP and IBR [66]	Reduction of electricity cost and improving consumer comfort	MILP	Residential
RTP [67]	Reduction of total cost of the energy hub	MINLP	General
ToUP [68]	Improving consumer comfort and reduction of energy bill	MINLP	Residential
RTP [69]	Reducing generation cost of utility	NLP	General
Direct load control (DLC) [70]	Reducing electricity bill	NLP and MINLP	General

5.1. Conventional Techniques Using Mathematical Optimization

The HEMS develops appliance operation schedules that satisfy one or more criteria while taking into account all of the underlying restrictions. Deterministic optimization-based approaches, which can be categorized into the following groups, are a traditional way to schedule household appliances. In this work, we focus on LP and NLP techniques, since they are the most widely studied algorithms in the field of appliance scheduling.

5.1.1. Linear Programming (LP)

The LP problem is a simplified version of an optimization problem in which the objectives and constraints are expressed by linear relationships. In other terms, to achieve the optimal solution, such as minimum cost or maximum profit, mathematical models are depicted as linear relationships [71,72]. It optimizes the linear objective functions concerning linear equality and inequality constraints. These problems primarily include binary programming [73,74] and mixed-integer linear programming [6,75]. LP problems have a relatively low computational burden and are used to solve low-scale optimization problems. Linear programming problems involve finding the best solution to achieve optimization objectives. Many researchers have applied LP methods to appliance scheduling. In [76], the authors proposed LP based scheduling mechanism to reduce the peak load and to balance the power consumption. The approach is evaluated on seven smart home appliances. It is observed that the LP scheduling technique achieves the effectiveness of the power consumption balance and can be useful for multiple homes as well.

Wang et al. [77] proposed mixed-integer linear programming (MILP) based technique to minimize electricity cost and improve consumer comfort. Single home with five appliances is considered with ToUP as a pricing scheme. The results show that power consumption and electricity bill is reduced by 5 and 58%, respectively. In [78], the MILP technique is used for scheduling to optimize cost, PAR, and consumer comfort. It is noted that the proposed approach achieves the said objectives and excess energy can be injected back to the main grid when the user demand is met. MILP based HEMS was proposed in [79] to schedule home appliances. The results demonstrated that the objective of improving consumer comfort while lowering the electricity cost is achieved.

5.1.2. Non-Linear Programming (NLP)

NLP is a technique for solving mathematical optimization problems with non-linear constraints and objective functions [80,81]. Many researchers have proposed NLP methods because it optimizes the cost and generates satisfactory results. Ref. [82] have used NLP techniques to achieve consumer comfort and reduction of energy costs. The pricing mechanisms like CPP, ToUP, RTP have been considered to evaluate the stochastic-based model. The results demonstrate that consumer comfort is improved and the cost is reduced. In [83], an NLP-based optimization approach is proposed for residential consumers in which the objective is to reduce electricity cost and PAR. In addition to the above-mentioned LP and NLP techniques, Table 5 (some of this table is adapted from [10]) summarizes a few more techniques for residential appliance scheduling.

Table 5. Comparison of conventional optimization techniques. (Part of this table was adapted from [10]).

Techniques	Mechanism	Characteristics
Linear Programming [6,73,75,84–87]	Mathematical Programming Model where the objective function is linear.	<ol style="list-style-type: none"> 1. It has a feasible solution and region. 2. The exact/optimal solution can be determined. 3. Objective functions have a fixed set of constraints. 4. It models a relationship between variables as linear to maximize or minimize an objective
Non-Linear Programming [81,88–91]	Mathematical Programming Model where the objective function is non-linear.	<ol style="list-style-type: none"> 1. The complex problem can be converted into an easy problem. 2. The sequence of sub-problems is solved. 3. The exact/optimal solutions can be found
Convex Programming [91–93]	Mathematical Programming Model where the objective function is convex.	<ol style="list-style-type: none"> 1. This method minimizes a convex or maximizes a concave objective function 2. Every local optimum is global optimum 3. The optimal set is convex 4. If the objective function is strictly convex, then the problem has at most one optimal point.
Dynamic Programming [81,92–95]	Mathematical Programming Model with no specific parameter and each problem has its own parameter.	<ol style="list-style-type: none"> 1. It breaks down a complex problem into simpler sub-problems. 2. It finds optimal solutions to these sub-problems. 3. Recursive relation is used to optimize the solution.

5.1.3. Convex Programming

Conic programming, least squares, geometric optimization, and Lagrange's method are used to tackle convex programming problems [93]. With recent advances in optimization algorithms, convex programming is now nearly as simple as linear programming. Convex programming techniques are usually used in demand response programs. In [96], the authors have used RTP evaluated convex optimization technique to minimize electricity cost and energy consumption.

