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Review

A Review of Energy Management Systems and Organizational Structures of Prosumers

Nemanja Mišljenović [1], Matej Žnidarec [1], Goran Knežević [1,*], Damir Šljivac [1] and Andreas Sumper [2]

1 Department of Power Engineering, Faculty of Electrical Engineering, Computer Science and Information Technology, Josip Juraj Strossmayer University of Osijek, 31000 Osijek, Croatia; nemanja.misljenovic@ferit.hr (N.M.); matej.znidarec@ferit.hr (M.Ž.)
2 Centre d'Innovació Tecnològica en Convertidors Estàtics i Accionaments (CITCEA-UPC), Departament d'Enginyeria Elèctrica, Universitat Politècnica de Catalunya. ETS d'Enginyeria Industrial de Barcelona, Av. Diagonal, 647, Pav. G, 23.25, 08028 Barcelona, Spain; andreas.sumper@upc.edu
* Correspondence: goran.knezevic@ferit.hr

Abstract: This review provides the state of the art of energy management systems (EMS) and organizational structures of prosumers. Integration of renewable energy sources (RES) into the household brings new challenges in optimal operation, power quality, participation in the electricity market and power system stability. A common solution to these challenges is to develop an EMS with different prosumer organizational structures. EMS development is a multidisciplinary process that needs to involve several aspects of observation. This paper provides an overview of the prosumer organizational and control structures, types and elements, prediction methods of input parameters, optimization frameworks, optimization methods, objective functions, constraints and the market environment. Special attention is given to the optimization framework and prediction of input parameters, which represents room for improvement, that mitigate the impact of uncertainties associated with RES-based generation, consumption and market prices on optimal operation.

Keywords: energy management system; prosumer; organizational structure; electricity market; renewable energy sources; prediction method; optimization framework; optimization method; objective function

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1. Introduction

In order to generate increasing volumes of electricity to meet the needs of the economy and improve living standards, a harmful impact on the environment is increasing. International agreements seek to solve the problem, from the 1997 Koyoto Protocol aimed at restricting and reducing greenhouse gases to the 2015 Paris Agreement, which aims to limit global warming to 1.5 °C compared to the pre-industrial level [1,2]. The European Commission follows the international agreement and aims to reduce greenhouse gas emissions by 40% by 2030 compared to 1990, according to [3]. To achieve its aims, the European Commission must work on reducing greenhouse gas emissions across the sectors of electricity generation, industry, office buildings, households and traffic. Moreover, according to [4], the European Commission aims to achieve zero greenhouse gas emissions by 2050. Due to the above, it started to encourage investments in RES and the purchase of electric vehicles (EV) and plug-in hybrid electric vehicles (PHEV) and a set of measures called the "Clean energy package for all Europeans" [5]. Furthermore, several main objectives follow from the package, namely energy efficiency in buildings [6], RES [7], energy efficiency [8], governance regulations [9], regulations and directives on electricity [10,11], risk preparedness, and a stronger role for the European Union Agency for the Cooperation of Energy Regulators (ACER) [12,13].

Research has shown that it is optimal to place distributed generation (DG) as close to consumption as possible [14]. Thus, electricity transmission losses are the lowest. The problem that arises is the voltage level at the point of common coupling with the distribution grid, especially in the case of minimum loads in the grid. Furthermore, in the case when electricity generation is significantly higher than electricity consumption, there is a change in the flow of electricity upwards into the grid, which can cause multiple problems. Hence, the losses increase significantly because power grid elements are significantly loaded. Apart from a voltage rise and an increase in losses, DG affects other power quality parameters such as flickers, asymmetry and harmonic voltage distortion. In addition to the above, protection problems occur as energy changes direction. For a more detailed description, we refer the interested reader to [15].

