

Review

Demand Side Management for Smart Houses: A Survey

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Abstract: Continuous advancements in Information and Communication Technology and the emergence of the Big Data era have altered how traditional power systems function. Such developments have led to increased reliability and efficiency, in turn contributing to operational, economic, and environmental improvements and leading to the development of a new technique known as Demand Side Management or DSM. In essence, DSM is a management activity that encourages users to optimize their electricity consumption by controlling the operation of their electrical appliances to reduce utility bills and their use during peak times. While users may save money on electricity costs by rescheduling their power consumption, they may also experience inconvenience due to the inflexibility of getting power on demand. Hence, several challenges must be considered to achieve a successful DSM. In this work, we analyze the power scheduling techniques in Smart Houses as proposed in most cited papers. We then examine the advantages and drawbacks of such methods and compare their contributions based on operational, economic, and environmental aspects.

Keywords: smart grids; power scheduling; demand side management



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1. Introduction

An electrical grid is a huge complex network designed to provide electricity to consumers to satisfy their increasing daily needs. In 2016, the International Energy Outlook 2016 Reference case ([https://www.eia.gov/outlooks/ieo/pdf/0484\(2016\).pdf](https://www.eia.gov/outlooks/ieo/pdf/0484(2016).pdf) (accessed on 11 June 2021)) projected a notable increase in worldwide energy demand over the 28 years from 2012 to 2040.

This global consumption increase has led to an urgent need to improve the existing (traditional) grid to meet the growing demand. This is because the traditional grid [1] still faces many issues as it operates the way it did many years ago. There are several problems that are related to the traditional, outdated grid: (1) it is a centralized grid, where power is carried from a central generator to the users. Usually, traditional grids are powered by non-renewable energy resources such as diesel and natural gas; (2) it has a one-way communication infrastructure, where the user is receptive and cannot include his power needs and preferences into the grid; and (3) it is not well equipped with advanced sensors and monitors which weakens its capabilities in detecting anomalies and problems. All these problems led to increasing the grid's vulnerability, leading to high failures and power outages risks. It is worth noting that the world has witnessed significant power blackouts [2] resulting in catastrophic consequences on the countries' economic and social situations. These blackouts were due to either natural or human-made disasters. Here are some most recent examples

- On 4 August 2019 [3], tens of millions lost power in Jakarta and surrounding cities. The outage happened two days following a 6.9 magnitude earthquake that struck Indonesia.
- On 12 October 2020 [4], India's financial capital in Mumbai suffered one of its worst blackouts in decades as technical glitches caused its power-transmission network to shut down, leaving millions of people without power for hours.
- On 9 January 2021 [5], a total grid collapse occurred in Pakistan, affecting 200 million people. The power outage was due to a frequency drop resulting from a "fault" at Guddu.
- From 13 February to 17 February 2021 [6], an enormous snowstorm caused over 5 million inhabitants to lose power across the United States.

Therefore, huge investments are required to make the existing grid more reliable and efficient. According to the International Energy Agency (<http://www.worldenergyoutlook.org/media/weowebiste/2008-1994/weo2003.pdf>) (accessed on 11 June 2021), the global expenditures needed in the energy sector over the period 2003–2030 are estimated at 16 trillion dollars.

In order to overcome the traditional grid limitations and provide reliable energy supplies, new services and opportunities have been emerging in the electricity domain. One renowned solution is the 'Smart Grid' (SG) concept. An SG is an electrical grid that uses digital technologies to provide better reliability and monitoring of the grid. Smart Grid is based on two-way communication infrastructure, enabling real-time information exchange between the electrical components. The SGs make the grid more flexible and intelligent, significantly improving efficiency, cost, and adaptability.

The SG is expected to transform the traditional grid by enabling two-way communications to enhance performance, security, economics, and sustainability of the generation, transmission, and electrical power distribution. However, Smart Grids face several limitations that need to be addressed [7–11] most importantly:

1. Smart Grid Security : Cyber-attacks [8,12,13] have become widely spread due to the grid's digitalization. One serious threat is the possibility to remotely switch off the SG operators, generating cascade damages on the grid. Hence, to reduce the grid invasions, one of the SG critical challenges is ensuring reliable identification of the components (for secure authentication and better traceability).
2. Electric Mobility: Electric vehicles (EVs) [14] will shape the energy market, contributing to significant changes in SGs, leading to a cleaner and more digitized environment. Therefore, the SG should model and resolve the EVs' local constraints and stability problems to benefit from their flexibility while ensuring the grid's stability.
3. Smart Grid Interoperability [15–17]: An SG usually consists of a considerable number of heterogeneous components such as power production, storage systems, electrical loads, and prosumers [18,19]. Such components are designed by various organizations with different protocols. The heterogeneity is also due to the diverse communication between the SG components and the main grid. Hence, there is an urgent need to develop an information model able to cope with the SG heterogeneity allowing a semantic and seamless interaction between the components.
4. Smart Grid Cooperation: An SG is a two-way communication infrastructure where the consumer can communicate and share his power needs with the grid. Consequently, good cooperation [20–22] should be established between the SG components to meet their needs. However, a non-cooperative SG will result in harmful operational, economic, and environmental consequences. From an operational prospect, a non-cooperative SG would increase the transmission and distribution losses by allowing the power exchange between distant components rather than favoring exchange between neighboring components. From an economic prospect, a non-cooperative SG would lead to a rise in the power costs by allowing components to exchange power with the main grid rather than exchanging power locally inside the SG, which is often more expensive. A non-cooperative SG would be environmentally harmful from an environmental prospect as it allows power exchange between the loads and the

pollutant non-renewable energy sources, rather than encouraging the exchange with the renewable sources.

Indeed, Information and Communications Technology (ICT) facilitated the move of power systems from one way to two-way communication systems. This transition allowed their components to communicate and express their needs in the grid, which produced a new concept called: Demand-Side Management (DSM) [23]. The DSM [24] refers to the planning and implementation of the utility companies' programs designed to influence consumer consumption (directly or indirectly) by reducing the system peak load and electricity costs. A proper DSM technique can maximize the SG efficiency. In general, DSM techniques can be classified into two main categories:

- Load shifting: involves encouraging the consumer to shift his power consumption from one period to another (on-peak to off-peak) to reduce energy costs and the power peak of the grids.
- Energy efficiency and conservation: consists of any technology that requires less energy or behavior that results in lower energy consumption.

Despite the importance of energy efficiency and conservation approaches, load shifting is our survey's focus and, more specifically power scheduling. Our choice is related to our belief that it is easier to motivate users to reschedule their needs rather than asking them to reduce their consumption. While power scheduling techniques have been discussed in the literature, to the best of our knowledge, none of them has addressed power consumption, storage, and production while considering the operational, economic, and environmental perspectives.

