smart cities

Review

Optimization Approaches for Demand-Side Management in the Smart Grid: A Systematic Mapping Study

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Abstract: Demand-side management in the smart grid often consists of optimizing energy-related objective functions, with respect to variables, in the presence of constraints expressing electrical consumption habits. These functions are often related to the user's electricity invoice (cost) or to the peak energy consumption (peak-to-average energy ratio), which can cause electrical network failure on a large scale. However, the growth in energy demand, especially in emerging countries, is causing a serious energy crisis. This is why several studies focus on these optimization approaches. To our knowledge, no article aims to collect and analyze the results of research on peak-to-average energy consumption ratio and cost optimization using a systematic reproducible method. Our goal is to fill this gap by presenting a systematic mapping study on the subject, spanning the last decade (2013–2022). The methodology used first consisted of searching digital libraries according to a specific search string (104 relevant studies out of 684). The next step relied on an analysis of the works (classified using 13 criteria) according to 5 research questions linked to algorithmic trends, energy source, building type, optimization objectives and pricing schemes. Some main results are the predominance of the genetic algorithms heuristics, an insufficient focus on renewable energy and storage systems, a bias in favor of residential buildings and a preference for real-time pricing schemes. The main conclusions are related to the promising hybridization between the genetic algorithms and swarm optimization approaches, as well as a greater integration of user preferences in the optimization. Moreover, there is a need for accurate renewable and storage models, as well as for broadening the optimization scope to other objectives such as CO_2 emissions or communications load.

Keywords: energy efficiency management; peak-to-average-energy-consumption ratio; energy cost; control; optimization algorithms

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Citation: Mimi, S.; Ben Maissa, Y.; Tamtaoui, A. Optimization Approaches for Demand-Side Management in the Smart Grid: A Systematic Mapping Study. *Smart Cities* **2023**, *6*, 1630–1662. https://doi.org/10.3390/smartcities6040077

Academic Editor: Isam Shahrour

Received: 11 May 2023
Revised: 21 June 2023
Accepted: 26 June 2023
Published: 30 June 2023

1. Introduction

Conventional electrical grids are built with the intent to widely distribute energy from a limited set of producers to all the subscribed consumers. Although they meet the challenges of the past, the integration of renewable energies, decentralized production and demand management have more than ever highlighted the limits of conventional electrical networks. Recently, the current Russian–Ukrainian conflict has illustrated the need for an adaptive smart electrical grid even more [1]. Indeed, part of the drone and missile attacks have targeted Ukrainian energy infrastructures, which could have been more resilient if they were smarter and especially re-configurable. The rest of the world is also affected by the current post-pandemic and war context: some countries in the European Union, such as France, are expecting to perform rotating load sheddings [2]. This is an exceptional situation.

The problem often lies in (1) the overload caused by spikes in the energy use pattern of a conventional grid (CG), and (2) the energy cost for the consumer. We observe during peak hours that energy consumption reaches threshold limits. This prevents the

CG from serving all its consumers, which could cause high risks of outages and physical damage to the grid due to overheating [3]. The smart grid (SG) positions itself as the modern solution for energy distribution in a bi-directional and agile manner [4]. Thanks to advanced communication technologies, one of the main advantages of the SG is flexible bi-directional demand management, where a 'win-win' situation between consumers and utility companies is expected [5], benefiting from an exchange of information between supply and demand. Demand-side management in the smart grid often consists of optimizing energy-related objective functions, with respect to variables, in the presence of constraints expressing electrical consumption habits. This can enable consumers to efficiently manage their consumption loads by shifting usage from on-peak hours to off-peak hours in order to 'flatten' the electricity consumption, increase the reliability of the network and avail various economic incentives [6]. For example, utility companies and grid operators encourage consumers to respond to their dynamic pricing models by declaring cheap prices of electricity at a certain time of day [7]. Recently, several studies have been conducted on detailed DSM approaches in residential, commercial and industrial networks, where researchers propose algorithms to optimize the energy cost and peak-to-average ratio (PAR). Other optimization objectives such as CO_2 emissions, waiting time and user preferences have also been proposed (despite systematically requiring a heuristic because of the problem's NP-hardness [8]). In this paper, we present the first (to our knowledge) systematic mapping study on PAR and cost optimizationapproaches for demand-side management in the smart grid. These techniques often use an exact algorithm or a metaheuristic to shift the loads consumption, or plan renewable energy use at the right moment according to pricing schemes and incentives provided by the supplier. This survey is the result of a deep analysis of hundreds of studies that deal with the subject. The purpose of this work is to give a structured *review* of the field during the last decade (2013–2022) in order to provide researchers with a clear image of the methods used and some open research issues.The remainder of the paper is structured as follows: in Section 2, we present as formally as possible the background: fundamental elements related to the smart grid, demand-side management, PAR, cost optimization and price models. Section 3 details the systematic mapping study research method: the initial paper selection process, mapping questions definition and results of the data extraction and classification (104 studies) according to the 13 criteria. Section 4 analyzes the state of the art comparatively and answers the mapping questions. In Section 5, we discuss open research issues and recommendations for PAR and cost optimization approaches. Section 6 concludes the paper.

2. Background

In this section, we present fundamental domain concepts: some necessary elements for understanding the peak-to-average ratio, and cost optimization for demand-side management in the smart grid.

We considered a basic intelligent grid model, which is close to several works studied in this paper, with the addition or elimination of some constraints. The energy of this proposed electrical network is shared by several users via the electrical line (solid line), as shown in Figure 1. The information of the network is shared via the communication line (dashed line). In a smart grid, the energy and information exchange is usually bi-directional. Each user is equipped with batteries and a smart meter capable of reporting the information centrally in order to globally optimize the energy consumption, and program electrical devices based on the information collected. Sometimes, other energy-producing equipment (e.g., solar panels or wind turbines) might be included in the network.

Due to the irregular consumer behavior, devices can be divided into three categories [9]:

1. Essential devices. They are interactive with minimal scheduling freedom, fixed power and operational periods. These devices require a steady power supply (e.g., lamps).
2. Shiftable devices. They have specific energy consumption profiles and elastic delays. Their operation period can be shifted (e.g., washing machines).

3. Throttleable devices. They have a fixed operating period but can accept adjustments in their power consumption, within a certain range (e.g., electrical vehicles).

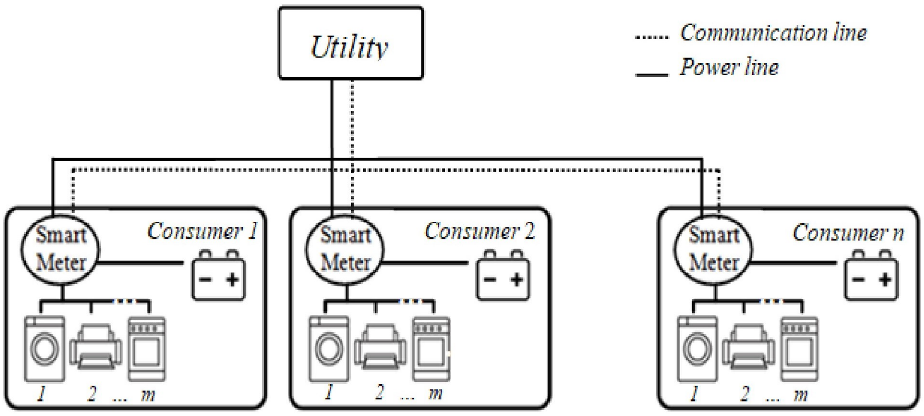

Figure 1. Intelligent grid model.

2.1. Load Demand Description

With no loss of generality, we considered $\mathcal{N}$ loads consumed by users, where $N \triangleq |\mathcal{N}|$ is the number of users. For each user $n \in \mathcal{N}$, let $\mathcal{M}_n = \{\mathcal{I}_n \cup \mathcal{S}_n \cup \mathcal{R}_n\}$ designate all household devices, where $\mathcal{I}_n$, $\mathcal{S}_n$ and $\mathcal{R}_n$ designate essential, shiftable and throttleable devices. For these three types of devices, we define the scheduling vector for energy consumption as:

$$e_{n,i} \triangleq \left[e_{n,i}^{1}, \ldots, e_{n,i}^{t}, \ldots, e_{n,i}^{T}\right], \tag{1}$$

$$e_{n,s} \triangleq \left[e_{n,s}^{1}, \ldots, e_{n,s}^{t}, \ldots, e_{n,s}^{T}\right], \tag{2}$$

$$e_{n,r} \triangleq \left[e_{n,r}^{1}, \ldots, e_{n,r}^{t}, \ldots, e_{n,r}^{T}\right], \tag{3}$$

Let $x_{n,t}$ denote the total energy consumed by user *n* during the time interval $t \in \mathcal{T} = \{1, \ldots, T\}$.

This means that:

$$x_{n,t} = \sum_{i,s,r \in M_n} e_{n,i}^{t} + e_{n,s}^{t} + e_{n,r}^{t} \quad t \in \mathcal{T}. \tag{4}$$

Therefore, the total daily energy demand of user n is:

$$\sum_{t \in \mathcal{O}_n} x_{n,t} = E_n. \tag{5}$$

For the battery profile vector of user n, it can be given as:

$$a_n = [a_{n,1}, \ldots, a_{n,t}, \ldots, a_{n,T}], \tag{6}$$

where $a_{n,t}$ must satisfy the maximum rate of charge and discharge,

$$-1 \leq a_{n,t} \leq 1 \tag{7}$$

$a_{n,t} > 0$ means that the battery of user *n* is being charged, $a_{n,t} < 0$ means that the battery of user *n* is being discharged and $a_{n,t} = 0$ is for when the battery is being idle.