The generation of electricity from RES depends significantly on natural resources, current solar irradiance and wind speed, and is therefore intermittent over the time horizon. The variability of electricity generation from RES can be predicted with certain accuracy, and hence new forecasting methods for the prediction of electricity generation from RES are constantly developing [16]. By integrating RES, every passive electricity customer becomes an active customer or prosumer that, in addition to electricity import from the grid, can export electricity to the grid. In order to optimally manage energy, the prosumer must have an EMS. There are several definitions of EMS in the scientific literature, and some of them are shown in this paper. An EMS can be defined as a superior system that coordinates and plans the operation of all DGs and elements within the prosumer and ensures optimal and reliable operation at minimal cost [17]. On the other hand, according to IEC 61970, an EMS is defined as: "a computer system that provides basic support services and a set of applications required for the efficient operation of electricity generation and transmission plants to ensure the security of supply at a minimum cost". The limitation of this definition refers only to the transmission system and the economic objective. EMS development is a multidisciplinary process which involves several aspects of observation that need to be considered. In order to find the optimal solution to the optimization problem in the shortest possible time, which is robust or resilient to the uncertainties associated with RES generation and consumption, new methods and approaches are constantly being researched and developed [18,19].

A common solution to solving these problems is the development of a system for optimal energy management and organizational structures of the prosumer in the distribution grid. This review paper mainly studies EMS at the prosumer level, and it can be concluded that it is impossible to maintain stable and efficient electricity grid operation without an EMS owned by prosumers and without interaction with the distribution system operator (DSO). Furthermore, the organizational structure of prosumers is also an essential factor for optimal power grid operation. The organizational structure can be divided according to the placement of prosumers in microgrid or prosumer communities, which is also analyzed in this review paper. In addition, managing RES using an aggregator [20–22] and a virtual power plant [23] approach can also be found in the scientific literature. Therefore, this review paper will give an overview of scientific papers providing a complete overview of EMS with several aspects of prosumers in different organizational structures. Aspects observed in this review paper are the control structure, an EMS (which contains types and elements, prediction of input parameters, optimization frameworks, optimization methods, objective functions and constraints) and the market environment of the prosumer. These aspects are important to observe and necessary to obtain an optimal solution.

In order to achieve the above objectives, it is necessary to ensure an EMS for prosumers and additionally to increase their flexibility. Increasing the flexibility of prosumers is necessary because RES are uncontrollable electricity sources. Consequently, integrating additional elements such as energy storage systems (ESS) and EV into one controllable unit and ensuring demand-side management (DSM) provide a high prosumer flexibility. Combined with ESS, EV and DSM, an EMS enables energy storage when energy is available, and controls devices based on price signals to minimize cost and/or avoid congestion (depending on the primary objective function). The importance of flexibility is presented additionally in the section dealing with energy storage technologies. To solve the multidisciplinary problem of EMS development, an increase in the number of scientific papers tackling this topic is observed in the scientific community. Therefore, as shown in Figure 1, three different directions from the aspect of the development of operational flexibility are observed in:

- EMS based on ESS [24–31];
- EMS based on DSM that integrates the most common demand response programs (DRP) [32–35];
- hybrid EMS that take into account both (mentioned above) [36–40].

Going deeper into EMS analysis, a different number and types of optimization objectives are observed in the scientific literature. Therefore, EMS can most frequently be divided into:

- an EMS with one objective [41–44];
- an EMS with multiple objectives [24,34,45,46].

Furthermore, when observing the types of EMS, the most common objectives are to minimize the cost of electricity and to maximize earnings in the energy market [25,30], while an additional objective is to minimize greenhouse gases emissions into the atmosphere [24,46,47]. In addition, the optimization methods used for EMS modeling are as follows:

- Classical mathematical programming methods [30,48,49];
- Methods based on an intelligent solution space search (metaheuristic methods) [24,35,50–52];
- Rule-based methods (RBA) [27,30];
- Multi-agent systems (MAS) [38,42,53–55];
- Artificial intelligence (AI) [56–58];
- Other approaches [59];
- Hybrid methods (a combination of several methods).