In this work, we address the following challenges in order to show the advantages and limitations of current solutions:

1. Operational: Several limitations can be mentioned regarding the operational aspect:
 - Consumer Comfort: thanks to the two-way communication protocols, SGs provide the consumers with the capacity to communicate and express their needs in the grid, which increases their integration and, consequently, their comfort. However, while the consumers enjoy their reduced electricity bills when shifting their consumption from on-peak to off-peak periods, they might experience inconvenience due to the inflexibility of getting power on demand.
 - Peak Load Reduction: the peak load [25] is a period when power demand on an electrical grid is at its highest. Reducing the peak load is very important and can be realized when the generated power matches the needed power. This would conduce to increase the reliability of the components and decrease the possible failures.
 - Threefold Scheduling Coverage: the key to successful power scheduling relies on considering the scheduling of not only the power production but also the consumption and storage because of their critical roles in shaping the peak load, reducing the electricity bills, and minimizing the gas emissions.
2. Economic: knowing that the electricity price relies on the demand and supply over a specific period, adequate scheduling is expected to shift loads during periods of high market prices (peak hours) and consequently minimize the electricity costs.
3. Environmental: renewable energy sources play an essential role in ensuring sustainable energy with less toxic emissions. Hence, it is essential to provide a power production scheduling that reduces the harmful emissions and effects on the environment by lowering simultaneous and excessive toxic power production and increasing the reliance on renewable energy sources.

This paper aims to provide a profound literature review of the most cited power scheduling techniques. In section two, the advantages and drawbacks of the existing methods concerning the aforementioned challenges are discussed. The final section concludes the work and opens up new perspectives.

2. Research Methodology

Research in the field of demand side management started in the last decade. Since then, few surveys have been conducted [26–28]. In [26], the survey mainly focused on analyzing the approaches based on their objective functions goals such as reducing the electricity bills, minimizing the power consumption, etc. In [27], the authors compared the scheduling techniques based on consumer interactions, optimization strategy, and time scale. The latest survey, published in 2019, reviewed some of the existing scheduling techniques per their objective functions, pricing schemes, and datasets [28]. We aimed through our survey to provide an actual and deeper analysis of papers that target the power scheduling related to demand side management. To conduct our survey, we used Publish or Perish tool (<https://harzing.com/resources/publish-or-perish> (accessed on 11 June 2021) in order to include a variety of data sources (e.g., Google Scholar and Microsoft Academic). We run two test categories:

- The first category was related to smart power scheduling in general (since demand side management is part of it). The objective here was to identify the most related impacting works. To do that, we run different combinations of the following keywords and synonyms: *Smart Home* and *Power Scheduling*. We found 980 papers, with the oldest paper published in 1999 and cited 71 times [29]. Out of the list, we extracted and analyzed those having high citations (>400) and addressing in a way or another the demand-side management. We considered 15 papers connected in a way that each work is a continuation or improvement for the previous one.
- The second category was related to demand-side management in particular. The objective here was to identify all the related works until now. To achieve this, we searched for the following keywords and synonyms: Smart Home, Power Scheduling, and Demand Side Management. Based on that, and after eliminating the duplicates and the unavailable papers, we gathered 14 additional articles, with the oldest published in 2011.

In order to understand the tendency of each category of papers, we used an unsupervised LDA-based clustering algorithm [30]. We observed the following:

- In the first category, we obtained the following keywords cloud (Figure 1). The papers were clustered into 10 clusters, semantically disjoint (except three of them) as shown in Figure 2. We also observed that main papers' topics were not fully addressing the demand-side management.
- In the second category, we obtained the following keywords cloud (Figure 3). The papers were clustered into two main clusters, visually disjoint but semantically closed when checking the terms shaping each cluster as shown in Figure 4. This demonstrates that the tendency of topics addressed in these papers is stable within this specific area of demand-side management.

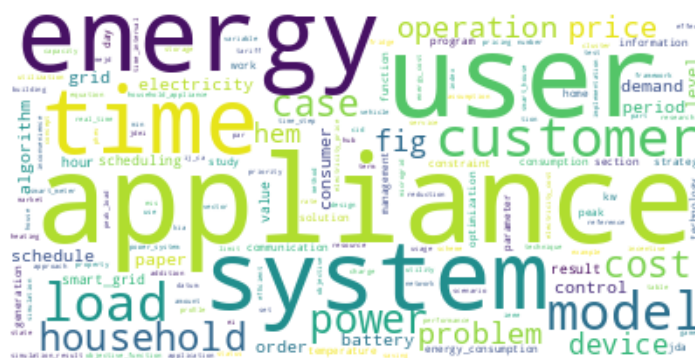


Figure 1. Keywords generated from the papers of the first category.

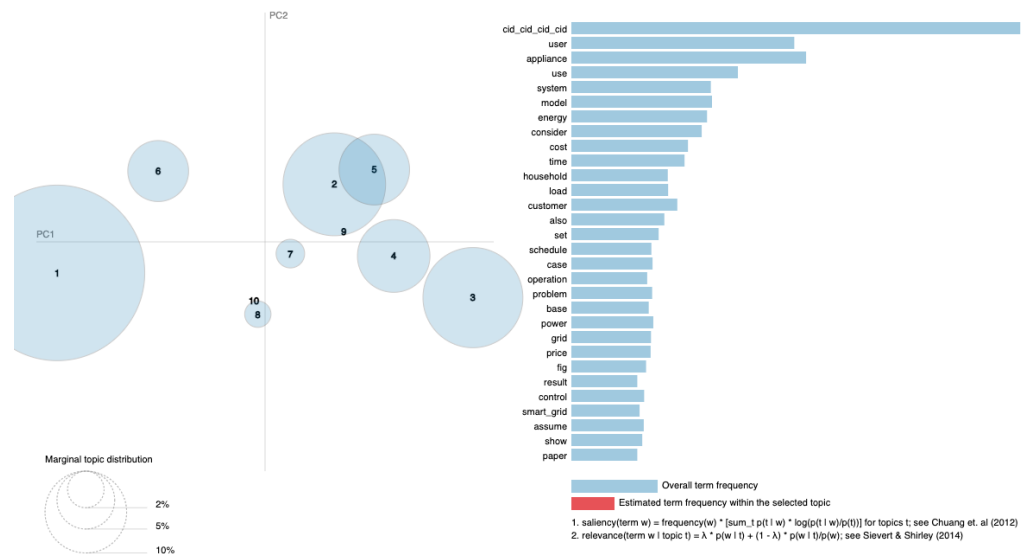


Figure 2. Clusters generated from the first category.

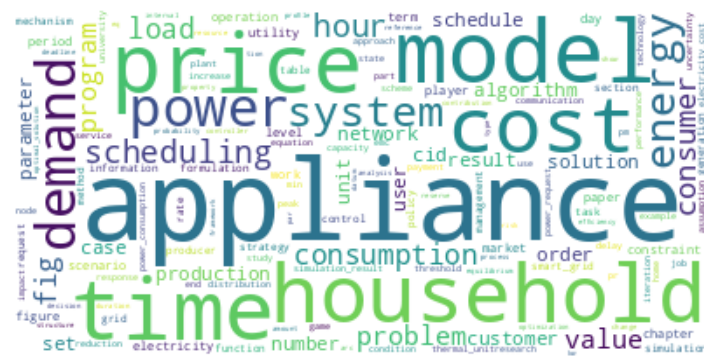


Figure 3. Keywords generated from the papers of the second category.