After every charging and discharging, the level of each battery must be less than its maximum capacity and greater than zero. The mathematical formulation of the constraint is:

$$0 \leq b_{n,0} + \sum_{j=1}^{t} a_{n,j} r_n \leq B_n, \forall t \in \mathcal{T}. \tag{8}$$

We assume that, at the end of a cycle T, there is no excess or shortage of energy. Thus, the charge level of the battery $b_{n,0}$ is always the same. This assumption can be expressed as below:

$$\sum_{t=1}^{T} a_{n,t} = 0 \tag{9}$$

During each time interval t, the energy supplied by the user's battery is less than the energy consumed by the user. The constraint is given as follows:

$$x_{n,t} + a_{n,t} r_n \geq 0 \tag{10}$$

Depending on the battery charge and discharge strategy, during each time interval, the load demand that user n has to purchase from the utility will be:

$$L_{n,t} = x_{n,t} + a_{n,t} r_n \tag{11}$$

Based on these definitions, the total consumed load by all users during time interval $t \in \mathcal{T}$ can be computed as:

$$L_t \triangleq \sum_{n \in \mathcal{N}} L_{n,t} \, . \tag{12}$$

2.2. Peak-to-Average Ratio

The peak-to-average ratio (PAR) is an important metric that can be monitored as an indicator of the disparity level between peak consumption and the average usage. Small PAR values indicate a stable and reliable system while, on the other hand, high values of PAR indicate an unbalanced electricity production with cost implications [9]. It can be formulated as follows [10]:

$$\mathrm{PAR} = \frac{\text{Peak energy consumption}}{\text{Average energy consumption}} \tag{13}$$

In a smart grid network, let L_p and L_a designate the peak load and average load. Mathematically, they are given by:

$$L_p = \max_{t \in T} L_t \tag{14}$$

and

$$L_a = \frac{1}{T} \sum_{t \in T} L_t. \tag{15}$$

The PAR of the load is represented by Γ_{PAR} and can be formulated as:

$$\Gamma_{PAR} = \frac{L_p}{L_a} = \frac{T \max_{t \in T} L_t}{\sum_{t \in T} L_t} \tag{16}$$

One of the two optimization objectives of surveyed studies can be formulated as follows:

$$\min \quad \Gamma_{PAR} \tag{17}$$

2.3. Electricity Pricing System

Time-based demand response programs offer consumers prices that vary over time and are defined based on the electricity cost over different time periods [11]. Customers obtain the notifications and have a tendency to consume less electrical energy in high-priced periods. Different pricing schemes were found in the works surveyed. They are as follows.

Time-of-use pricing (ToU) is the utilization of fixed prices at different time intervals, which can be different hours in the day or different days in the week [11]. In the off-peak period, the effectiveness of these systems for reducing total energy consumption is limited, as consumers receive no practical incentive to decrease their demands. The consumers' response is triggered by the fact that the prices are lower during off-peak hours and relatively higher during peak hours [12,13].

Critical peak pricing (CPP) has a kind of similitude to ToU pricing with regard to fixed tariffs over different time periods. However, due to occasional systemic stress, the price of at least one period may change, regularly in most cases [14]. Usually, participating customers receive information of the new energy price one day in advance. As in the case of ToU, the CPP is not economically efficient for customers, owing to the predefined prices. In addition, the ratio between the peak and off-peak price is lower on a ToU program than in CPP event days [15]. In the variable period CPP, the utility controls the start time of the event and its duration, which imposes a limited number of hours for the event. For example, the utility can trigger an event (CPP) 20 times in a year for a maximum of 4 h for each event and a maximum of 60 h each year [13,16].

Real-time pricing (RTP) requires maximum customer cooperation. As part of an RTP program, the energy supplier advertises the electricity tariff on a continuous basis; rates are determined and announced before the beginning of each period (for example, 30 min in advance [17]). Therefore, two-way communication capabilities are important for successful implementation. In an RTP-based system, the installation of an energy management controller (EMC) is required at customer premises in order to increase the speed of decision making. This will guarantee a significant reduction in the electricity bill [18]. However, an RTP implementation requires continuous real-time exchange between the energy supplier and the consumers, which is unattractive from the customer's point of view [19]. In addition, the great flow of information exchanged between the energy supplier and EMCs and the lack of efficient smart meters besides scheme complexity can be real barriers for that type of systems. Day-ahead RTP (DAP) is an alternative solution based on RTP in which the planned real-time prices for the next day are announced in advance to customers according to the price of that day [13].

2.4. Energy Cost Model

Utilities use cost functions to set prices for customers. A utility is supposed to sell consumers energy from cheaper sources, such as solar, wind or hydro generators, before switching during peak hours to more expensive fuel generators. These cost functions are designed to encourage consumers to adapt specific consumption behaviors.

A smart cost function is required to reduce the impact of selfishness on consumer behavior. Let us denote $C_t(L_t)$ as the cost that consumers must pay to providers for an amount of energy L_t during time $t \in \mathcal{T}$. A good cost function selection must meet various requirements that influence the operation of demand management.

First, the utility provider is under charge for meeting all consumer needs, so the cost function depends on the total consumption of all consumers L_t during some time $t \in \mathcal{T}$. Moreover, the cost function varies according to the time period: the cost increases during peak periods due to the high prices declared by the utility provider. Other cost function assumptions are:

- The cost function is an increasing demand function [20].

$$C_t(L_t^a) \geq C_t\left(L_t^b\right) \quad \forall L_t^a \geq L_t^b \tag{18}$$

- The cost function is convex or strictly convex [20].

$$C_t\left(\theta L_t^a + (1-\theta)L_t^b\right) < \theta C_t(L_t^a) + (1-\theta)C_t\left(L_t^b\right) \qquad \forall t \in \mathcal{T}, 0 < \theta < 1 \tag{19}$$

When the user can produce and sell energy back, it means $L_t < 0$. This signifies that the user can pay a negative amount for this energy. In other words, the user cost function is $C_t(L_t) < 0$. In this case, the quadratic cost function, $C_t(L_t) = L_t^2$, is obviously not satisfying this condition. Alternatively, we can try $C_t(L_t) = L_t^2 \sin(L_t)$, which is not convex and not satisfying the negativity condition. We set an increasing linear cost function $C_t(L_t) = k \times L_t$ that is convex but not strictly convex. We note that *k* is a parameter suggested to give cost values close to those of the quadratic cost functions.

In addition to the conditions of the cost function, the utility makes profits at any given time *t*, where the sale price is always higher than the purchase price:

$$C_t(L_t) > |C_t(-L_t)| = -C_t(-L_t) \quad \forall t \in \mathcal{T} \tag{20}$$

This condition restricts users from making excessive purchasing and selling.

3. Systematic Mapping Study

The aim of this part is to express the intention of the mapping study, outline the specific steps to achieve the goal and formulate research problems to be investigated. Taking some inspiration from the guidelines in [21], a protocol in five successive processes was adopted, leading to the final systematic map, shown in Figure 2, as described below.

1. *Research directives* define the study protocol and identify the dimensions to be analyzed, as well as the research questions that need to be answered.
2. *Data collection* identifies primary studies by using search strings on several selected scientific databases.
3. *Screening of the papers* brings together the articles related to the inclusion and exclusion criteria defined in the protocol.
4. *Key-wording using the abstract* identifies and combines keywords to seek high-level understanding about the nature and contribution of the research, thereby generating an organized classification.
5. *Data extraction mapping* maps the existing literature according to the defined criteria and answers the research questions.

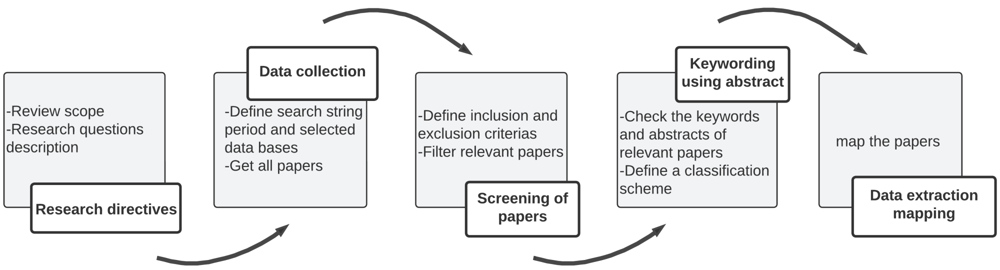

Figure 2. Systematic mapping study protocol.

3.1. Research Directives

This section presents the adopted research protocol and the research questions description. The protocol includes the object of study (cost and PAR reduction approaches), its purpose (mentioned previously), preliminary research questions, the search strategy, the criteria of selection and the extraction form of data. Lastly, the protocol presents an overview of the articles selected in terms of countries and year of publication. The five research questions (RQs) for this systematic mapping review are as follows:

RQ1. What are the most used algorithms and techniques for peak and cost reduction?
RQ2. What type of energy source has been chosen (e.g., utility grid, renewable or storage)?
RQ3. What type of building has been treated (e.g., residential, commercial, industrial)?
RQ4. What are the optimization objectives of the algorithms cited?
RQ5. What type of energy pricing has been chosen ?

3.2. Data Collection

In order to include relevant articles and exclude irrelevant articles, the research strategy for this study included querying reference databases with custom search strings, followed by a manual filtering of results using the predefined inclusion and exclusion criteria.

To minimize the risk of missing relevant articles, four reference databases were queried:

- MDPI data bases (https://www.mdpi.com/, accessed on 31 December 2022);
- Elsevier ScienceDirect (www.sciencedirect.com, accessed on 31 December 2022);
- SpringerLink (https://link.springer.com, accessed on 31 December 2022);
- IEEExplore (http://ieeexplore.ieee.org, accessed on 31 December 2022).

The main areas of focus include control systems, intelligent computation methods and algorithms, simulation tools, user preferences, comfort, building types and the source of supply.

3.3. *Screening of Papers for Inclusion and Exclusion*

The selection filter for the published studies included the following inclusion and exclusion criteria:

3.3.1. Inclusion Criteria

The inclusion criteria are:

1. Articles focusing on DSM in SGs.
2. Articles proposing algorithms and control systems for optimizing PAR and reducing cost.
3. Articles published between 1 January 2013 and 31 December 2022.
4. Articles dealing with cost optimization and PAR reduction.

3.3.2. Exclusion Criteria

The exclusion criteria are:

1. Reviews and surveys. Only first-hand research work is considered.
2. Articles not related to the research.
3. Non-peer-reviewed articles.

3.4. *Keywording and Selection Strategy*

A multi-stage selection process was designed to provide an overview on algorithms and methods used in SGs for PAR/cost optimization and to map their frequencies of publication over time.