5.1.4. Dynamic Programming (DP)

The optimization problem is divided into several smaller sub-problems [81] and each sub-problem is sequentially addressed one by one using the DP approach. Samadi et al. [97] proposed a cost minimization scheme for shifting household appliances. The day is divided into different time intervals and dynamic programming is used for each interval to schedule the appliances.

5.2. Heuristic and Meta-Heuristic Optimization Techniques

For solving large problems, conventional techniques using mathematical optimization are computationally expensive. Heuristic and meta-heuristic techniques offer good alternatives. They rely on the high-level procedure to search for solutions resulting in a lower computational burden than conventional techniques. The heuristic techniques are particularly useful for the problems where it is useful to find one sub-optimal solution. Meta-heuristics are very popular optimization algorithms for solving formidable optimization problems. They are more efficient than conventional techniques with mathematical optimization because of the large search space to find an optimal solution [98]. The meta-heuristic algorithms include particle swarm optimization [99,100], the genetic algorithm [100,101], ant colony optimization [100], wind-driven optimization [102], and bacterial foraging optimization [103], among others. The most used meta-heuristic algorithms are population-based algorithms. The main goal of these algorithms is to find a near-optimal solution with a relatively low computation burden as compared to conventional techniques. The meta-heuristic algorithms are global optimization algorithms and can be used for solving high scale constrained optimization problems.

5.2.1. Overview of Prominent Meta-Heuristic Algorithms (GA, PSO, and ACO)

In 1975, John Holland introduced a concept of genetic algorithm (GA) to solve search space and optimization problems by natural evolution like mutation, selection, crossover, inheritance [104–108]. GA is a well-established technique used for solving optimization problems [109,110]. It is an evolutionary algorithm and is inspired by the evolution of human beings from generation to generation. It is based on selection, mutation, and crossover parameters. At every iteration, mutation and crossover operators produce new individuals. To select a fitter individual among newly generated and previous individuals, a stochastic-based selection operator is used. GA is used for scheduling the residential appliances in optimal way [111]. An RTP-based pricing scheme is used. It achieves the objective of balancing demand and available supply. The results show that electricity-saving is 5%. In [112], the authors have used optimal scheduling of air conditioners and inverters using GA to achieve electricity bills and peak load reduction. They have used RTP as a pricing scheme that is notified to the user a day in advance. Genetic-algorithm-based load scheduling for DSM is used for optimizing electricity cost and consumer comfort [113,114]. Particle swarm optimization is the most commonly used meta-heuristic algorithm for solving optimization problems [23,115–121].

In [23], the authors have used binary PSO abbreviated as BPSO to achieve the objective of total electricity cost minimization. A total of 19 appliances have been used in the study and scheduling is done over a 16-hour time horizon to satisfy the requirement of the consumer. The results show that BPSO performs better than single swarm PSO. A mutation operator-based PSO-enabled appliance scheduling technique was developed in [115] for a large-scale distribution network for over 20310 consumers. Binary PSO-based optimal scheduling techniques for electric heaters are used for 200 households [116]. It is observed that the peak load of the utility is minimized and consumer comfort is maximized. In [117], PSO was used for DSM optimization problems to achieve minimum electricity bills for consumers. The experimental results show that PSO performs better than GA. In [121], the fuzzy-based PSO technique is used to solve the scheduling problem to minimize the power losses of the system. Ref. [120] have used binary PSO for reducing total cost and total consumption of electricity.

Ant colony optimization algorithm was introduced in 1992 by Dorigo [122,123]. The solution to any optimization algorithm can be determined by the optimal path of the graph. ACO algorithm possesses special characteristics like self-organization, self-healing, self-protection [124]. It is used for solving a discrete optimization problem. Extensive research has been done in the area of ACO for scheduling the appliances. In [124], the day ahead schedules are obtained using ACO enabled self-optimization technique. In this work, only shiftable appliances are considered. Okonta et al. [125] designed the scheduling technique based on ACO. The study focuses on electricity bills, consumer comfort, and the ToUP pricing scheme. Rahim et al. [126] proposed a load scheduling technique to reduce peak load, electricity cost, and PAR. They have used ToUP and IBR pricing tariffs to avoid complexity in the calculation of energy bills. Hazra et al. [127] presented a scheduling technique with demand response, fuzzy logic, and ACO. The results show the reduction in bill and improvement in consumer comfort. The characteristics of the aforementioned techniques are summarized in Table 6. Along with these prominent meta-heuristic techniques, there exist numerous population-based meta-heuristic algorithms for appliance scheduling which are discussed in this section.