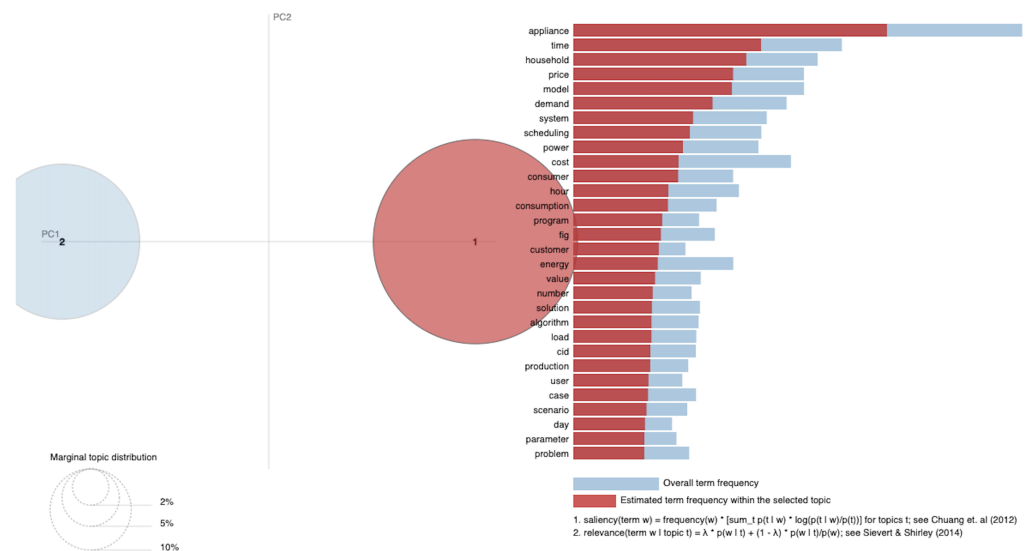


Figure 4. Cont.

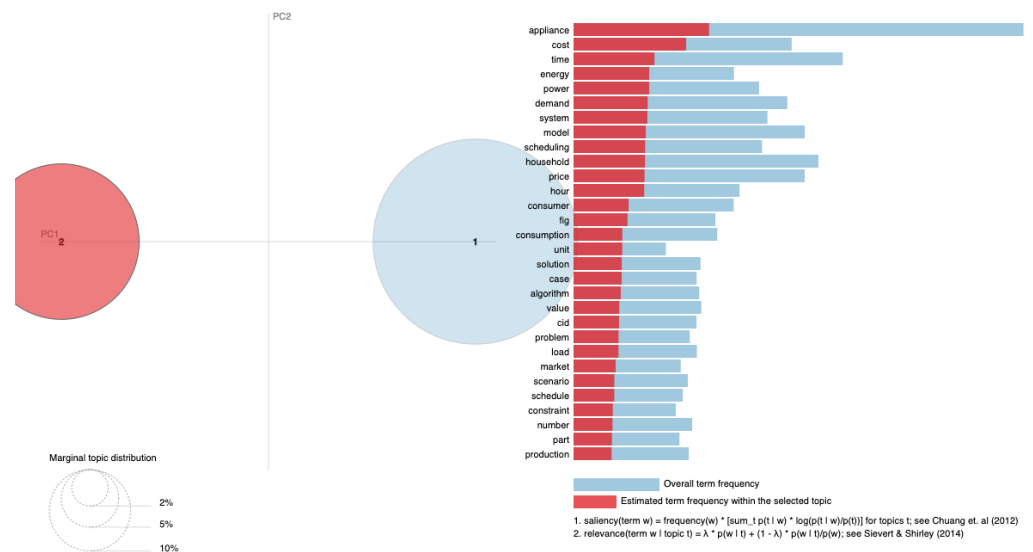


Figure 4. Keywords of the two clusters generated from the second category.

In the following sections, we will detail each category separately.

3. Power Scheduling for Smart Home Approaches

In this section, the approaches are categorized based on the optimization technique used to perform the power scheduling. The following nine different optimization techniques were identified: MILP (Mixed Integer Linear Programming), VCG (Vickrey–Clarke–Groves Auction), BPSO (Binary Particle Swarm Optimization), IPM (Interior-point method), CPSO (Cooperative Particle Swarm Optimization), SHM (Shrinking Horizon Method), NLP (Non-Linear Programming), Nash Equilibrium, LP (Linear Programming). Hence, we identified four main optimization categories: CPLEX, including the linear and non-linear programming techniques; Game theory-based including the Vickrey–Clarke–Groves auction and Nash Equilibrium techniques; Swarm-based including the cooperative and binary particle swarm optimization; and Spatial methods, including the interior-point and shrinking horizon methods, to compare and analyze the effectiveness of each category.

3.1. CPLEX Techniques

In [31], a Home Energy Management (HEM) system is developed using a Mixed Integer Linear Programming (MILP) approach. The proposed HEM considers the priority of appliances' operation based on Demand Response (DR) programs while considering the energy prices. To achieve this, the authors assigned a Value of Lost Load (VOLL), which determines each appliances' operation's priority based on time-varying tariffs. These tariffs include the Time of Use (TOU) and the Inclining Block Rate (IBR). The optimization problem's objective aims at reducing the power cost of the consumer and represented as:

$$\text{Min}(\text{Cost}) = \text{EC} + \text{RC} \quad (1)$$

where:

$$\text{EC} = \sum_{t \in T} \gamma(t)E(t) = \alpha * El + \beta * (E - \delta) \quad (2)$$

and

$$\text{RC} = \sum_{a \in A} \text{VOLL}_a L E_a \quad (3)$$

Cost is the overall cost paid by the consumer, *EC* is the energy cost function of the consumer, and *RC* is the reliability cost. For *EC*, *t* is the time step-index and *T* is the maximum time for scheduling; *E(t)* is the electricity consumption at *t*, $\gamma(t)$ is the TOU tariff at time *t*. *El* is the electricity consumption per day that should be lower than the

threshold δ , while $(E - \delta)$ is the electricity consumption. For RC, a is the appliances' index, and A is a set of appliances. Additionally, $VOLL_a$ is the VOLL of an appliance a , predefined by the consumer based on the value of the appliance's operation for him, and LE_a is the energy loss of an appliance a . Experiments showed that using appliances operation prioritization can lead to an electricity cost reduction of 7.5 %.