In order to perform the search and establish the search string, we derived the main terms of the mapping questions and checked their synonyms, as well as alternative spellings. The search string is formulated as follows:

```
Demand Side Management AND optimization
AND smart grid AND PAR AND Cost AND algorithm
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Some synonyms of the previous keywords and similar expressions (e.g., "Energy Efficiency Management" and "Energy Resource Management", instead of "Demand Side Management") have also been used at later stages to make sure that the search was as extensive as possible.

The research process (Figure 3) was applied on each of the four databases, and the results were filtered according to inclusion and exclusion criteria, as recommended in the systematic mapping study guidelines [21]. Then, on 684 potentially relevant papers, further selection (typical of an SMS) was performed iteratively on the title, then abstract and then full text to obtain in the end only 104 primary studies.

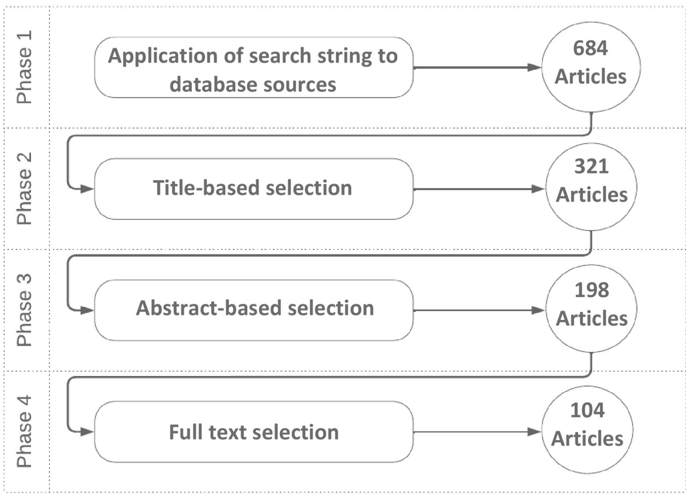

Figure 3. Primary selection study protocol.

3.5. Data Extraction and Classification

This subsection presents the final result of the selection process as a synthetic Tables 1–8 gathering the 104 primary studies. The 13 classification criteria are:

1. *Ref:* the paper reference;
2. *Year:* the year of publication;
3. *Country:* the country of the study;
4. *Journal/Conference:* the publication venue;
5. *Building sector:* residential, commercial or industrial;
6. *Energy source:* utility, renewable, or energy storage;
7. *Control Schemes:* the general type of control scheme (e.g., heuristic, exact method, hybrid);
8. *Algorithm/method:* the algorithm/method name used by authors;
9. *Pricing scheme:* the pricing scheme hypothesis (e.g., time of use, real time, day-ahead pricing);
10. *The optimization objectives:* (e.g., PAR, cost, communications, appliances waiting time);
11. *User comfort:* is user comfort taken into account in the optimization?
12. *User preferences:* are user preferences taken into account in the optimization?
13. *Simulation tool:* is there a simulation tool involved in the optimization?

Table 1. Comparative table of PAR and cost optimization approaches.

Ref.	Year	Country	Journal/Conference	Building Sector	Energy Source	Control Schemes	Algorithm/Method	Pricing Scheme	Optimization Objective(s)					User Comfort	User Preferences	Simulation Tool
									PAR	Cost	CO_2 Emission	Communication	Average Waiting Time			
[22]	2022	Saudi Arabia	Processes	Residential	Utility ESS RES	Meta-heuristic technique	Ant colony optimization (ACO)	Fixed price	√	√	√	–	–	–	–	MATLAB 2018b
[23]	2022	Pakistan	IEEE Access	Residential	Utility RES	Meta-heuristic technique	Artificial bee colony	RTP ToU DAP CPP	√	√	√	–	√	√	–	MATLAB
[24]	2022	Romania	Computers and Industrial Engineering	Residential	Utility	Meta-heuristic technique	Signaling game model for optimization	RTP ToU	√	√	–	–	√	–	–	–
[25]	2022	France	Applied Energy	Residential	Utility ESS RES	Hybrid technique	Particle swarm optimization and binary particle swarm optimization	ToU	√	√	–	–	√	√	–	–
[26]	2022	India	Journal of The Institution of Engineers (India): Series B volume	Residential	Utility	Meta-heuristic technique	Particle swarm optimization	RTP	√	√	–	–	–	–	–	MATLAB
[27]	2022	Pakistan	Energy Systems	Industrial	Utility RES	Meta-heuristic technique	Genetic algorithm	ToU	√	√	–	–	–	–	–	–
[28]	2022	UAE	Cluster Computing	Residential	Utility	Meta-heuristic technique	Grey wolf optimizer	RTP	√	√	–	–	√	√	–	–
[29]	2022	Portugal	Energy	Residential	Utility RES	Meta-heuristic technique	Genetic algorithm	RTP	√	√	–	–	–	√	√	Python
[30]	2022	China	Computers and Electrical Engineering	Residential	Utility RES ESS	Meta-heuristic technique	Grey wolf optimization	RTP	√	√	–	–	–	–	–	–
[31]	2022	India	Measurement: Sensors	Residential	Utility	Meta-heuristic technique	Eagle hard optimization	ToU	√	√	–	–	–	–	–	–
[32]	2022	Pakistan	Sustainable Energy Technologies and Assessments	Industrial	Utility RES ESS	Meta-heuristic technique	Lion's algorithm	DAP	√	√	–	–	√	√	–	MATLAB
[33]	2022	Iran	Knowledge-Based Systems	Residential	Utility RES ESS	Meta-heuristic technique	Multi-objective arithmetic optimization algorithm	CPP RTP	√	√	–	–	√	√	–	–
[34]	2022	Iran	Journal of Building Engineering	Residential Commercial Industrial	Utility	Hybrid technique	Simplex and improved grey wolf optimization	ToU	√	√	–	–	–	–	–	MATLAB and CPLEX
[35]	2022	Pakistan	Energies	Residential	Utility	Hybrid technique	Earth worm algorithm and harmony search algorithms	RTP	√	√	–	–	√	√	–	MATLAB

Table 2. Comparative table of PAR and cost optimization approaches.

Ref.	Year	Country	Journal/Conference	Building Sector	Energy Source	Control Scheme	Algorithm/Method	Pricing Scheme	Optimization Objective(s)					User Comfort	User Preferences	Simulation Tool
									PAR	Cost	CO_2 Emission	Communication	Average Waiting Time			
[36]	2022	Saudi Arabia and Pakistan	IEEE Access	Residential	Utility RES ESS	Hybrid technique	Ant colony optimization and teaching–learning-based optimization	RTP	√	√	√	–	√	√	√	MATLAB
[37]	2022	Saudi Arabia	Sustainability	Residential	Utility RES ESS	Hybrid technique	Enhanced differential evolution and genetic algorithm	RTP	√	√	√	–	√	√	–	MATLAB R2018b
[38]	2022	Iraq	Inventions	Residential	Utility ESS RES	Meta-heuristic technique	Bald eagle search optimization algorithm	RTP	√	√	–	–	–	–	–	MATLAB and ThingSpeak
[39]	2022	India	Energies	Residential	Utility	Meta-heuristic technique	Remodeled sperm swarm optimization	RTP	√	√	–	–	–	–	–	Python GUROBI
[40]	2022	Pakistan	Sustainability	Residential	Utility ESS RES	Meta-heuristic technique	Cuckoo search algorithm and mixed-integer linear programming	RTP	√	√	–	–	–	–	–	–
[41]	2022	Taiwan	Sustainability	Residential	Utility	Meta-heuristic technique	Non-dominated sorting genetic algorithm	RTP	√	√	–	–	√	√	√	–
[42]	2022	india	2022 International Virtual Conference on Power Engineering Computing and Control	Residential	Utility	Meta-heuristic technique	Sine–cosine algorithm	RTP	√	√	–	–	√	√	–	MATLAB
[43]	2022	India	International Conference on Power Electronics and Renewable Energy Systems	Residential	Utility	Hybrid technique	Antlion optimization	RTP	√	√	–	–	–	–	–	–
[36]	2022	Saudi Arabia and Pakistan	IEEE Access	Residential	Utility RES ESS	Hybrid technique	Ant colony optimization and teaching–learning-based optimization	RTP	√	√	√	–	√	√	√	MATLAB
[37]	2022	Saudi Arabia	Sustainability	Residential	Utility RES ESS	Hybrid technique	Enhanced differential evolution and genetic algorithm	RTP	√	√	√	–	√	√	–	MATLAB R2018b
[44]	2021	Brazil	Journal of Cleaner Production	Residential	Utility ESS RES	Meta-heuristic technique	Nonlinear programming, genetic algorithms, ant colony systems and particle swarm optimization	RTP	√	√	–	–	–	–	√	
[45]	2021	India	Journal of Building Engineering	Residential	Utility RES	Meta-heuristic technique	Least slack time-based scheduling	RTP ToU CPP	√	√	–	–	–	√	–	–
[46]	2021	Saudi Arabia	2021 IEEE 4th International Conference on Renewable Energy and Power Engineering	Residential	Utility	Meta-heuristic technique	Genetic algorithm	RTP	√	√	–	√	–	–	–	–

Table 3. Comparative table of PAR and cost optimization approaches.

Ref.	Year	Country	Journal/Conference	Building Sector	Energy Source	Control Schemes	Algorithm/Method	Pricing Scheme	Optimization Objective(s)					User Comfort	User Preferences	Simulation Tool
									PAR	Cost	CO_2 Emission	Communication	Average Waiting Time			
[47]	2021	Pakistan	IEEE Access	Residential Commercial	Utility ESS RES	Hybrid technique	Genetic algorithm, wind-driven optimization and particle swarm optimization	DAP	√	√	√	–	√	√	–	MATLAB
[48]	2021	Pakistan	Energies	Residential	Utility ESS RES	Hybrid technique	Genetic algorithm and ant colony optimization	RTP	√	√	√	–	√	√	–	MATLAB R2013b
[49]	2021	Saudi Arabia	Mathematics	Residential Commercial Industrial	Utility ESS RES	Meta-heuristic technique	Particle swarm optimization and the strawberry optimization	RTP ToU	√	√	–	–	√	–	–	–
[50]	2021	Pakistan	Energies	Residential	Utility ESS RES	Hybrid technique	Firefly algorithm and lion algorithm	DAP	√	√	–	–	√	√	–	MATLAB
[51]	2021	Jordan	Multimedia Tools and Applications(s)	Residential	Utility	Hybrid technique	Grasshopper optimization algorithm and differential evolution	ToU and CPP	√	√	–	–	√	√	–	MATLAB
[52]	2021	India	Sadhana	Residential	Utility RES	Hybrid technique	Genetic algorithm and particle swarm optimization	DAP	√	√	–	–	–	–	–	NI LabVIEW.2015
[53]	2021	Romania	Journal of Optimization Theory and Applications	Residential	Utility	Hybrid technique	Stackelberg game	ToU	√	√	–	–	–	–	–	–
[54]	2021	Egypt	Energy Reports	Residential commercial	Utility RES	Meta-heuristic	Cuckoo optimization algorithm	ToU	√	√	–	–	–	–	–	MATLAB
[55]	2021	Pakistan	IEEE Access	Residential	Utility ESS RES	Hybrid technique	Hybrid genetic ant colony	RTP	√	√	√	–	√	√	–	MATLAB R2018a
[56]	2021	Pakistan	International Journal of Energy Research	Residential	Utility ESS RES	Hybrid technique	Hybrid genetic ant colony optimization	RTP	√	√	√	–	√	√	–	MATLAB R2013b
[57]	2021	Pakistan	International Conference on Emerging Technologies	Residential	Utility	Meta-heuristic technique	Jaya algorithm	ToU and CPP	√	√	–	–	√	√	–	MATLAB 2014a
[58]	2020	China and Pakistan	IEEE Access	Residential Commercial Industrial	Utility	Hybrid technique	Hybrid bacterial foraging and particle swarm optimization	DAP CPP ToU	√	√	√	–	√	√	–	–