Table 6. Comparison of meta-heuristic algorithms [10].

Meta-Heuristic Algorithms	Mechanism	User-Defined Parameters	Characteristics
Genetic Algorithm [104–108,128]	Inspired by the natural evolution of human beings	Population size, number of parents, selection, crossover, mutation and termination criteria.	<ol style="list-style-type: none"> 1. The chromosome genes are responsible for developing new solutions. 2. The genes denote the decision variable which contains discrete or continuous values. 3. The selection criteria and population size affects the search space. 4. The convergence of the solution depends on the selected solution and termination criteria.
Particle swarm optimization [128–132]	Swarm base technique inspired by the social the behavior of birds flock.	Initial inertia weight, final inertia weight, population size, termination criteria.	<ol style="list-style-type: none"> 1. The particle position in each dimension acts as a decision variable. 2. Fitness function value depends on the distance between particles and food. 3. The solution of the optimization problem using PSO is calculated by the updated distance from which the particle is moved to find a new solution. 4. The convergence rate of the solution is determined by the termination criterion, the running time of the the algorithm, and the objective function.

Table 6. Cont.

Meta-Heuristic Algorithms	Mechanism	User-Defined Parameters	Characteristics
Ant Colony optimization [128,133–136]	Inspired by social the behavior of ant species.	Population size, evaporation rate, pheromone, termination criteria.	<ol style="list-style-type: none"> 1. The path of the ant acts as a decision variable. 2. The path from nest to food determines the solution to the optimization problem. 3. The decision space depends on the fitness function and fitness value of the solution 4. The convergence rate depends on the run time of the algorithm, termination criteria, objective function, and the number of iterations.

5.2.2. Population-Based Meta-Heuristic Algorithms

Genetic algorithms and strawberry algorithms are used by researchers in [137] to address appliance scheduling problems. A smart home with 15 appliances was selected to achieve minimum cost, PAR, and maximum consumer comfort. The experimental results show that GA outperformed SBA in achieving the optimization objectives. The cost and PAR were reduced by 1.1 and 8.8% as compared to SBA, and consumer comfort was improved by 10%. In [138], GA, CSOA, and CSA were used for minimizing the cost, PAR, and waiting time. The pricing mechanisms used were RTP and CPP with 12 home appliances. It is noted that CSOA outperforms CSA and GA in reducing the electricity cost and PAR for both pricing schemes, and CSOA obtained the minimum trade-off for waiting time. Tariq et al. [139] addressed flower pollination algorithm (FPA) and harmony search algorithm (HSA). CPP scheme is used for the implementation of scheduling of 16 smart home appliances. The simulation results show that FPA performed better than HSA by 11 and 2% in terms of reduction of cost and 23 and 21%, respectively, in terms of PAR. However, HSA outperforms FPA in maintaining the user comfort trade-off. The authors of [140] used a gray wolf optimizer (GWO) for scheduling 38 home appliances to reduce PAR and cost. The performance of GWO was compared with GA. The results show that GWO outperforms GA by 4.6 and 17%, respectively, for electricity cost and PAR. Reference [102] proposed WDO based residential appliance scheduling for smart homes. It is observed that WDO performs better than PSO by 8 and 10% for PAR and energy cost.

EWA and HSA based optimization technique was used for 6 home appliances by implementing ToUP as a pricing scheme [141]. The results show that EWA works better for cost reduction while HSA performs better than EWA while considering PAR. In [142], BFO based load scheduling technique is used for minimizing the cost and peak load. BFO algorithm managed to handle a large number of appliances and showed better results than evolutionary heuristic algorithm. It reduced cost and PAR by 10 and 7%, respectively. The study in [143] developed GWO and BFO-based home appliance management wherein the appliances were classified into two categories. BFO and GWO achieved 45 and 55% cost reductions. In [144], Zafar et al. evaluated the performance of home energy management systems with the help of three algorithms namely, HSA, BFO, and EDE. It was observed that HSA performed better than BFO and EDE in terms of cost and PAR reduction. The existing optimization techniques are not suitable for handling complex optimization problems and are non-flexible in nature. They were found not incapable of handling cost optimization and consumer comfort maximization of the residential households with a large number of appliances [102,145,146]. Thus, we move towards hybrid heuristic optimization techniques.

Apart from the aforementioned techniques, a few more meta-heuristic techniques are summarized in Table 7.

Table 7. Meta-heuristic techniques.