In [32], the authors developed a framework for home appliances scheduling to reduce the electricity cost for their operation based on time-varying electricity tariffs using MILP. To do so, the authors discretized the execution time into time slots. Then, they denoted the number of appliances for scheduling as n and uninterruptible energy stages for each appliance. Also, they modeled the power profiles describing real continuous decision variables as P_{ij}^k , which represents energy provided for the energy stage j for appliance i at a given time k . To identify whether a particular energy stage is being attended to or not, the auxiliary binary variables consisting of two values are used, denoted as $x_{ij}^k \in \{0, 1\}$. If an appliance is being processed then $x_{ij}^k = 1$. Otherwise, the decision variables are not required since there is no appliance being processed. Two sets of binary decision variables are required to design a decision problem. $s_{ij}^k = 1$, indicates an appliance i is already finished at a given time slot k then $x_{ij}^k = 0$, which means there is no appliance being processed. t_{ij}^k denotes the other set of decision variables, which indicates if an appliance is changing after processing stage $j - 1$ and is waiting to begin stage j . Therefore, the proposed scheduling problem is a minimization cost function, subject to energy and timing constraints. The cost function is used to reduce the power cost for an appliance's operation based on a daily electricity tariff. Thus, the total power cost for the operation of all home appliances is:

$$\sum_{k=1}^m c^k \left(\sum_{i=1}^N \sum_{j=1}^{n_i} P_{ij}^k \right) \tag{4}$$

where c^k indicates electrical energy tariff for given time slot k . Several energy constraints were introduced to ensure that energy requirements are completed for each energy stage and whether the energy stage is attended or not. The timing constraints need to design endpoints on energy stage processing time for the uninterruptible operation, sequential processing, between-phase delay, and user time preference. A classical optimization paradigm is represented as follows:

$$\begin{aligned} P_{ij}^k &\in R, \forall i, j, k \\ x_{ij}^k &\in \{0, 1\}, \forall i, j, k \\ s_{ij}^k &\in \{0, 1\}, \forall i, j, k \\ t_{ij}^k &\in \{0, 1\}, \forall i, k \forall j = 2, \dots, n_i \end{aligned} \tag{5}$$

The proposed approach realized about 47% of maximum cost saving.

In [33], the authors proposed an optimal management system for a microgrid integrated with a Vehicle-To-Grid (V2G) system, electric vehicle (EV) system, and renewable energy resources to allow the system to generate different kinds of elements. This can be achieved by considering the EV with its state-of-charge (SOC), three load profiles, critical, adjustable and shiftable load, and the effectiveness of the microgrid components within the advance price. The objective function is:

$$\begin{aligned} (a) \sum_{t \in T} \Delta_T (C^{I_2} (P_t^{I_p} + P_t^{I_s}) + C_t^{I_1} (P_t^{I_p} - P_t^{I_s})) \\ + (b) \sum_{t \in T} \sum_{w \in W} \Delta_T C^{EV} P_{t,w}^{EVd} \\ + (c) \sum_{t \in T} \Delta_T K^A (D_t^A - d_t^A) \end{aligned} \tag{6}$$

where (a) indicates the cost related to the grid-tie, i.e., the power exchanged to the grid and the power acquired from the grid). $C^{I_2}(P_t^{I_p} + P_t^{I_s})$ denotes the total cost for power acquired from the grid and power exchanged to grid, and $C_t^{I_1}(P_t^{I_p} - P_t^{I_s})$ denotes energy in the advance price for power acquired from the grid and for power exchanged to the grid, (b) indicates the energy being discharged from the electric vehicle's battery, and (c) indicates the adjustable load not being delivered. Experiments showed a 10 % cost reduction.

In [34], a new convex programming (CP) system was proposed to manage different appliances' power consumption. The authors considered four types of appliances: schedule-based appliances with interruptible load (SA-IL), uninterruptible load (SA-UL), battery-assisted appliances (BAs), and Model-based appliances (MAs). Renewable energy sources are also incorporated. The proposed system handles schedule-based appliances (SAs) focusing on the 'on' and 'off' status of the home appliances, which are indicated by the binary decision variables. The binary decision variables $\{x = 0, 1\}$ are relaxed initially from integer to continuous values $\{x \geq 0, x \leq 1\}$ in order to prevent the use of complicated mixed integer non-linear program (MINLP). This is achieved using an L_1 regularization term, which is added in the objective function to change it into a convex programming problem, where the continuous values can produce the best schedules for the appliances by considering the price information. Also, the DR optimization problem is retained as a convex problem. The appliances are characterized by a characteristic function and a convex constraint. The characteristic function $C_a(e_{a,t})$ can compute consumer's energy consumption dissatisfaction $e_{a,t}$ or quantity in relation with energy consumption $e_{a,t}$. It can also be used to represent the property of the SAs. The characteristic function can also be referred to as L_1 regularization term, which is convex, makes it possible to prevent the mixed integer problem. On the other hand, the convex constraint is associated with the appliance's operating constraints and can be assumed to have a linear equality function $L_{a,t}(e_{a,t}) = 0$ and convex inequality function $F_{a,t}(e_{a,t}) \leq 0$. The renewable energy sources can provide energy of v_t up to an estimated energy limit at different times t of $V(t)$, the net energy is denoted by $u_t = \sum_{a \in A} e_{a,t} - v_t$ at time t i.e., the difference between total energy consumed and energy produced from renewable energy. The DR problem with its constraints is written as:

$$\begin{aligned} \min \sum_{t \in T} P_t(u_t) + \sum_{t \in T} \sum_{a \in A} C_a(e_{a,t}) \\ \text{where :} \\ u_t \geq \max\{0, \sum_{a \in A} e_{a,t} - v_t\}, t \in T \\ 0 \leq v_t \leq V(t), t \in T \\ L_{a,t}(e_{a,t}) = 0, a \in A, t \in T \\ F_{a,t}(e_{a,t}) = 0, a \in A, t \in T \end{aligned} \quad (7)$$

u_t is energy consumed at time t , $P_t(u)$ is the energy price at a given time t for consumption of u_t and $\sum_{t \in T} P_t(u_t)$ is the total cost. Users' dissatisfaction of an appliance $a \in A$ is modelled as $C_{a,t}(e_{a,t})$, where $e_{a,t}$ denotes the amount related with energy assumption $e_{a,t}$. The DR problem is subject to operating constraints. The types of appliances are important for the DR problem formulation and for the functions for users' dissatisfaction because they rely on them. The L_1 regularization provides a more effective solution which is closer to the optimal solution than other solutions. There is a slight deviation which is normally not more than 1%. The proposed approach realized about 14% of maximum cost saving.

In [35], the authors addressed the same problem with a different angle by incorporating two interesting concepts:

- The incentive: consists of encouraging users to consume during peak hours so to reduce their consumption,
- the inconvenience: aims at finding the minimal difference between baseline and optimal schedule of devices.

This has led to solve the optimization problem using the MINLP algorithm, which utilizes the Mixed Integer Programming (MIP) [36] and the Non-Linear Programming (NLP) [37] using the following objective function:

$$\text{Min} \sum_{t=1}^T \sum_{j=1}^I [P_i(\gamma_t * U_{i,t}^{opt} - \beta_t * \delta(U_{i,t}^{bl} - U_{i,t}^{opt})) * \Delta.t + (U_{i,t}^{bl} - U_{i,t}^{opt})^2] \quad (8)$$

where P_i is the rated power of the appliance i , $U_{i,t}^{opt}$ is the new on/off status of the appliance i at time t , and $U_{i,t}^{bl}$ is the baseline on/off status of the appliance i at time t .

$$\delta(U_{i,t}^{bl} - U_{i,t}^{opt}) = 1 \text{ if } (U_{i,t}^{bl} - U_{i,t}^{opt}) > 0. \delta(U_{i,t}^{bl} - U_{i,t}^{opt}) = 0 \text{ if } (U_{i,t}^{bl} - U_{i,t}^{opt}) < 0.$$

Related simulations results showed that consumers would be able to reduce of about 25% their electricity cost.