[20]	2020	Pakistan	Multidisciplinary IEEE Access	Residential	Utility	Hybrid technique	Grey-wolf-modified enhanced differential evolution algorithm	DAP	√	√	–	–	√	√	–	–

Table 4. Comparative table of PAR and cost optimization approaches.

Ref.	Year	Country	Journal/Conference	Building Sector	Energy Source	Control Schemes	Algorithm/Method	Pricing Scheme	Optimization Objective(s)					User Comfort	User Preferences	Simulation Tool
									PAR	Tariff/Cost	CO_2 Emission	Communication	Average Waiting Time			
[59]	2020	South Korea	IEEE Transaction on Smart Grid	Residential	Utility ESS	Heuristic technique	Game theory	RTP	√	√	–	–	–	–	–	–
[60]	2020	Pakistan	IEEE Access	Residential	Utility ESS RES	Hybrid technique	Hybrid genetic particle swarm optimization	RTP	√	√	√	–	√	√	–	MATLAB
[61]	2020	Spain	EEEICand ICPS Europe	Industrial	Utility	Heuristic technique	Linear programming	DAP	√	√	–	–	–	–	–	–
[62]	2020	South Korea	IEEE Access	Residential	Utility ESS RES	Hybrid technique	Particle swarm optimization (PSO) and binary particle swarm optimization	DAP	√	√	–	–	–	–	–	Cplex/ Dicopt
[63]	2020	India	Peer-to-Peer Networking and Applications	Residential	Utility ESS RES	Hybrid technique	Adaptive neuro-fuzzy inference system	RTP	√	√	–	–	√	–	–	MATLAB
[64]	2020	Singapore	Applied Energy	Residential	Utility ESS RES	Meta-heuristic technique	Game theory and genetic algorithm	RTP	√	√	–	–	–	–	–	–
[65]	2020	Pakistan	Applied Science	Residential	Utility	Meta-heuristic technique	Multi-verse optimization sine–cosine algorithm	DAP	√	√	–	–	√	–	–	–
[66]	2020	Poland	IET Smart Grid	Residential	Utility ESS RES	Heuristic technique	Fuzzy logic	RTP	√	√	–	–	–	–	–	C++ with OOP
[67]	2020	Algeria	Optimization and Engineering	Residential	Utility	Meta-heuristic technique	Harris hawks optimization	RTP and CPP	√	√	–	–	–	–	–	MATLAB
[68]	2020	Pakistan	Electronics	Residential Commercial Industrial	Utility	Meta-heuristic technique	Dragonfly algorithm	DAP	√	√	–	–	√	–	–	–
[69]	2020	Pakistan	Electronics	Industrial	Utility	Meta-heuristic technique	Grasshopper optimization algorithm and cuckoo search optimization algorithm	DAP	√	√	–	–	√	√	–	MATLAB
[70]	2020	Pakistan	Electronics	Residential Commercial Industrial	Utility	Meta-heuristic technique	Dragonfly algorithm	DAP	√	√	–	–	√	–	–	–
[71]	2020	Pakistan	Advanced Information Networking and Applications	Residential	Utility	Meta-heuristic technique	Flower pollination algorithm and Jaya optimization algorithm	CPP	√	√	–	–	√	√	–	MATLAB 2017a

Table 5. Comparative table of PAR and cost optimization approaches.

Ref.	Year	Country	Journal/Conference	Building Sector	Energy Source	Control Schemes	Algorithm/Method	Pricing Scheme	Optimization Objective(s)					User Comfort	User Preferences	Simulation Tool
									PAR	Tariff/Cost	CO_2 Emission	Communication	Average Waiting Time			
[72]	2019	Pakistan	Sustainability	Residential	Utility ESS RES	Trajectory search family	Dijkstra algorithm	DAP	√	√	–	–	√	√	–	MATLAB 2014a
[73]	2019	South Africa	Energy	Residential	Utility ESS RES	Evolutionary algorithms	Improved differential evolution algorithm	DAP	√	√	–	–	√	√	–	–
[74]	2019	Pakistan	Web, Artificial Intelligence and Network Applications	Residential	Utility	Meta-heuristic technique	Runner updation optimization algorithm	CPP RTP	√	√	–	–	–	–	–	MATLAB
[75]	2019	Ethiopia	IEEE CSEE	Residential	Utility RES	Meta-heuristic technique	Grey wolf optimizer	ToU	√	√	–	–	–	–	–	–
[76]	2019	Korea	Future Generation Computer System	Residential	Utility	Meta-heuristic technique	Mutation ant colony optimization	ToU	√	√	–	–	√	–	–	MATLAB Visual C# on Visual Studio 2010 compatible with. NET framework 4.0
[77]	2019	Pakistan	Process MDPI	Residential Commercial	Utility	Meta-heuristic technique	Grasshopper optimization algorithm and bacterial foraging optimization	DAP	√	√	–	–	–	–	–	MATLAB
[78]	2019	Pakistan	Artificial Intelligence and Network Applications	Residential	Utility	Meta-heuristic technique	Strawberry algorithm and earthworm optimization algorithm	RTP CPP	√	√	–	–	√	–	–	–
[79]	2019	Taiwan	IEEE International Conference on Systems, Man and Cybernetics	Residential	Utility	Meta-heuristic technique	Search economics for home appliances scheduling	DAP	√	√	–	–	–	–	–	C++ Clang++
[80]	2019	India	Microprocessors and Microsystems	Residential	Utility ESS RES	Hybrid technique	Glow-worm swarm optimization and support vector machine	DAP	√	√	–	–	–	–	–	MATLAB 2018 a
[5]	2019	China	Energies	Residential	Utility ESS RES	Heuristic technique	Game theory	DAP	√	√	–	√	–	–	√	MATLAB 2013a -YALMIP -ILOG's CPLEX v.12 CPLEX
[81]	2019	UAE	Ambient Intell Human Comput Springer	Residential	Utility	Hybrid technique	Harmony search algorithm and enhanced differential evolution	RTP	√	√	–	–	√	√	–	MATLAB
[82]	2018	Pakistan	Energies	Residential	Utility	Heuristic technique	Genetic harmony search algorithm	RTP andCPP	√	√	–	–	√	√	–	MATLAB 2014b
[83]	2018	Kenya	Power and Energy Engineering	Residential	ESS RES	Hybrid technique	Bayesian game theory	RTP	√	√	–	–	–	–	–	–
[84]	2018	USA	IEEE Trans. Smart Grid	Residential	Utility	Stochastic technique	Game theory	RTP	√	√	–	√	–	–	–	IBM ILOG CPLEX

Table 6. Comparative table of PAR and cost optimization approaches.

Ref.	Year	Country	Journal/Conference	Building Sector	Energy Source	Control Schemes	Algorithm/Method	Pricing Scheme	Optimization Objective(s)					User Comfort	User Preferences	Simulation Tool
									PAR	Tariff/Cost	CO_2 Emission	Communication	Average Waiting Time			
[85]	2018	USA	IEEE Green Technologies Conference	Residential Commercial	Utility ESS	Heuristic technique	PSO	ToU	√	√	–	–	–	–	–	–
[86]	2018	Thailand	IEEE Transaction on Smart Grid	Residential	Utility ESS RES	Heuristic technique	Fuzzy low-cost operation	ToU	√	√	–	–	–	–	–	–
[87]	2018	Iran	IEEE Smart Grid Conference	Residential	Utility ESS Conventional-Units	Hybrid technique	Unnamed scheduling and fuzzy logic	DAP and ToU	√	√	√	–	–	–	–	GAMS -MILP and CPLEX
[88]	2018	Pakistan	IEEE International Conference on Advanced Information Networking and Applications	Residential	Utility	Hybrid technique	Enhanced differential harmony binary particle swarm optimization	RTP	√	√	–	–	–	√	–	MATLAB
[89]	2018	Romania	Computers and Industrial Engineering Elsevier	Residential	Utility	Evolutionary optimization technique	Shifting optimization algorithm	ToU	√	√	–	–	–	–	–	MATLAB 2016a
[3]	2018	Pakistan	IEEE International Conference on Advanced Information Networking and Applications	Residential	Utility	Hybrid technique	Enhanced differential harmony binary particle swarm optimization	RTP	√	√	–	–	–	√	–	MATLAB
[90]	2018	Pakistan	IEEE International Conference on Advanced Information Networking and Applications	Residential	Utility	Hybrid technique	Bacterial foraging tabu search	RTP	√	√	–	–	√	√	–	MATLAB
[4]	2018	China	Neural Comput and Applic	Residential Industrial	Utility ESS RES	Heuristic technique	Game theory	# Equilibrium market	√	√	–	–		–	–	Cplex DECIS OSL-SE
[91]	2018	Brazil	Springer International Conference, PAAMS	Residential	Utility	Meta-heuristic technique	Gravitational search algorithm	RTP	√	√	–	–	–	–	–	LPG
[92]	2017	Pakistan	Advances in Network-Based Information Systems	Residential	Utility	Meta-heuristic technique	Bacterial foraging optimization and strawberry algorithm	RTP	√	√	–	–	√	√	–	MATLAB
[93]	2017	India	IEEE International Conference on Electrical, Instrumentation and Communication Engineering	Residential	Utility	Evolutionary optimization technique	Unnamed scheduling	DAP	√	√	–	–	–	–	–	MATLAB
[94]	2017	India	IEEE International Conference on Power Systems	Residential Commercial Industrial	Utility	Meta-heuristic technique	Multi-objective particle swarm optimization	DAP	√	√	–	–	–	–	–	MATLAB
[95]	2017	UK	IEEE Trans. Ind. Inf	Residential	RES		Artificial immune algorithm	DAP	√	√	–	–	–	–	–	–
[96]	2017	Pakistan	Advances in Network-Based Information Systems	Residential	Utility	Meta-heuristic technique	Enhanced differential evolution	ToU	√	√	–	–	√	–	–	–

Table 7. Comparative table of PAR and cost optimization approaches.

Ref.	Year	Country	Journal/Conference	Building Sector	Energy Source	Control Schemes	Algorithm/Method	Pricing Scheme	Optimization Objective(s)					User Comfort	User Preferences	Simulation Tool
									PAR	Tariff/ Cost	CO_2 Emission	Communication	Average Waiting Time			
[97]	2017	India	Sustainable Cities and Society	Residential	Utility	Linear programming	Mixed-integer linear programming	ToU	√	√	–	–	–	–	–	GAMS/ CPLEX
[98]	2017	Pakistan	Advances on P2P, Parallel, Grid, Cloud and Internet Computing	Residential	Utility	Meta-heuristic technique	Crow search algorithm	RTP	√	√	–	–	√	√	–	MATLAB
[99]	2017	Pakistan	IEEE International Renewable and Sustainable Energy Conference	Residential	Utility RES ESS	Heuristic technique	Knapsack algorithm	RTP	√	√	–	–	–	–	–	–
[100]	2017	Pakistan	Advances in Intelligent Networking and Collaborative Systems	Residential	Utility	Meta-heuristic technique	Enhanced differential evolution & Strawberry Algorithm	RTP	√	√	–	–	√	√	–	MATLAB
[101]	2017	UK	IEEE International Conference on Smart Energy Grid Engineering	Residential	Utility	Unnamed technique	Unnamed scheduling	RTP	√	√	–	–	–	–	–	–
[102]	2017	Pakistan	Advances on P2P, Parallel, Grid, Cloud and Internet Computing	Residential	Utility	Meta-heuristic technique	Flower pollination algorithm	RTP	√	√	–	–	√	–	–	MATLAB
[103]	2016	India	IEEE National Power Systems Conference	Residential Commercial Industrial	Utility	Meta-heuristic technique	Particle swarm optimization	DAP	√	√	–	–	–	–	–	–
[104]	2016	Australia	Applied Energy Elsevie	Residential	Utility	Unnamed technique	Unnamed scheduling	RTP	√	√	–	–	–	–	–	–