Scheme	Objective	Limitations
GA [147]	Reduction of electricity cost and PAR	The complexity of the system is ignored
GA [148]	Reduction of electricity cost and PAR	Installation cost is ignored
GA [149]	Reduction of electricity cost	PAR and consumer comfort is neglected
GA [110]	Reduction of electricity cost and PAR	The consumer comfort factor is ignored
GA, BPSO, ACO[100]	Reduction of electricity cost and PAR and maximization of consumer comfort	Computational complexity is not considered.
BPSO [150]	Reduction of electricity cost	Consumer privacy is not considered
HSA [151]	Reduction of operational cost	Consumer comfort is ignored.
BFOA [152]	Reduction of electricity cost	The tradeoff between cost and consumer comfort is not considered.
GA, BPSO, WDO [153]	Reduction of electricity cost with affordable PAR	The trade-off between cost and PAR is ignored.

5.3. Hybrid Heuristic Techniques

A combination of two or more algorithms is considered a hybrid approach. Compared with single algorithms, the hybrid algorithms perform better for cost reduction, PAR reduction, and consumer comfort satisfaction. A hybrid evolutionary approach with PSO and neuro-fuzzy logic is proposed in [154] to eliminate the uncertainties of electricity rates. A forecasting model is designed 24 h ahead of time to cater to varying electricity prices. In [155], a combination of GA and PSO is used to consider non-linear optimization. The simulation results show that the proposed method is effective for the DSM optimization problem.

Javaid et al. [103] have designed a hybrid genetic wind-driven algorithm (HGWD) for the residential sector in the smart grid. The results show that HGWD performed better than GA and WDO individually by 10 and 33%, respectively, in terms of electricity cost. HGWD reduced consumer comfort by 40%, electricity cost by 30%, and PAR by 17%. Ahmad et al. [156] introduced hybrid approach (HGPSO) combining GA and PSO which performs better than GA, BFO, BPSO, and WDO. The percentage of cost reduction for GA, BFO, BPSO, and WDO was 9.8%, 15.4%, 19.5%, 15.8%, respectively. The hybrid model HGPSO produced a bill reduction of 25.12%. Similarly, PAR reduction for GA, BFO, BPSO, and WDO was 14.09%, 22.10%, 3.30%, 33.54%, respectively, while HGPSO reduced the PAR by 24.88%.

Iqbal et al. [157] presented 3 hybrid approaches for cost and PAR reduction. (1) WDO+GWO named WDGWO, (2) GA+WDO named WDGA, and (3) BPSO+WDO named WBPSO. The simulation results were performed and it is noted that WDGWO, WDGA, and WBPSO performed better than existing heuristic techniques. The results also show that the proposed scheme efficiently minimizes PAR and cost. Manzoor et al. [158] proposed teaching-learning genetic optimization (TLGO) combination of TLBO and GA. A day ahead pricing scheme is used for residential load management. The results have shown that the cost-saving with GA, TLGO and TLBO was 31, 33 and 31.5% respectively. The hybrid approach TLGO also had low customer discomfort which is 1.83 in comparison with 2.37 and 2.14 for GA and TLBO, respectively. Javaid et al. [159] combined bat algorithm (BA) and crow search algorithm (CSA) to propose hybrid bat crow search algorithm (BCSA). CPP pricing scheme was incorporated in the design of HEMS. The results showed that BCSA reduced the cost by 31.19% as compared to 28.32 and 26.70% for BA and CSA,

respectively. Awais et al. [160] proposed a novel hybrid algorithm by combining a bacterial foraging optimization algorithm (BFO) and flower pollination algorithm (FPA). RTP and CPP pricing schemes are incorporated to achieve the reduction of EC and PAR. It is noted that for both pricing schemes, the hybrid approach HBFPA performs better than BFO and FPA for reduction of cost and PAR with a reasonable waiting time. Apart from the aforementioned techniques, several hybrid heuristic techniques are studied in the literature which are summarized in Table 8 (extension of techniques reviewed in [16]).

Table 8. Hybrid heuristic techniques. Extension of techniques reviewed in [16].