In [38], a HEMS using a MILP is proposed to evaluate and generate a scheduling pattern for household appliances subject to cost and peak demand restricting based on DR schemes. It considers thermostatic and non-thermostatically controllable appliances, EVs, energy storage systems (ESS), and a distributed generation (DG). The EV discharges energy from the vehicle to the household (V2H) or vehicle to grid (V2G), and the ESS is used as a backup. A thermostatically controllable appliance such as AC and a non-thermostatically controllable appliance such as a washing machine are also used. Two energy consumption limits are imposed on consumers. The first is the “hard” power limit, which requires users to consume energy for just a few hours, depending on how long their DR program is. The second is the “soft” power limit imposed, which helps manage the amount of power consumed daily. It requires consumers to pay for excessive use of energy. This approach aims to reduce consumers’ electricity costs. The objective function of this approach is:

$$\text{min}(\sum_t (P_t^{grid} \cdot \Delta T \cdot \lambda_t^{buy} - P_t^{sold} \cdot \Delta T \cdot \lambda_t^{sell})) \quad (9)$$

where P_t^{grid} , P_t^{sold} denotes power obtained from the grid and power sold to the grid respectively. λ_t^{buy} , λ_t^{sell} denotes price power purchased from the grid and power sold to grid respectively. ΔT represents time interval.

The authors in [39] proposed another solution that considers grouping the electricity loads by day periods into three time zones, each representing a cluster with its expected loads to be launched during a given period. The cost required to satisfy the power needs of a given cluster is computed as follows:

$$C_j = \sum_{m=1}^K \sum_{h \in T_j} \{(E_{h,m} + B_{h,m}^c - B_{h,m}^d) * r_h\} \quad (10)$$

where $E_{h,m}$ is the power purchased by m to meet appliance needs at period h , K is the number of appliances, $B_{h,m}^c$ and $B_{h,m}^d$ are the charging and discharging power profiles, and r_h is the power price. In order to satisfy the consumers’ requirements, at the lowest cost in each period, linear programming was applied in resolving the optimization problem with the following objective function:

$$\text{Min} \sum_{j=1}^3 (C_j) \quad (11)$$

Simulation results showed a 20% of peak load reduction and a 17% of costs savings.

In [40], an energy hub model for residential is developed and is integrated into an automated decision system. This solution considers the consumer energy consumption, energy storage, and energy production elements. In the energy hub, a central hub controller is used in the decision-making to produce a schedule for energy hub components by making use of the formulated model, external information (energy price, weather forecast, emission forecast, etc.), and parameter settings. Different mathematical problems resulting in a

MILP problem have been formulated for household appliances such as freezers, washing machines, lighting, solar panels, and storage devices. The proposed approach aims to decrease consumers' power usage, the energy price of consumers, reduce gas emissions, and decrease consumer peak loads. The objective function is:

$$\min(w_1 * J_1 + w_2 * J_2 + w_3 * J_3 + w_4 * J_4) \quad (12)$$

where $J_1, J_2, J_3,$ and J_4 represent the objective functions of energy cost of consumer, energy consumption of consumer, total emissions costs peak load charges respectively; and $w_1, w_2, w_3,$ and w_4 represent weights added to the objective functions, respectively. Experiments showed a 20 % cost reduction.

3.2. Game Theory Based Techniques

In [41], the authors developed a Vickery-Clarke-Groves (VCG) system with the sole aim of shifting the energy consumption to off-peak hours regularly to increase the social welfare for consumers which will help in ensuring the efficient consumption of energy by consumers. VCG mechanism retrieves information from users for utility companies and determines the energy consumption schedule and price for each user. The following is the problem formulated:

$$\text{maximize}_{x_n \in X_n, n \in N} \sum_{n \in N} \sum_{a \in A_n} U_{n,a}(x_{n,a}) - \sum_{t \in T} C_t(\sum_{n \in N} l_n^t) \quad (13)$$

The VCG uses a unified price to assign power for all users. It is implored to convince users in disclosing their utility functions. Users are required to provide their utility function, which results in a vector w_n and a set of constraints x_n both denoted as a single matrix. Depending on w_n for each user n , $U_{n,a}$ is used to identify the utility function and U_n to identify the utility function vector of each user n . For U , the VCG system selects the vector for energy consumption $x(U)$ as the result for the problem formulated above. The optimal energy consumption vectors and the payments are computed as:

$$x(U) = \text{argmax}_{x_n \in X_n, n \in N} \sum_{n \in N} \sum_{a \in A_n} U_{n,a}(x_{n,a}) - \sum_{t \in T} C_t(\sum_{n \in N} l_n^t) \quad (14)$$

$$\theta(U) = -(\sum_{m \in N-n} \sum_{a \in A_n} U_{m,a}(x_{m,a}) - \sum_{t \in T} C_t(\sum_{m \in N} l_m^t)) + h_n(U_{-n}) \quad (15)$$

To maximize each energy consumption $x_n \in X_n$ for each user $n \in N$. Where l_n^t is the overall load of the user at time $t \in T$. $U_{n,a}(x_{n,a})$ represents the utility function for each appliance $a \in A_n$ and $x_{n,a}$ is the scheduled consumption vector. Cost term $C_t(\cdot)$ represents the energy consumption variable, x_n for each user n and causes the problem formulation to become a utility maximization problem and a cost minimization problem. Part of the properties of the VCG mechanism need to be validated in order to make any modification to the problem formulation. It proposes that, the optimal consumption vectors and payments to be used in choosing electricity price values and declaring the Utility function vector $U_n = U_n$ for each user n is a dominant strategy. A Clarke tax, $h_n(U_{-n})$ will be integrated into the payment structure excluding user n which will lead to an efficient allocation.

$$h_n(U) = \sum_{m \in N-n} \sum_{a \in A_n} U_{m,a}(x_{m,a}(U_{-n})) - \sum_{t \in T} C_t(\sum_{m \in N} l_m^t(U_{-n})) \quad (16)$$

where $x_{m,a}$ denotes VCG allocation choice. Therefore, the payment of user n is:

$$\theta(U) = -(\sum_{m \in N-n} \sum_{a \in A_n} U_{m,a}(x_{m,a}(U)) - \sum_{t \in T} C_t(\sum_{m \in N} l_m^t(U))) + \sum_{m \in N-n} \sum_{a \in A_n} U_{m,a}(x_{m,a}(U_{-n})) - \sum_{t \in T} C_t(\sum_{m \in N} l_m^t(U_{-n})) \quad (17)$$

Payment of user n is the difference between the social welfare of other users with the presence of user n and social welfare of other users without user n . The proposed approach realized about 48% of maximum cost saving.