[105]	2016	Pakistan	Applied Sciences	Residential	Utility	Heuristic technique	Knapsack optimization	ToU	√	√	–	–	–	√	–	MATLAB
[106]	2015	Singapore	IEEE Innovative Smart Grid Technologies	Residential Commercial Industrial	Utility	Meta-heuristic technique	Particle swarm optimization	DAP	√	√	–	–	–	–	–	MATLAB
[107]	2015	India	IEEE Power, Communication and Information Technology Conference	Residential	RES	Meta-heuristic technique	2D particle swarm optimization	DAP	√	√	–	–	–	–	–	MATLAB
[108]	2015	Pakistan	IEEE International Conference on Network-Based Information Systems	Residential Commercial Industrial	Utility	Meta-heuristic technique	Genetic algorithm	RTP	√	√	–	–	–	–	–	–
[109]	2015	South Africa	IEEE Innovative Smart Grid Technologies	Residential	Utility	Evolutionary technique	Daily maximum energy scheduling	ToU	√	√	–	–	–	–	–	MILP CPLEX

Table 8. Comparative table of PAR and cost optimization approaches.

Ref.	Year	Country	Journal/Conference	Building Sector	Energy Source	Control Schemes	Algorithm/Method	Pricing Scheme	Optimization Objective(s)					User Comfort	User Preferences	Simulation Tool
									PAR	Tariff/Cost	CO_2 Emission	Communication	Average Waiting Time			
[110]	2015	Pakistan	Energy Research	Residential	Utility	Meta-heuristic technique	Genetic algorithm	RTP	√	√	–	–	√	–	–	–
[111]	2015	Italy-france	Computer Communications	Residential	Utility	Heuristic technique	Game theory	RTP	√	√	–	–	–	–	–	–
[112]	2014	Japan	2014 International Conference on Electronics, Information and Communications	Residential	Utility ESS	Convex optimization technique	Unnamed scheduling	RTP	√	√	–	–	–	–	–	–
[113]	2014	China	IEEE International Joint Conference on Neural Networks	Residential	Utility	Meta-heuristic technique	Stackelberg game and genetic algorithm	RTP	√	√	–	–	–	–	–	IBM CPLEX
[9]	2014	Singapore	IEEE Journal of Selected Topics in Signal Processing	Residential	Utility	Distributed schemes	Distributed algorithm	RTP	√	√	–	–	–	–	–	–
[114]	2013	UK	Soft Computing	Residential	Utility	Meta-heuristic technique	Stackelberg game and genetic algorithms	RTP	√	√	–	–	–	–	–	–
[115]	2013	Iran	2013 13th international conference on environment and electrical engineering	Residential	Utility	Meta-heuristic technique	Genetic algorithm	RTP	√	√	–	–	–	–	–	MATLAB
[116]	2013	China	2013 IEEE international conference on communications workshops	Residential	Utility	Heuristic technique	Linear programming	RTP	√	√	–	–	–	–	–	–

4. Mapping Questions Results and Analysis

This section presents answers to the mapping questions and analyzes global trends.

In general, there has been a growth of interest in this topic, particularly since 2017 as shown in Figure 4. The relative increase in this topic was approximately 85%: from three selected studies in 2013 up to an average of nineteen selected studies between 2021 and 2022. This can be considered as an indicator of how electricity management and control methods have gained importance in recent years.

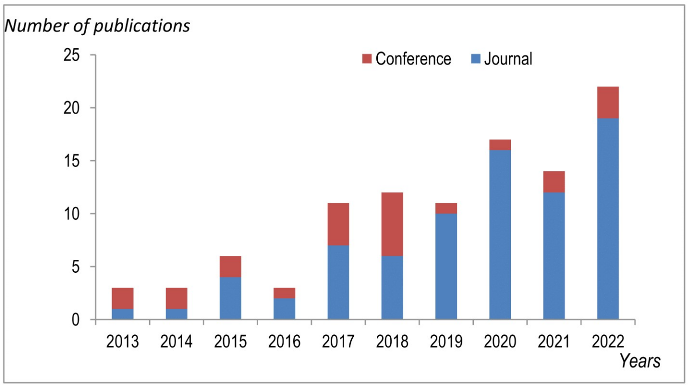

Figure 4. Number of publications on the web by year and type of articles.

Moreover, the proportion of journal papers tends to increase throughout the years, which indicates a certain maturity of the field. Pakistan (Figure 5) in particular seems very interested in PAR and cost optimization approaches. India, Saudi Arabia, Iran, China and South Korea follow. Most of these are Asian and emerging countries, with a strong urban population growth. Thus, they go through a very important increase in energy demand in a short period of time [117], which justifies the need for optimization.

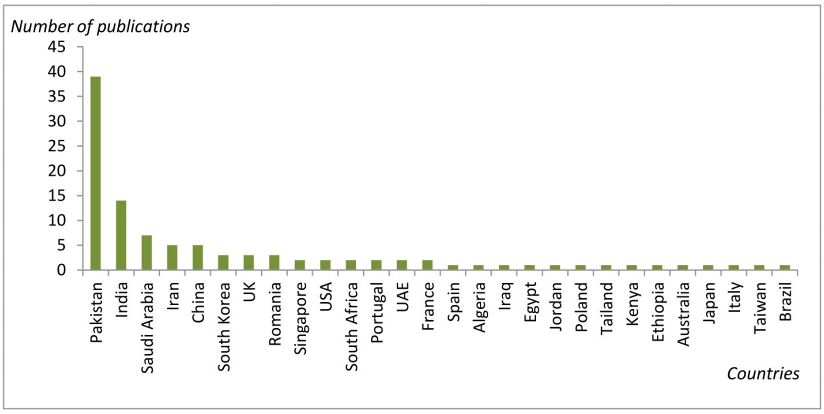

Figure 5. Number of surveys per country.

The rest of the section is dedicated to answering every research question and providing an analysis of the global trends.

RQ1. *What are the most used algorithms and techniques for peak and cost reduction?*

Optimization is the process of determining the state of decision variables that give the best value for single or multi-objective functions. First of all, what is striking is the diversity of used algorithms (Figure 6) for solving only two optimization problems: peak and cost reduction. This can be seen in the multiple (sometimes original) names given to heuristics: dragonfly, earth worm, lion, grey wolf, etc.

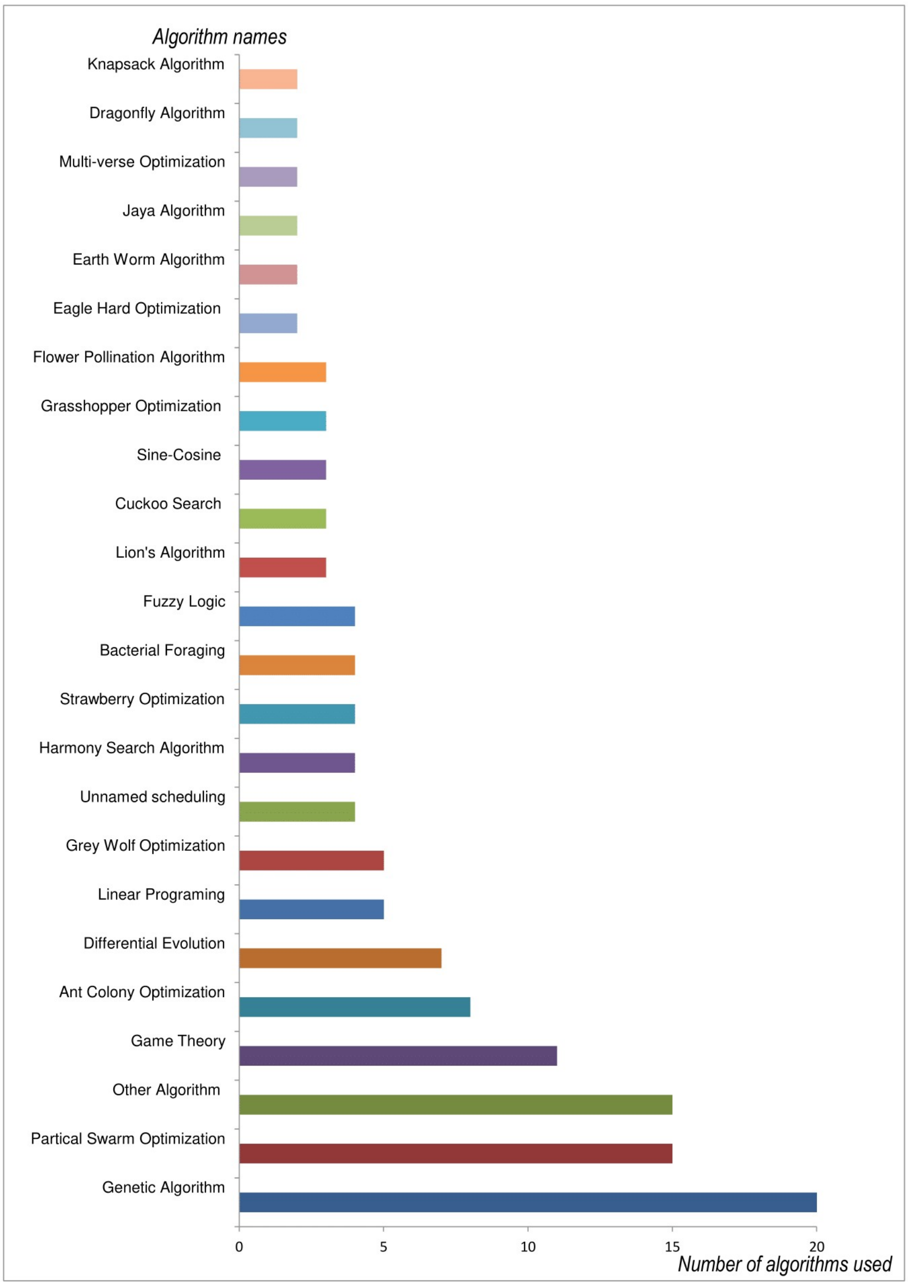

Figure 6. Algorithms used for peak and cost reduction.

This diversity could be a manifestation of Wolpert et al.'s *No Free Lunch Theorem* [118], which states that: "Roughly speaking we show that for both static and time dependent optimization problems the average performance of any pair of algorithms across all possible problems is exactly identical". The implications are that there is no optimization algorithm that performs best for all problems. Although the problem seems the same (peak and cost optimization), in practice, the formalization differs in the survey papers, and the multi-objectives too (e.g., CO_2 emission, waiting time). This might justify the multiplicity of optimization heuristics. Nevertheless, the sheer number of algorithms is still, in our point of view, a little bit *inflated*. Sometimes, papers try to use 'yet another' heuristic with a unique name to prove the originality of the paper's contribution with regard to the state of the art.

The peak and cost optimization algorithms that we found can be classified into the following categories: (1) analytical and exact algorithms; (2) heuristics (approximate algorithms).

Analytical and exact algorithms were the main approach for problem optimization, before the advent of heuristics. Some of them are based on the first and second-order derivatives of the objective functions. They can efficiently find the exact optimum for linear or convex problems, for example. In the works that we surveyed, these approaches are used, but usually with another approximate algorithm. Some instances that we found include linear programming, nonlinear programming, dynamic programming and integer programming [4,40,44,116]. However, exact methods are inefficient and very slow in more complex (NP-hard ones, for example) problems with many local optima, stochastic or unknown search space, many objectives (e.g., with user preference inclusion) and renewable sources integration. This is why their proportion in our particular case is relatively small compared to approximate algorithms.

These are commonly called heuristics. Metaheuristics define classes of heuristics; that is, conceptual frameworks and rules to devise a good approximate algorithm that might converge to a global optimum [119]. However, metaheuristics are probabilistic in nature and controlled by parameters such as population, elite population size, number of generations, etc. In most of the studies, there is a concern that adjusting the parameters is an extremely critical problem, as it can directly affect the performance of the techniques. An incorrect setting can lead to an increase in computation time or a local optimum [120]. Possible taxonomies for metaheuristics are [119]: (1) evolution-based; (2) swarm-based; (3) human-based; (4) physics based; (5) math-based.

Evolution-based algorithms are inspired by the Darwinian law of natural selection. They iteratively change a population of solutions using evolutionary operators (i.e., selection, cross-over, mutation), to improve the solutions quality, hoping to converge to the global optimum. *genetic algorithms* (GAs) and *differential evolution* are two instances used for cost/peak optimization. The first ones are the most popular in our study [29,46,52,70,102,108,113,121], perhaps because they are notoriously good for scheduling tasks (our present use case), and more generally for complex discrete structures optimization. What is also striking is the hybridization between GAs and other types of heuristics (e.g., genetic/ant colony hybrid optimization).

Swarm-based algorithms replicate the social interactions of certain living beings (e.g., bacteria, birds, wolves, lions). Usually, the social interactions considered are related to survival (e.g., hunting, mating). Individuals from the swarm also share information, which influences their behavior in the following iterations. Some examples that we found are: particle swarm optimization [103], ant colony optimization [76], grey wolf optimization, bacterial foraging [77], lion's algorithm [50] and cuckoo search [54]. According to our cumulative statistics, these types of algorithms are *frequent* in optimizing the PAR and energy consumption cost. A possible reason is that they require fewer parameter tunings. However, the specific meta-heuristic of particle swarm optimization is less used than genetic algorithms because it is less adapted to discrete constraint problems.

Human-based metaheuristics take their inspiration from social interactions and human behavior. We found one instance of such algorithms published in IEEE Access [36], mixed with a swarm-based algorithm: teaching–learning-based optimization with ant-colony-based heuristics. Physics-based algorithms tend to explore the search space using agents that respect physical laws. They are practically inexistent in our study. Math-based heuristics are only based on mathematical equations and do not obtain their inspiration from a natural phenomenon. Few instances have been found for the peak/energy cost optimization problem: sine–cosine [42,65] or multi-objective arithmetic optimization.