Method	Objective	Pricing Scheme
GA and DWO [103]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP
GA and PSO [156]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP
GA and BFOA [161]	Electricity cost reduction PAR reduction Consumer comfort maximization	ToUP, RTP, CPP
EDE and TLBO [162]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP
GA and HSA [163]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP, CPP
FPA and BFOA [160]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP, CPP
FPA and BAT [164]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP
GA and TLBO [164]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP
GA and FPA [164]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP
HSA and BFOA [165]	Electricity cost reduction PAR reduction Consumer comfort maximization	ToUP
GA and MFO [166]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP
FPA and TS [167]	Electricity cost reduction PAR reduction Consumer comfort maximization	RTP

5.4. Soft Computing-Based Appliance Scheduling

Soft computing techniques are used to solve the existing complex problems where output results are imprecise and fuzzy in nature. Among many soft computing applications,

appliance scheduling is one of them. In the literature, soft computing techniques have been successfully applied to an appliance scheduling problem. Based on types of soft computing techniques, the scheduling can be classified as fuzzy-logic-based scheduling and artificial-neural-network-based scheduling as shown in Figure 7.

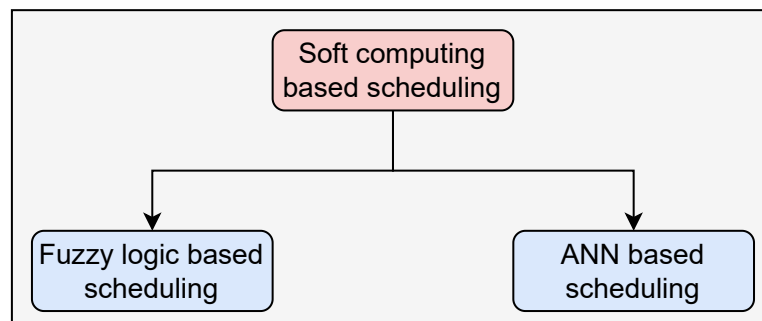


Figure 7. Soft-computing techniques.

5.4.1. ANN-Based Scheduling

An artificial neural network is a machine learning approach having numerous applications because of its adaptability, self-organization, and real-time fast solution. ANN is a universal approximator that uses supervised learning to solve scheduling problems. Feedforward network architecture is commonly used among all ANN topologies. There are two ways we can solve appliance scheduling problems using ANN; one is training an individual ANN for each appliance [168] and the other considers training a single ANN to schedule multiple appliances [169]. In [170], ANN-based adaptive control logic is developed for providing thermal comfort. The proposed method used 2 predictive models that resulted in better thermal comfort than the conventional logic. More recently, ANN based model is used for maintaining energy efficient smart home using DR signals and energy consumption patterns [171–173]. The study in [174] presented an ANN-based model and the branch and bound approach is used for optimization. The results have shown 5% energy saving. An ANN-based home energy management system is developed for optimal scheduling of appliances in [175] which selects appropriate learning rates and neurons. In [176], ANN-GA based hybrid model is designed for scheduling home appliances to reduce the grid energy usage. However, it fails to schedule a large number of appliances. The study in [177] involves an ANN-based HEMS model for minimizing the EC and achieving energy flexibility.

5.4.2. Fuzzy Logic-Based Scheduling

Fuzzy-logic-based techniques are used for monitoring and controlling home appliances for many years. Since fuzzy techniques are simple, adaptable, flexible, and have the capability in dealing with uncertainties and non-linearities [178,179]. Reference [180] proposed a fuzzy controller which minimizes electricity consumption and controls indoor building factors. The study in [181] designed the fuzzy controller which shows 76% of annual energy saving for the electric lighting. A day-ahead pricing for solving a scheduling problem involving an air conditioner is used in [182]. A fuzzy logic model was designed for it [183] addressed the residential home appliance scheduling problem using applied fuzzy logic. The user comfort factor was taken into consideration with the day-ahead pricing scheme. A novel intelligent-agent-based appliance scheduling is used in [184]. The experiment results show 3% energy saving while maintaining user comfort. In [185], the adaptive fuzzy controller is developed for achieving thermal comfort in the heating ventilation and air conditioning (HVAC) system. Fuzzy-logic-based design is used for controlling the HVAC system in [186]. The simulation results showed that the thermal comfort factor is achieved. The study in [187] classified the appliances according to consumption patterns and designed the fuzzy controller to control illumination and HVAC systems.