In [42], the authors developed a scheduling algorithm aiming at saving energy while relying on renewable energy sources. Based on game-theory, the provided solution allows players (consumers) to generate storage schedule vectors as possible strategies. The objective function was defined as follows:

$$P_i(s_i, s_{-i}) \sum_{h=1}^H (s_i^h + l_i^h) \quad (18)$$

where s_i is the storage schedule vector of all the players expect i , $P_i(s_i, s_{-i})$ is the power price determined using a continuous and supply curve, and l_i^h is the amount of power required by the player i at time h . Thus, the solution computes the Nash equilibrium which corresponds to the storage schedule s_i that minimizes the global generator costs given by $\sum_{H=1}^{h-1} \int_0^{q_h} b_h(x) dx$, where $b_h(\cdot)$ is the supply curve and q_h is the the total amount of power traded by all the players at time h .

Simulation results showed possible electricity bill saving of 13% per consumer with a storage capacity of 4KW.

3.3. Swarm-Based Techniques

In [43], a framework for residential users is proposed based on a pricing scheme and a Binary Particle Swarm Optimization (BPSO) to organize the appliance's energy consumption and operations. This can be achieved using the Smart Scheduler (SS) integrated into the HEMS in the model, which uses price signals provided by the grid to regulate consumer's power consumption with regards to the price of energy. The SS helps in scheduling appliances to predict energy consumption and reduce the customer's energy price by changing the energy demand to low peak periods rather than high peak periods. It uses the grid's energy, electricity generated through renewable resources, and energy from storage systems. Based on BPSO, the SS computes and produces a scheduling pattern for all the appliances. Also, it monitors the daily time horizon and decides to finish the operation of household appliances based on the scheduling pattern produced. The objective function proposed by the authors is:

$$\min \left(\sum_{t=1}^{24} (C_h) \right) \quad (19)$$

subject to:

$$\sum_{a=1}^N \sum_{h=1}^{24} E_{h,a} \leq E_{grid} \quad (20)$$

Experiments showed a 19.36 % cost reduction.

In [44], the authors propose a scheduling algorithm with the aim of reducing consumer dissatisfaction and the energy cost of a neighborhood of houses. They used the Cooperative Particle Swarm Optimization (CPSO) to find the optimal scheduling of the appliances of two categories: power-shift appliances and time-shift appliances. The algorithm uses the following objective function:

$$\begin{aligned} & \text{Min} \sum_{t=1}^T \sum_{j=1}^S [I_{ij}(t) * U_{ij}(t) + \alpha * (\gamma(t) * \sum_{j=1}^S P_{ij}(t))] \\ & + \beta * \left(\sum_{t=1}^T \sum_{j=1}^S * P_{ij}(t) - 1/|T| * \sum_{i=1}^N \sum_{t=1}^T \sum_{j=1}^S P_{ij}(t) \right)^2 \end{aligned} \quad (21)$$

where T is the set of time interval, N is the set of houses, S is the set of appliances, $I_{ij}(t)$ is a Boolean denoting the status (On/Off) of the appliance j in i at time t , $U_{ij}(t)$ denotes the

dissatisfaction of operating an appliance j in house i at time t . In other terms, it represents the difference between the desired temperature and the actual indoor temperature for the space heater at time t , and the difference between the desired hot water temperature and the actual hot water temperature for the water heater at time t , $\gamma(t)$ is the electricity sale price at time t , and $P_{ij}(t)$ is the working power of the appliance j in house i at time t . Experimental results showed the positive impact of the consumption coordination in decreasing the peak loads and reducing the power costs by 6.4%.

3.4. Spatial Techniques

In [45], the authors presented a new energy consumption planning algorithm whose purpose is twofold: (1) to reduce electricity bills and (2) balance total energy demand. To achieve this, the authors proposed an approach based on game theories. Each player (consumer) has a strategy that corresponds to all appliances' consumption schedules represented as a vector. The objective function of each consumer n a strategy x_n can be represented as follows:

$$\text{Min} \sum_{h=1}^H C_h \left(\sum_{n \in N} \sum_{a \in A_n} x_{n,a}^h \right) \quad (22)$$

where C_h is the cost function, $x_{n,a}^h$ is the schedule appliance a . The pseudo-code of the distributed algorithm proposed is provided in Algorithm 1.

Algorithm 1: Executed by each consumer $n \in N$

```

Randomly initialize  $x_n$  and  $x_{-n}$ 
repeat
  Do (at random time instances)
  Solve the objective function using IPM
  if  $x_n$  changes compared to current schedule then
    Update  $x_n$  according to the new schedule
    Broadcast the message  $l_n$  to the other consumers
  if a control message is received then
    Update  $l_n$  accordingly
until no new schedule is announced

```

Initially, the power consumption schedule is generated randomly for each player. The authors considered that initially, the players do not necessarily know each other or know their respective consumption. A loop is executed until the algorithm converges with an objective function that is solved using the IPM [37] algorithm, generating a new schedule for each player and informing all the other players about the newly generated schedule. This is repeated as long as there is a new schedule announced. The simulation results showed that the proposed algorithm supports achieving both objectives and makes it possible to reduce each consumer's electricity bills and reduce the peak loads. Experiments showed a 72 % cost reduction.

With the same objective (reducing the electricity bills of the consumers), the authors of [46] propose another interesting scheduling approach while considering the consumers' preferences. Note that these preferences have been considered here by including the time intervals where energy scheduling is performed. The consumption has been defined as a vector $X_i = [x_{i,1}, x_{i,1}, \dots, x_{i,H}]$ for each unit i , where H consists of M segments comprised of m time intervals (i.e., $H = M * m$). Then, the scheduler has been designed as a shrinking horizon optimization problem [47] defined as follows:

$$\mathcal{S}^{(j)}(H) = \sum_{h=jm-m+1}^{jm} \mathcal{S}(t_h) + \sum_{h=jm+1}^{jm} \hat{\mathcal{S}}(t_h) \quad (23)$$

where $\mathcal{S}^{(j)}(H)$ is the total electricity cost in the j^{th} optimization step, $\sum_{h=jm-m+1}^{jm} \mathcal{S}(t_h)$ is the energy cost for m intervals in the j^{th} time segment based on actual electricity prices, and $\sum_{h=jm+1}^{jm} \hat{\mathcal{S}}(t_h)$ is the estimated energy cost based on the forecasted electricity prices for subsequent time intervals.

The proposed model optimizes the end user's electricity cost by 12.16 % while meeting preferred comfort levels.