Game theory [122] is another mathematical model that studies the outcome and optimal strategies for situations where agents interact with each other according to a set of fixed rules. This theory includes four elements: players, information that they have, their possible actions and the payoffs. Stackelberg games are an instance of this theory where there is a leader (in our instance, the energy producer) and n followers (in our instance, the consumers). The best response is called the Stackelberg–Nash equilibrium, with the producer supplying maximum renewable energy and consumers minimizing tariffs by appliances shifting. In our survey, these types of algorithms are used more than 10 times [4,5,20,53,59,83,113,114,123,124], which is as often as very other popular swarm-based metaheuristics. They are also often hybridized with genetic algorithms in order to choose the actions.

Fuzzy logic [125] is an interesting inference paradigm that we found when studying papers related to peak/energy cost optimization. It manipulates variables with levels of truth represented by a real number between 0 and 1. The inference rules from this type of logic are used to decide when to use the appliances (shifting and scheduling).

We noticed that population-based metaheuristics are much more used for cost/peak optimization than single-solution ones. The first type improves a set of candidate solutions iteratively (as opposed to one candidate solution). Single-solution heuristics are preferred when the fitness function is computationally intensive. In this case, calculating the energy cost based on the consumption schedule is fairly straightforward, which explains what we have.

Another important aspect is the dataset used as the input to the algorithms and its impact on the optimization effectiveness. During our data collection, we identified three major input categories: real-world, pre-generated and randomly generated data. Real-world data were not popular in the 104 selected studies [45,70]. The problem might be in the fact that a real-world dataset is often small and tied to a specific application, which is a preferred option only in particular cases. Moreover, in certain instances, researchers seek to prove the good performance of their proposed algorithm with adapted data. On the other hand, artificial and randomly generated data are more popular [49,61,84]. They give a large amount of data, which provides useful information on the characteristics of the compared optimization algorithms. The difficulty is to rationalize their link with the real performance of the algorithms.

On all these types of data, the great frequency of use of genetic algorithms and particle swarm optimization shows their good exploration/exploitation capabilities of the solution space. Many comparative studies [65,69,70] rank them amongst top algorithms for optimizing PAR and cost. Their rank (relative to each other) varies from one study to another, depending on the multi-objective optimization function (e.g., cost, PAR, waiting time) and also according to the conditions and input parameters (e.g., number of users, integration of renewable or storage systems).

In addition to the dataset impact, for the same algorithm, there are environmental factors that influence the results: the programming language, skills of the programmer and computer environment used to test the algorithm.

RQ2. *What type of energy source has been chosen?*

Energy supply source types were also studied in our paper. The utility grid supply was large as it comprises 96% of the literature, while renewable energy occupies 35% and storage power systems occupies 32%.

The proportion of renewable and storage energy systems are close (35% vs. 32%). This can be explained by the fact that they are usually used together (e.g. solar panel with battery) in an installation.

What is striking is that renewables are not used as often as we expected (a third of the literature), although, with the current world's climatic and energetic situation, they are fundamental. This might be because the emerging countries (not yet mature for generalized renewable use) are the most represented in the studies. It can also be explained by (1) problems of integration into the system; (2) an increased difficulty in solving the optimization problem.

Regarding the first reason, the requirement of a large area for installation and the reliability of protection circuits to isolate them from the existing network whenever necessary is a great challenge. The lack of technically qualified manpower and a poor selection of the optimal place for the implementation will also affect the integration of this type of energy system. The fluctuating and unpredictable nature of renewable energy sources such as photo-voltaic solar and wind turbines require complex technologies and a deep study starting in the site, evaluating the impacts on the network. All of this is especially true in emerging countries, which are very well represented in our survey (Figure 5). The cost of the batteries (although there are historical improvements [126]) is also sometimes a negative factor.

Regarding the second reason, there is an increasing complexity induced by adding intermittent renewable energy sources and battery storage systems in the optimization. This is in part due to (a) the lack of good models; (b) the lack of accurate data sets (e.g., solar and wind); (c) the complexity of the resulting optimization problem [127,128].

RQ3. *What type of building has been treated?*

A demand response program can increase its effectiveness by taking into consideration the types of consumers to which it applies. Typically, they are either *residential*, *commercial* or *industrial*. Their needs are completely different in terms of energy, load and equipment used. However, it is important to keep in mind that the prerequisite to energy consumption optimization is always good energy building design [129] (e.g., insulation, shape, envelope system, orientation), which can improve energy efficiency by up to 50%.

In our systematic mapping study, we noticed from (Figure 7) the predominance (96%) of the residential building type, followed by the other two (in the same proportions: 15% vs. 13%). This could be because residential buildings are much more common than the others. Moreover, they present very interesting challenges due to the unpredictable consumption pattern. Industrial buildings follow because of some specific challenges linked to critical equipment and the availability of a sensor architecture by default. Commercial buildings also present interesting challenges due to the heating, cooling and lighting growing energy demands. We also noticed that papers usually tackle either one type of building or all of them at the same time.

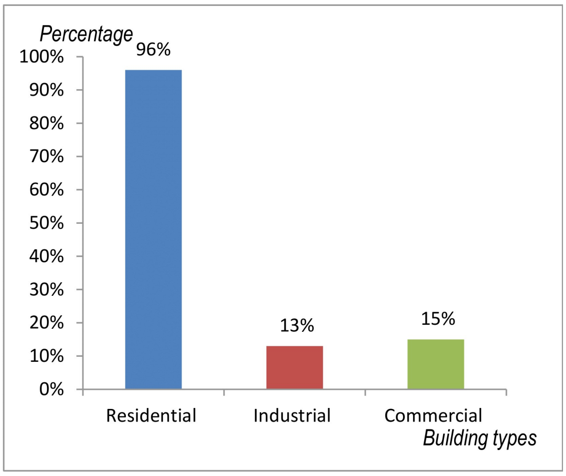

Figure 7. Building type trends.

Regarding residential buildings, the design of an effective DR program is very complicated, mainly because of the fluctuating consumption patterns, which require vigilant modeling: individual human behavior is sometimes unpredictable. The DR program applied should not assume that all customers have the same energy consumption patterns, as mentioned in [130]. In the reviewed studies, we found that all residential consumers can be grouped into five different categories:

1. *Long-range consumers* are able to shift their consumption over a wide range of time following changes in prices;
2. *Real-world postponing consumers* have a perception depending only on current and future prices;

3. *Real-world advancing customers* have a perception depending only on current and past periods;
4. *Real-world mixed consumers* are a mix of postponing and advancing consumers, taking into account the past, present and future;
5. *Short-range consumers* do not optimize their load and are only concerned and worried about the power price at the current time.

That is why, although the residential sector constitutes the bulk of buildings, the optimization has to be *adaptive* by taking into account the consumer's profile as a variable in the models.

Regarding industrial consumers, they are very-high-energy users. Thus, the optimization impact is huge, if carried out correctly. However, although the infrastructure is already equipped with sensors, measurement technologies and personal operators, the challenge of a demand response program exists [32,61,69]. In our survey, we confirmed that the implementation of DR is complicated because of the *critical* loads in industrial plants. A simple service disconnection may cause a break of production, and millions of dollars of financial loss. In fact, some manufacturing systems exhibit hard real-time constraints where scheduling must be performed with high accuracy [131]. This is why the optimization has to take into account inelastic and critical load demand and only act on non-critical consumption loads.

Finally, regarding commercial buildings, what transpires in the works that we studied is that commercial sectors present an important part of the total electricity consumption, which is expected to increase. Water heating, cooling, space heating, lighting, refrigeration and ventilation are the main electrical energy consumers. Computers, electronics and other loads are classified as miscellaneous electrical loads, which include plug loads and all hard-wired ones that are not responsible for cooling, lighting, water heating or space heating. The reduction in their electrical consumption can be obtained either by the adoption of energy-efficient construction technologies or by controlling the energy consumption behavior of buildings thanks to the price elasticity of energy demand.