5.5. Appliance Scheduling from Other Perspectives

Apart from aforementioned techniques, there are other HEMS strategies which aim to schedule and control home appliances from artificial intelligence (AI), coordination and sharing methods, energy storage systems and incentive-based DR perspectives. Artificial intelligence techniques are controlled by mimicking human thoughts and embedding human intelligence into the machines. AI based scheduling techniques are mostly used for energy optimization and forecasting purposes. These techniques are generally classified into machine learning, deep learning, reinforcement learning, etc. With the recent technological advancements in smart grid infrastructures, various communication technologies and sensors are deployed which generates huge volume of data. This data needs to be subsequently processed. In the context of appliance scheduling problem, various data science and machine learning based techniques have emerged which target smart home energy management [188,189]. In [190], authors have comprehensively discussed various machine learning algorithms for demand forecasting and load management in residential sector. In the literature, various deep learning and reinforcement learning approaches have been proposed which aim to schedule appliances with maximum rewards [171,191]. In [192], the authors proposed cost optimization strategy based on deep reinforcement learning for home energy management. Lissa et al. [193] proposed deep reinforcement learning based model to handle energy savings and consumer comfort. A deep reinforcement learning approach is developed to determine optimal DR scheduling strategy [194]. Apart from these techniques, number of researchers are focusing on energy storage systems based DR implementation in recent years. Previously, the storage devices were not used because of their high cost, economic reasons and short time span of the batteries. However, in recent years, due to emergence of renewable energy sources (RES), DR implementation with energy storage systems (ESS) has become prominent in home energy management. Energy storage is the ultimate solution to overcome challenges associated with RESs. Batteries can be used to store the renewable power which in turn reduces the dependency on grid supply. The consumers are encouraged to store the power in storage devices when prices are low. The effect of ESS and RES for home energy management is discussed in [195]. The results show that storage devices can certainly be one of the solutions for reducing electricity consumption in peak hours. Wang et al. [196] integrated PV power generation and electrical energy storage (EES) into smart grid and proposed hybrid electrical energy storage (HEES). The proposed system shows 73.9% average profit enhancement for the cost of energy during a given day. The authors of [197] proposed a system equipped with both battery system and grid energy to schedule the electrical appliances. In this system, the batteries are charged when electricity tariffs are cheaper and used for running appliances when tariffs are high.

Aliabadi et al. [198] presented a comprehensive review on coordination and sharing of electricity in neighborhood areas for smart home energy management. The authors of [199] proposed a coordination mechanism for neighboring households with PV battery systems. A predictive control model based on dynamic programming is designed to increase the energy exchanged within neighborhood. A centralized coordinated DR for neighborhood is proposed by [200]. The proposed DR model helps in achieving consumer satisfaction. The authors of [201] proposed coordinated DR for smart homes. The proposed approach shows the reduction of peak load and peak losses. In [202], authors have used peer-to-peer energy trading strategy with prosumer concept. The DR implementation is performed in two phases. Each smart home appliance is scheduled using BPSO algorithm with RTP model and energy trading is carried out between prosumers and consumers based on DR implementation. The simulation results show that the electricity cost is minimized without affecting the consumer comfort of both prosumers and consumers. In [203], the authors proposed a power scheduling algorithm based cost efficiency model to improve consumer comfort. A trade off between consumer comfort and electricity cost is taken into consideration. The results show that the proposed method saves the electricity cost and improves consumer comfort factor. In [204], multiobjective home energy model is imple-

mented using PSO and MILP techniques for prosumer-based energy management. The experiment demonstrates that the maximization of consumer comfort is achieved. A hybrid genetic ant colony optimization algorithm is proposed using photovoltaic battery system to reduce electricity cost, alleviate peak load and maximize consumer comfort [205]. The authors of [206] proposed mixed integer programming based sharing technique for smart home energy management. The underlying system is capable of exchanging electricity through sales and purchases. The proposed approach determines optimal day ahead energy scheduling of home appliances. In [207], the authors proposed decentralized scheduling model for sharing the renewable energy among interconnected smart homes. The results show the reduction in electricity cost and PAR without affecting the consumer comfort. A day ahead decentralized coordination approach is proposed for appliance scheduling and energy sharing to reduce electricity cost of consumers [208]. In [209], the authors proposed a starvation free optimal energy sharing in distributed households environment in which surplus energy of a prosumer smart home is exchanged with other consumer smart homes. DSM and DR implementation is broadly discussed with challenges involved in DSM, optimization techniques in DSM and application of storage devices such as battery ESS and EVs in [210]. In DR implementation, most of the existing literature focus on price-based DR. However, there are fewer studies mentioning incentive-based DR in residential sector. In incentive-based schemes, the consumers are under contractual agreement with utility companies which allow them to conduct load management programs to reduce the electricity cost. The incentive-based DR programs are classified into direct load control, emergency DR, interruptible services, capacity market programs, demand bidding and ancillary services market. Direct load control (DLC) is an important aspect of incentive-based DR implementation. DLC is offered to residential users which enables utility companies to remotely switch off the consumer's equipment [69]. The consumers who participate in DLC program are offered monetary incentives in advance to reduce the consumption below defined thresholds [211,212]. In [213], the authors proposed practical load scheduling optimization method for energy management using incentive-based DR. Interruptible services encourage the involved consumers to shift their load from peak hours to off-peak hours or allow them to shut down the load during emergencies failing which users may get penalty [214,215]. Emergency DR programs are used when demands are high and grid is affected by unplanned fault events. In such emergency situation, consumers reschedule their loads to reduce the stress on grid. In turn, they receive monetary benefits based on the requested levels of load reduction [216,217]. In [218], the authors proposed an incentive-based demand response optimization (IDRO) model which is used to cost-effectively schedule smart home appliances for minimum usage during peak hours. In demand bidding, the involving consumers are offered rewards based on their participation in the electricity trading for reducing their consumption. It is a market based program in which consumers bid for the load they wish to reduce [219].