In [48], the authors developed a smart home energy management (HEM) system. It aims at monitoring, optimizing energy, improving reliability, and conserving energy for distribution systems. HEMS architecture consists of several components: an advanced metering infrastructure (AMI) such as smart meter ensuring communication between power utilities and energy consumers, home appliances, i.e., schedulable appliances such as washing machine, iron, etc., which operates automatically to finish their task and non-schedulable appliances such as a printer, refrigerator, etc., which works manually to complete an operation. It also consists of energy storage used to store energy from the grid or renewable sources such as wind, solar, etc., which helped improve the quality and efficiency of energy. Plug-in electric vehicles (PEVs) are also used to provide power to other home appliances. Two energy scheduling strategies are implemented: an incentive-based demand response and the price-based demand response. In the price-based DR, a pricing scheme is used, tracing the electricity price varying hourly. In the incentive-based DR, the users are motivated to modify their consumption induced by non-price signals, for which the involved users receive compensations. Findings showed that the home scheduling strategies for smart appliances and renewable energy had reduced household electricity costs and increased power utilization from electric power utilities.

4. Smart Power Scheduling for DSM Approaches

Similar to the previous section, the approaches are categorized based on the optimization technique used to perform the power scheduling. Hence, we identified three main optimization categories: CPLEX, including the linear, stochastic linear, and non-linear programming techniques, Game theory-based, including the Nash Equilibrium techniques, and Genetic optimization techniques. Here we noticed the great use of genetic optimization that plays an essential role in giving the "Smart" aspect of the scheduling.

4.1. CPLEX Techniques

In [49], the authors presented a stochastic mixed-integer linear programming model for scheduling a wind integrated Smart Energy Hub (SEH). The model fulfills thermal and electrical demands and maximizes revenue by considering the volatility of power prices in the different hours. The authors proposed a DR program to achieve an economical operating schedule by shifting from moments of peak prices to off-peak prices.

The algorithm uses the following objective function to minimize the SEH operational costs taking into consideration the start-up and shut-down constraints:

$$\begin{aligned} \text{Min} \sum_{t \in NT} \{ \sum_{w \in NW} p_w * (\sum_{i \in CH} OC_{i,w,t}^{CHP} + \sum_{j \in CB} OC_{j,w,t}^{Boiler} \\ + PC_{w,t} + GB_{w,t} - GS_{w,t}) + SUC_t + SUD_t \} \end{aligned} \quad (24)$$

where: OC^{CHP} is the operation cost of CHP unit at time t and scenario w , OC^{Boiler} is the operation cost of boiler at time t and scenario w , $PC_{w,t}$ is the penalty cost at time t and scenario w , $GB_{w,t}$ is the cost of purchasing electricity from network at time t and scenario w , $GS_{w,t}$ is the income of selling electricity to network at time t and scenario w , SUC_t is the start-up cost of SEH at time t , and SUD_t is the shut-down cost of SEH at time t .

In [50] an optimum production side scheduling is proposed to analyze the impacts of dynamic pricing on demand patterns and achieve a dynamic price variation. The main goal of the day-ahead energy market clearing procedure is to minimize the total costs associated with electricity production as follows:

$$\text{Min} \sum_{t \in T} \sum_{i \in I} (SUC_i * y_{i,t} + SDC_i * z_{i,t}) + \sum_{t \in T} \sum_{i \in I} \sum_{f \in F} c_{i,f} * b_{i,f,t} \quad (25)$$

where $SUC_i * y_i$ is start-up cost of unit i , $SDC_i * y_i$ is shut-down cost of unit i , $c_{i,f}$ is marginal cost of step f of unit i marginal cost function, and $b_{i,f,t}$ is portion of step f of the i -th unit's marginal cost function loaded in hour t .

In [51], the authors present two power demand scheduling policies to reduce the operational cost of a power grid. In the first policy, Threshold Postponement (TP), the controller decides (based on the current consumption) whether to serve a new demand request at arrival or delay it. On the other hand, per the Controlled Release (CR) policy, a new request is activated immediately if the current power consumption is lower than the set threshold. Otherwise, it waits until it approaches the deadline or until the consumption falls below that threshold. The results have shown that the CR policy resulted in an 18–24% reduction in cost compared to the default one.

In [52] the authors developed a strategy for scheduling the electric water heater consumption based on the PV production forecasting. The goal of the proposed method is twofold, consisting of maximizing the PV self-consumption while reducing the overall energy bill. A linear optimization problem was presented, shown below.

$$\text{Min}_{P_e} \sum_i^N |\max(P^s) - P_i^s / \max(P^s)| P_i^e \quad (26)$$

where P^s is the forecasted PV energy, P^s is the water heater power consumption profile. Experiments showed a reduction in energy bill of 15% compared to the traditional thermostatic controller saving around 0.15 euro per day.

4.2. Game Theory Based Techniques

In [53], the authors proposed two distributed reinforcement learning algorithms to model the power consumption scheduling problem for a group of residential users. The idea behind this is that each device of the system produces its best schedule autonomously, based on the difference between the paid electricity price and the cheapest schedule. A Markov chain is used to model the decision problem where each proposed schedule is linked to a chain state, updated using the users' electricity bills, formalized as follows:

$$\text{Min}(U_n(I_n, I_{-n})) = \sum_{t \in T} (y_{nt} * c_t(y_t)), \forall n \in N. \quad (27)$$

where U_n is the utility of player n , I_n is the set of strategies of player n , y_{nt} is the power demand of a player n , at time slot t , C_t is the cost function, y_t is the total power demand of all users at time slot t . Experiments achieved 5% of electricity price reduction.

The authors in [54] presented a residential power scheduling model to achieve a trade-off between the user discomfort and the electricity payments. To do so, the authors identified two appliances' categories: those having flexible starting time and work continuously with a fixed power and others with flexible power in a predefined working time. In this model, the consumers will adjust their power scheduling based on the one-day-ahead published electricity price. A convex optimization programming model is proposed considering two components: the first component in the objective function indicates the electricity payments, and the second represents the total discomfort. Experiments showed decreased electricity bills when using the day ahead pricing compared to the flat price.

4.3. Genetic Optimization Techniques

The authors in [55] modeled a load schedule algorithm for shiftable and non-shiftable appliances via a distribution channel based on day-ahead, hour-ahead prices, and real-time imbalances. This channel acts as an aggregator that collects the appliances' schedules. Then, it decides what to turn off and on to reduce the peak load and the delay cost

of the appliances. To do so, they used a genetic algorithm to optimize the following objective function:

$$\text{Min} \sum C_i * P^t + d_n^i * \lambda_n^i \quad (28)$$

where C_i is the power consumption of the user i , P^t is the day-ahead price at time t , λ_n^i is the delay price of the appliance n of the user i , and d_n^i is the maximum delay time.

Results showed 85% per day of cost savings of price-based scheduling and 100 dollars per day of total cost savings of power-based scheduling.

In [56] the authors proposed four power-demand scheduling scenarios to reduce the peak demand in an SG. The focus of the proposed scenarios is on both task and energy scheduling. The programs consider the number of appliances of different power demands and different operational times for each consumer. The authors labeled the four scenarios as the Default Scenario (used to determine the power consumption upper bound), Compressed Demand Scenario (CDS), Delay Request Scenario (DRS), and Postponement Request Scenario (PRS). The paper analyzes and provides examples of each scenario. In terms of power consumption, PRS did better than the other scenarios, with a 14.7% reduction, where power requests arrive at the Central Load Controller when the power consumption exceeds the first threshold are postponed for a constant time until the power consumption drops below a second threshold.