RQ4. *What are the optimization objectives of the cited algorithms?*

The main objectives of demand-side management algorithms studied in this paper are to reduce the peak-to-average ratio and minimize the cost of consumption. That is why, naturally, 100% of the papers (Figure 8) tackle these two aspects. Note that there is a natural reduction in the cost and peak when the papers include renewable (cheaper) energy data.

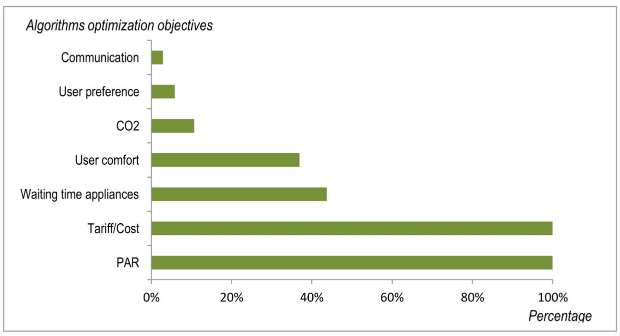

Figure 8. Algorithms optimization objectives.

However, we notice that there are other 'secondary' optimization objectives: the waiting time of appliances and user comfort come in second place, with around 41% and 35% each. Finally, communications, CO_2 emissions and user preferences are considered in only very few studies.

These results can be explained by the fact that the appliances waiting time and comfort are usually intertwined with PAR and cost optimization. Otherwise, a naive cost-minimizing solution would consist of shifting all appliances to the moments with cheaper electricity. In practice, the PAR and cost reduction are often constrained by time intervals I_a ,where the appliance function can be freely shifted. Optimizing these two objectives consists of choosing the functioning periods that minimize them in these intervals. Often, there is a trade-off between this optimization and the delay that the appliance waits to start functioning in I_a.

Regarding user comfort, it is usually computed using the priority of loads as defined by the user or a set of differences elevated to a certain exponent. These differences depend on the schedulable or non-schedulable nature of appliances. They can represent (a) the appliance waiting time; (b) the gap between optimal appliance power and real power. Depending on the exponent and also on a multiplication factor, discomfort can be computed differently, influencing the optimization. However, very often, the factors and exponents are close (e.g., 2 for the quadratic Taguchi loss function [132]).

Regarding CO_2 emissions, they are not considered very often. Since their reduction is often a consequence of maximizing renewable energies use, this could be linked to the smaller proportion of renewables data sets used in the works (Figure 9). The majority of research on CO_2 emissions cited in this survey does not use data from source-specific emission testing or continuous emission monitors. This is because they are not always available from individual sources. They use emission factors, which are representative values linking the quantity of the atmosphere pollutant to the type of activity (energy production) associated with their emissions [23,36,47,48,55,87,87]. Usually, these are the averages of the available data of acceptable quality. This provides sometimes approximate results for the CO_2 optimization objective.

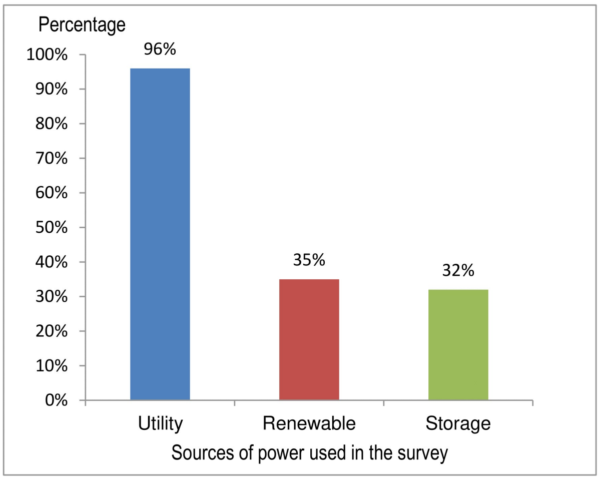

Figure 9. Building supply source trends.

Finally, what is very surprising is the lack of explicit consideration for user preferences as well as communications [5,46,84]. There are very few data documenting exchanged information between the loads and the control system during real-time connectivity (e.g., the RTP case) because it requires a large frequency bandwidth and communication equipment capable of encrypting the information transmitted to the control system to preserve consumer privacy. Not taking into account preferences or communications does not allow the user to make the compromise between payments and comfort. It impacts interactivity, which could hinder adoption in the consumer market.

RQ5.*What type of energy pricing has been chosen?*

Figure 10 shows the various pricing schemes (pricing scheme definitions in Section 2.3) used in the reviewed papers. Real-time pricing (RTP) is the most used, with a proportion of a little less than half the studies (48%). It is followed by day-ahead pricing (DAP) and time-of-use pricing (ToU), with fairly equivalent proportions (respectively, 24% and 18 %). Finally, critical peak pricing (CPP) has a proportion of only 10%.

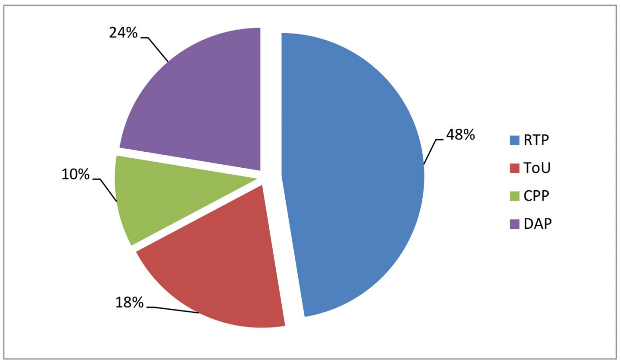

Figure 10. Electricity pricing scheme.

A possible explanation is that RTP is theoretically the most efficient way to adapt the demand to utility constraints. This is because it constantly (sometimes every 15 min) updates the prices according to the wholesale electricity market or utility's production cost. However, note that it costs a large amount of communications (as well as metering infrastructure), which is surprisingly not often taken into account in the optimization (Figure 8). Thus, we argue that, if communication were considered in the multi-objective optimization, the pricing schemes frequency of use would radically change in the works.

DAP is a good compromise between complexity and efficiency, which justifies the second position. Day-ahead pricing advertises prices for the next day, making it more relaxed (thus more realistic) than RTP. Time-of-use (ToU) pricing is more rigid, and thus less popular in the studies: it consists of the classic attribution of fixed prices according to particular time periods (in the day or week). Thus, it does not give any useful incentive or information to the user during off-peak periods. Finally, critical peak pricing is an extension of ToU with so-called 'exceptions' where prices are increased for specific time periods.

5. Discussion

In this section, based on the comparative analysis of the 104 studies, and the answers to the five research questions, we attempt to provide to the research community a list of *Open Issues* and *Recommendations* for the future.

5.1. Algorithmic Hybridization

Our systematic mapping study clearly shows the need for the efficient *hybridization* of two or more algorithms by taking the advantages of several strategies during a cycle, or during each cycle in the same optimization [3,35,90,133]. For complex problems that are often NP-hard (e.g., including energy storage systems with intermittent renewable energy sources), a simple new generation algorithm may fail to obtain a practical and good solution. Exact algorithms, on the other hand, are usually not adapted, as they often impose computing first or second-order derivatives and require the linearity or convexity of problems.

We recommend a combination of an evolution-based metaheuristic with a swarm-based one [52]. They are both population-based algorithms that are adapted to our problem because (1) with renewables integration, the problem space becomes very big, and needs an efficient global search; (2) the fitness function is relatively easy to compute (energy cost), which disqualifies the motivation for single-point search methods (as used in [90]).

More specifically, the motivation lies in the fact that GAs in particular are good for exploration and less adapted to exploitation (which is quite the opposite for swarm-based algorithms [134,135]). Indeed, from the technical point of view, GAs solutions' (considered as chromosomes) crossover operation provides excellent search capabilities in the solution space [136]. It consists of choosing one or multiple 'points' on both parent chromosomes and swapping genes to the point's left/right between the parents. However, the only exploitation operator in GAs is the mutation, which limits the change in chromosomes offspring. Apart from very efficient exploitation, note that swarm optimization takes into account the interaction between solutions (considered as swarm particles). Particle swarm optimization in particular promotes it by allowing for a faster information flow between particles: each one updates its position using its own pass experience (p_{best} in the mathematical notations), as well as following the best particle's movement (global interaction).

Thus, in the final model, the idea could be to alternate between GAs iterations (diverse offspring generation for exploration) and swarm optimization iterations (offspring are guided by the particle 'movement' of their parents) until the maximum number of iterations or the termination condition is met. The chromosomes generation would be initially set to 0. A GA iteration would select parents for mating, cross them over and add them to the population. Swarm optimization could improve the population's fitness in the next iteration. The best individuals would then be selected and produce the new generation for GAs.

5.2. Interactive and Real-Time User Preference Consideration

Very few (around 6) from the 104 studied papers, (Figure 8) consider user preferences in the optimization problem. Among the most notable works, there are those of He et al. [5] and Liu et al. [9]. In [5], a distributed demand-side management control mechanism is proposed that finds an optimal consumption/prediction routine, taking into consideration fluctuating prices and user choice. In the surveyed works, one of the suggestions is defining a "User Convenient" schedule and "Grid Convenient" one [9]. The idea is to compute metrics quantifying the deviation between them. However, for a general adoption, most algorithms lack real-time interactivity. This task is also a part of transitioning from research results to consumer-market-friendly solutions, which is not always easy.