5.6. Key Points and Observations

Following are the key points and observations of the review.

- In the manuscript, we have listed demand-side management strategies for appliance scheduling, which include classical techniques, LP based techniques [6,71–79], NLP based techniques [80–83,88–91], convex programming and dynamic programming [81,92–96], genetic algorithm [104–108,128], particle swarm optimization [128–132], ant colony optimization [128,133–136], population based meta-heuristic algorithms [102,137–146], hybrid-heuristic algorithms [103,154–167], artificial neural network based soft computing techniques [168–177], fuzzy logic based techniques [178–187], artificial intelligence based techniques [171,188–194], storage system-based techniques [195–197], sharing and coordinating neighborhood techniques [198–210], consumer comfort maximization techniques [200,202–205,207,210], and incentive-based DR [69,211–219].
- We provided a brief overview of important components of the smart grid to manage household consumption daily. The smart grid components include demand-side

management, demand response programs, home energy management systems, and smart home appliances.

- The demand-side management strategies and techniques are very effective and have shown immense potential in residential appliance scheduling to manage users' consumption patterns. However, a few issues need to be addressed to improve and enhance the power system.
- LP-based optimization is used when the constraints and objective functions are linear. It is capable of providing the optimal solution. Moreover, it is fast and has high solution speed. The problem arises when a non-linear problem is deduced into a linear one, which may lead to an inaccurate solution.
- The NLP method provides a local or global optimum solution. It provides simpler solutions to complex problems, and similarly to LP techniques, NLP has a high computational burden and is unable to solve high scale optimization problems.
- Conventional techniques such as LP and NLP are best suited for finding exact solutions, but fail to solve high dimensional and computationally expensive optimization problems.
- Heuristic and meta-heuristic algorithms are relatively faster techniques capable of finding the near-optimal appliance schedules. However, some of the meta-heuristic techniques can take time without satisfactory solutions due to their convergence nature.
- The efficiency of GA can be improved for a large number of iterations. However, the algorithm can provide misleading results. The PSO implementation is complex because of the long tracking process and poor response. The ACO uses pheromone evaporation and weighing parameters as the standard parameters to solve the optimization problem, as opposed to GA, which uses population size, crossover probability, and mutation probability. PSO uses swarm size, iterations, and neighborhood size as parameters.
- GA, PSO, and ACO have fast convergence speeds given that a good set of parameters must be defined. However, GA cannot converge easily in the presence of noise. ACO convergence rate is faster than GA.
- The prominent conventional and meta-heuristic optimization algorithms are LP, NLP, GA, PSO, and ACO. All these algorithms are used to solve the same optimization problem of appliance scheduling. However, they vary in terms of efficiency, convergence, and reliability.
- GA, PSO, ACO are meta-heuristic evolutionary optimization algorithms that use different search spaces to obtain the optimum schedules. They exhibit high efficiency and high system independence.
- Soft computing techniques are used to solve complex and real world problems. They are faster and do not require mathematical models for computation.
- Fuzzy logic models are integrated with meta-heuristic algorithms to solve the residential appliance scheduling problem. These algorithms can provide the best possible results for the reduction of energy consumption without affecting consumer comfort.
- Hybrid and modified algorithms were found better in terms of performance and results than a single algorithm.
- Energy storage systems in smart homes such as electric vehicles, batteries are promising technologies that maintain the flexibility and robustness in the smart home and will change the grid scenario completely in the near future.
- From our detailed review, it was observed that a single algorithm may not be best to solve the complex optimization problem because of its low convergence rate, low performance, high complexity of constraints, etc. Thus, modified and hybrid algorithms are used to solve those complex problems because of their convergence rates, performances, uncertainties. As a result, the modified and hybrid algorithms outperform the single algorithms.
- Based on the conducted review, most of the papers in the literature focus on residential consumers and ignore industrial consumers. The amount of electricity consumption in industrial sector is huge in comparison with total electricity provided by utilities.