In [57], the proposed scheduling method combines the Real-Time Pricing (RTP) model with the Inclining Block Rate (IBR) model to achieve lower electricity costs for the residents and end-users while at the same time reducing the power Peak-to-Average Ratio (PAR). High PAR can lead to damage to the entire electricity system. Due to the non linearity of the optimization problem, the proposed scheduling method uses a Genetic Algorithm (GA) to solve the problem. Simulation results show a reduction in the average electricity cost by 15.5% during three months, and the PAR is reduced from 4.26 to 3.42.

In [58], a Hybrid Genetic Ant Colony Optimization (HGACO) system is proposed as the basis of an optimization methodology that uses real-time pricing signals and power generation from utility and photovoltaic battery systems to adapt consumer power usage patterns. The objective function was developed to reduce electricity costs, minimize carbon emissions, reduce user frustration, and alleviate PAR through the scheduling of consumers' energy consumption. Three scenarios are used for the simulations conducted in order to evaluate the optimization algorithm proposed. The three scenarios are: without photovoltaic-battery systems, with photovoltaic systems, and with photovoltaic-battery systems. The simulation results revealed that the scenario that does not include photovoltaic-battery systems produced electricity cost reduction by 49.51%, carbon emission reduction by 48.1%, and peak load reduction by 25.72%. The second scenario results, which included photovoltaic systems, led to reductions in electricity cost, carbon emission, and peak load by 55.85%, 54.22%, and 21.69%, respectively. Finally, the third scenario included photovoltaic battery systems and produced electricity cost, carbon emission, and peak load savings by 59.06%, 57.42%, and 17.40% respectively.

5. Comparative Analysis of Dsm Techniques

In this section, we compare current DSM approaches [31–35,38–46,48–58] while highlighting their strengths and drawbacks concerning the challenges presented in Section 1). An important DSM aspect is its capability to achieve multi-objective scheduling. In that, the scheduling should consider not only the electricity costs but also toxic emissions, unnecessary transmission losses, and the peak load. A comparative table is presented in Table 1.

Table 1. Comparative table of the selected power scheduling techniques.

Approach	Operational Criteria			Economic Criterion	Environmental Criterion
	Consumer Comfort	Peak Load Reduction	Threefold Coverage	RES Integration	Optimization Technique
[31]	✓	✓	×	✓	MILP
[32]	✓	×	×	×	MILP
[48]	✓	✓	×	✓	Modular
[34]	✓	✓	×	✓	CPLEX
[41]	✓	×	×	×	VCG
[33]	✓	×	×	✓	MILP
[43]	✓	✓	×	✓	BPSO
[38]	×	✓	×	✓	Convex Optimization
[40]	✓	×	×	✓	MILP
[45]	×	✓	×	×	IPM
[44]	✓	✓	×	×	CPSO
[46]	✓	×	×	×	SHM
[35]	✓	×	×	×	MILP and NLP
[42]	✓	×	×	✓	Nash Equilibrium
[39]	✓	✓	×	×	LP
[49]	×	✓	×	✓	Stochastic MILP
[50]	×	✓	×	×	MILP
[53]	×	×	×	×	Nash Equilibrium
[55]	✓	✓	×	✓	Genetic
[51]	×	✓	×	×	Stochastic MILP
[56]	✓	✓	×	×	Recursive Formulas
[52]	×	×	×	✓	LP
[54]	✓	✓	×	×	CPLEX
[57]	×	✓	×	×	Genetic
[58]	×	✓	×	✓	Genetic

1. Operational Criteria

- **Consumer Comfort:** A main criterion to be considered when developing a DSM technique is the consumer's preferences. Besides reducing the electricity bills, the proposed schedule should also reduce the delay in receiving the desired power. For instance, recharging a consumer's EV at 7:20 a.m instead of 7:00 a.m before leaving to work (at 7:30 a.m.) will result in a deficiency in the battery charging and increase the risk of the EV breakdown. This criterion was addressed in many approaches in different ways. In [44], the user's comfort is ensured by decreasing the gap between the desired and the actual hot water and indoor temperature. In [32,34,39,42,43,48,54–56], the satisfaction is measured by the delay time between the expected start time and the actual operation of the appliances. In [31], consumer satisfaction is considered by assigning a VOLL value to denote a home appliance's operation based on its electricity cost; the appliance with the highest VOLL value has the highest priority. In [41], the system schedules the appliances' operation based on the user's time preference. In [33], it gives the user the privilege to control the household's energy and stored energy. [40] considers user satisfaction by providing users the freedom to choose what is more convenient for them. Contrary to [38,45,49–53,57,58], which lacks this aspect.
- **Peak Load Reduction:** This criterion was addressed in most of the papers [31,34,38,39,41,43–45,48–51,54–58], where the authors aimed at shaving the peak load when scheduling the consumption. However, this aspect was not fully considered in [32,33,35,40,42,46,52,53].
- **Threefold Scheduling Coverage:** By definition, a DSM technique shapes the consumption plans in different ways, such as monetary incentives and behavioral change through education. This explains the single purpose of all the approaches [31–35,38–46,48–58] aiming at scheduling the consumption only without considering the generation and storage scheduling. However, orchestrating the three mechanisms helps increasing user comfort by scheduling a power generator that avoids delays in delivering the desired power. Also, it lowers the toxic emissions

by prioritizing the RES generation when available. Also, it is essential to consider the prosumers' [18], referring to some devices' ability to PROduce and conSUME simultaneously. Hence, a DSM technique should also consider the heterogeneity of the SG components.

2. Economic Criterion

- Electricity Bills Reduction: All the selected DSM methods [31–35,38–46,48–58] target electricity bills reduction. It is essential to note that the results depend on several parameters such as the heterogeneity and numbers of appliances, energy sources, and storage, and hence do not reflect the efficiency of the approaches.

3. Environmental Criterion

- RES Integration: There is a broad expansion of renewable energy, which provides lower toxic environmental impact than conventional energy technologies. Hence, an environmental-friendly DSM should include renewable energy sources. The models proposed in [33,34,38,40,42,43,48,49,52,55,58] use energy from the main grid, renewable resources, and storage systems to operate the appliances. However, the only power source considered in the remaining papers [31,32,35,39,41,44–46,50,51,53,54,56,57] is the main grid.

6. Conclusions

This paper reviews several highly cited research papers in power scheduling as well as a collection of papers targetting power scheduling in Smart Homes. The various Demand-Side Management (DSM) approaches discussed in these papers and their proposed algorithms for scheduling household appliances were analyzed and examined. Our review aimed to explore the methods' capability to address operational, economic, and environmental challenges.

From the operational perspective, our analysis showed that the current techniques limit their focus to consumption scheduling and cannot cope with the power production and storage scheduling. From an economic perspective, our survey found that the primary goal of all the existing DSM is to reduce electric bills. However, many DSM techniques do not integrate renewable energy sources, which negatively impacts the environment. Hence, an ideal DSM should cover the scheduling of power production, consumption, and storage while considering user comfort and simultaneously reducing electricity bills.

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