The ideal commercial system could be pictured as a control screen (or tablet)-based system that is user interactive and optimizes in real time. The user preference has to be the priority to enable the customer acceptance of the system, as advocated by Liu et al. [9]. The real-time aspect switches the optimization parameters completely as, for example, the user no longer has a clear set of schedule intervals for their appliances, but a mere approximate prediction of the future. The algorithm also has to involve a very fast optimization heuristic.

Finally, in a commercial system, practical concerns have to be taken into account, such as *response/decision fatigue*. In smart grid/user interactions, the right balance between information sharing and communication payload has to be found to prevent overwhelming the customer. For example, in RTP, a frequent price change every 15 min might discourage the consumer from interacting and also bloat the communication channel between the energy supplier and consumer.

5.3. Accurate Renewable Energy and Storage Systems Integration

Accurate renewable energy and storage systems integration in PAR and cost reduction optimization is another open research issue. As we can see in Figure 9, less than half of the works tackle these issues.

In reality, when the customer integrates intermittent renewables and batteries, the optimization problem changes completely. Instead of being an appliance-shifting problem, the customer schedules their appliances while respecting certain functioning time intervals. They have the possibility to use battery/renewable energy, as a wildcard, to reduce the utility energy peak [36,37,47].

This integration cannot be performed if accurate models for intermittent renewable energy, which take into account their inherent *uncertainty and unpredictability*, are not proposed. In addition to this, there is an increasing need for more datasets [137] that could enable building these models. Finally, throughout our reviewing, we found that encouraging the adoption of integrated energy systems (IESs) is also very important in this context. An IES [138] incorporates renewables, storage and thermal technologies in the grid, unifying all of them with regard to the user.

5.4. Broadening the Scope of PAR Optimization

Throughout our review, we noted a general trend in optimization objectives where PAR and cost are considered in every study. Interest in CO_2 emissions and communications optimization is emerging yet remains marginal (Figure 8). Most studies focus on residential buildings as opposed to commercial and industrial plants. This highly contrasts with the significant proportion of studies originating in emerging countries (Figure 5), with a rapid development of industrial high-energy consumption plants. A fast transformation was emphasized in the COP27 [139] (Sharm-El-Sheikh) as a contributing factor in the climate change acceleration.

We advocate for more research effort in the direction of industrial/commercial buildings energy optimization, as well as taking into account 'secondary' optimization objectives such as communications and gas emissions. Some industries in particular (e.g., aluminium production consumes approximately 70 GJ/tonne) are huge energy consumers. The impact of a small algorithmic improvement can thus greatly reduce electrical consumption. In most of the works [32,61,69,131] that tackle industrial buildings, the following four singularities of the energy consumption make the optimization difficult: (1) HVAC and lighting are not the most energy consuming (as opposed to residential buildings); (2) most processes run at standard speeds with strong inter-dependencies and no possibility of interruption [61]; (3) safety and critical time are often hard constraints; (4) different rates from the residential ones are applied. All these constraints can breed creativity in the design of new PAR and cost optimization algorithms. Finally, some algorithms that successfully manage big commercial buildings could be re-adapted to optimize the consumption of groups of residential buildings (macro-scale), which exhibit some similar macro-consumption patterns.

Regarding CO_2 and communications optimization, we found that they were insufficiently addressed in the surveyed works [37,46,47,74]. Usually, researchers try to maximize user satisfaction (represented by waiting time, comfort and, less often, preference) because of the traditional trade-off with cost. However, in the current climate change context, gas emissions (4.69 metric tons per capita in 2022 [140]) produced by fuel-based power generators, for example, should not be considered as externalities. This goes hand in hand with accurate renewable energy integration (see Section 5.3) because it is low in carbon dioxide emissions. It also poses the problem of precisely quantifying the CO_2 emissions as a function of a used energy source. In general, the electricity emission factor (CO_2/MWh) is used, although it is not always accurate. Finally, communications optimization is very rare in the works that we surveyed. However, its impact is also important in our context, regarding: (1) decision fatigue (especially in the real-time pricing scheme) due to too much information; (2) exposing the network to potential attacks (eavesdropping, jamming, false injection). Some original works [36] propose in their scheme a single-way communication from the control center to the user to preserve confidentiality with minimal overhead.

6. Conclusions

In this paper, we conducted the first (to our knowledge) systematic mapping study on peak-to-average-ratio and cost optimization approaches for demand-side management in the smart grid. Reviewed works cover a *decade*: 1 January 2013 to 31 December 2022. Following a systematic and reproducible methodology, we selected 104 publications defined as "original research" from four different scientific databases, and classified them according to 13 comparison criteria. Then, we analyzed these works according to 5 research questions linked to algorithmic trends, energy source, building type, optimization objectives and pricing schemes. Some main findings are: (i) the predominance of the genetic algorithm (adequate for discrete optimization problems), but with a significant use of various swarm-based metaheuristics; (ii) an insufficient focus on renewable and storage systems because of their inherent unpredictability and uncertainty; (iii) a bias toward residential buildings, although industrial ones are highly energy consuming; (iv) a preference for real-time pricing schemes despite their communications cost.

We identified a set of recommendations for the research community: (1) a hybridization between the strength of evolution-based heuristics in solving discrete scheduling problems and the speed/accuracy of swarm-based heuristics; (2) developing real-time user preference optimization mechanisms to encourage commercial adoption; (3) developing accurate renewable (or storage) models despite their inherent uncertainty/unpredictability; (4) broadening the scope of optimization to industrial buildings and 'secondary' objective minimization (e.g., CO_2 emissions, communications).

In future works, we intend to focus on real-time user preference considerations, as it is a very interesting research area, with multiple challenges. This implies developing fast parameterizable approaches with a trade-off between speed and optimality. This will surely be the subject of a more detailed systematic literature review (SLR) by us. An SLR details a specific area of research and answers questions related to it, while a systematic mapping study structures the current state of the art.

Author Contributions: All authors have participated in the conceptualization, methodology, analysis of results and writing of the article. All authors have read and agreed to the published version of the manuscript.

Funding: This work was financially supported by the National Center of Scientific and Technical Research (CNRST), Morocco.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

i	essential appliances
s	shiftable appliance
r	throttleable appliance
n	consumer
t	time interval [s]
T	total number of time intervals in a day
$\mathrm{e}^{\mathrm{t}}_{\mathrm{n,i}}$	essential energy consumed by user n during time interval t [Wh]
$\mathrm{e}^{\mathrm{t}}_{\mathrm{n,s}}$	shiftable energy consumed by user n during time interval t [Wh]
$\mathrm{e}^{\mathrm{t}}_{\mathrm{n,r}}$	throttleable energy consumed by user n during time interval t [Wh]
$\mathrm{x}_{\mathrm{n,t}}$	total consumed energy by user n during time interval t [Wh]
E_{n}	total daily energy demand of consumer n [Wh]
$\mathrm{b}_{\mathrm{n,0}}$	battery level at the beginning of the day for consumer n [Wh]
B_{n}	battery capacity of user n[Wh]
r_{n}	maximum rates of battery charge/discharge of user n [Wh]
$\mathrm{a}_{\mathrm{n,t}}$	battery charging/discharging schedule for user n during time interval t
$\mathrm{L}_{\mathrm{n,t}}$	load demand to be purchased by user n from the utility during time interval t [Wh]
$\mathcal{O}_{\mathrm{n}}$	operating time slot of consumer n
L_{p}	peak load of the smart grid network [Wh]
L_{a}	average load of the smart grid network [Wh]
C_{t}	cost function

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