Most of the electricity is used for industrial automation, which includes manufacturing, construction, mining, printing, etc., where high loads are involved. The utility companies face a lot of challenges in order to fulfill this huge demand. Some of the challenges include maintaining an adequate electricity supply and cybercriminals launching cyber-attacks. Thus, we recommend studying the Industrial Appliance Scheduling Problem (IASP) and surveying DSM techniques for industrial users too.

6. Conclusions and Future Directions

This manuscript provides a review of highly cited recent and old articles on DSM for the residential appliance scheduling problem. Demand-side management techniques and types of demand response programs are discussed in detail. We presented a comprehensive take on home energy management systems focusing on conventional, heuristic, meta-heuristic, and hybrid heuristic techniques. In conventional techniques, the main focus is on LP and NLP optimization. The conventional techniques are used for finding exact solutions, but they fail to find the optimal solutions for computationally expensive problems, such as RASP, because of their complex nature. Furthermore, prominent meta-heuristic algorithms such as GA, PSO, and ACO were discussed with other population based heuristic algorithms. We also addressed soft-computing techniques, namely, artificial neural networks and fuzzy logic. Soft computing techniques provide the best possible results without affecting the consumer comfort. A comparison between various residential appliance scheduling approaches was given in terms of various factors, including electricity cost, peak load, and consumer comfort. Apart from these, a brief overview of artificial intelligence techniques, sharing and coordination techniques, storage-system-based techniques, and incentive-based techniques was also presented. From the detailed survey, it was observed that modified and hybrid techniques show better results than a single algorithm in terms of convergence, complexity, and performance. Looking forward, the demand response programs can be further investigated for wholesale electricity market where competition and bidding is involved. The residential appliance scheduling schemes can play a pivotal role in facilitating a microgrid as a power system solution in the future for energy efficiency. In a smart grid, renewable energy sources are crucial for attaining a sustainable grid and can be included in the system. However, integrating RESs with a grid to solve appliance scheduling problems with cost-effective implementation requires further investigation. Hybrid-based optimization algorithms improve the convergence and computational time of the DSM optimization problems. However, when solving the optimization problem, type of optimization should be taken into consideration in the future. Additionally, in cases of industrial DR implementation, a similar kind of survey is required for the industrial appliance scheduling problem. RASP is a scheduling problem where appliances are scheduled in a time-wise manner. Thus, for scheduling purposes, operating system concepts such as priority scheduling, CPU scheduling, and shortest job first scheduling can be incorporated to solve the problem.

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Abbreviations

The following abbreviations are used in this manuscript:

ACO	Ant Colony Optimization
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
BFO	Bacterial Foraging Optimization
BFOA	Bacterial Foraging Optimization Algorithm
BPSO	Binary Particle Swarm Optimization
CP	Convex Programming
CPP	Critical Peak Pricing
CSA	Cuckoo Search Algorithm
DAP	Day Ahead Price
DLC	Direct Load Control
DP	Dynamic Programming
DR	Demand Response
DSM	Demand-Side Management
EC	Electricity Cost
ECS	Energy Consumption Scheduler
EDE	Effective Differential Evolution
EES	Electrical Energy Storage
EsS	Energy Storage Systems
EWA	Earth Worm Algorithm
FA	Firefly Algorithm
FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GWO	Grey Wolf Optimization
HEMS	Home Energy Management System
HEMSs	Home Energy Management Systems
HEES	Hybrid Electrical Energy Storage
HGWD	Hybrid Genetic Wind Driven
HSA	Harmony Search Algorithm
HVAC	Heating Ventilation Air Conditioning
IBR	Inclined Block Rate
ICT	Information and Communication Technology
IDRO	Incentive-based Demand Response Optimization
LOT	Length of Operational Time
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-linear Programming
MO	Manually Operated
MOA	Manually Operated Appliances
NLP	Non Linear Programming
NS	Non Shiftable Appliances
PAR	Peak-to-Average Ratio
PSO	Particle Swarm Optimization
RASP	Residential Appliance Scheduling Problem
RESs	Renewable Energy Sources
RTP	Real Time Pricing
SBA	Strawberry Algorithm
SG	Smart Grid
SI	Shiftable Interruptible appliances
SNI	Shiftable Non-Interruptible appliances
TLBO	Teaching-Learning-Based Optimization
TLGO	Teaching Learning Genetic Optimization
ToUP	Time-of-Use Pricing
WDO	Wind Driven Optimization
WT	Waiting Time

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