Based on a thorough review of the scientific literature, it can be seen that authors mostly use mathematical methods, while other approaches have been receiving increasing attention lately.

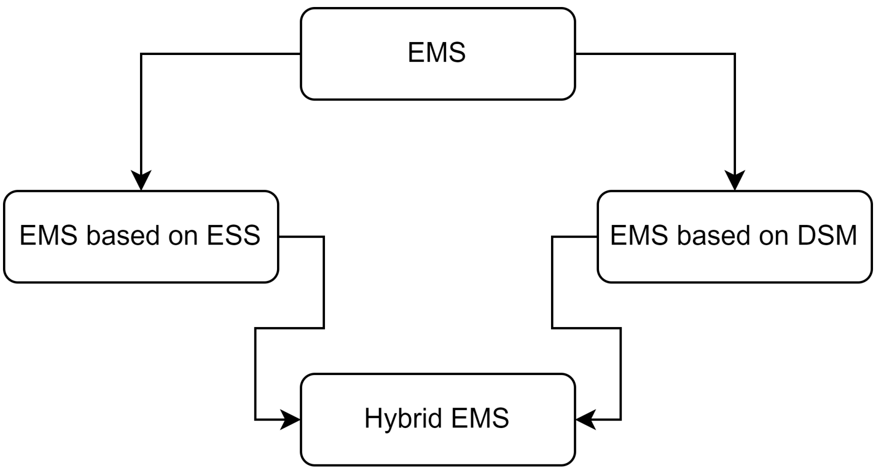

Figure 1. Classification of EMS in the scientific literature.

An overview of energy management in power distribution systems is presented in [60]. Classifications in terms of objective functions, energy management approaches and optimization approaches have been developed, and the constraints, challenges and future work have been presented [60]. Furthermore, ref. [60] notes that energy management, as well as a literature review, is related to microgrids, while the prosumer (as a smaller unit) is neglected. Moreover, the authors do not provide an overview of optimization frameworks or show the importance of predicting input data for an optimization model. Furthermore, as parts of the optimization framework, the time step and the scheduling horizon of optimization play an important role in the robustness of the optimization model output results. In [60], the authors mention very briefly the market environment and performance of the electricity market. The market environment is particularly important because in addition to various market mechanisms, it significantly affects the scheduling of prosumer flexibility in operation. In [61], the authors provide an overview of the home EMS and present the importance of integrating ESS and RES into the home EMS. Furthermore, an overview of residential DRP and household energy management methods is given, but optimization frameworks are neglected. Ref. [62] gives an overview of prosumer energy management and energy sharing in smart grids. The authors show the importance of prosumer energy management, as energy management is based on the objective function, energy sharing and the creation of a prosumer community. Moreover, the authors give an overview of optimization methods, but it is noted that the selected papers mostly do not contain RES integrated into an EMS. Optimization frameworks are also neglected that contain time steps which are very important for the optimality of the optimization model results. In [19], the authors give a detailed overview of the optimization methods applied to solving the microgrid EMS problem. In this review, the authors also pay less attention to the review of optimization frameworks. In [63], the authors give a classification of microgrids and a detailed division of microgrid EMS divided by the authors into classical methods of EMS, EMS based on a metaheuristic approach, EMS based on a genetic algorithm, EMS approach based on AI, and EMS based on other approaches. It can also be noticed that the divisions with regard to the optimization frameworks are neglected in the paper [63]. Furthermore, the authors focused predominantly on city-level microgrids, while building-level microgrids were neglected [63]. Therefore, our work is based more on building-level microgrids.

An optimization framework plays an important role since it directly affects the robustness of the obtained optimization results because they depend on the temporal resolution (the optimization time step) and uncertainty (predictions) of the input data such as electricity consumption, electricity generation and the electricity price. The accuracy of input data prediction is directly related to the accuracy of the results obtained from the optimization model. From the summary of the review papers, it can be concluded that previous review papers lack analysis of the optimization frameworks used, input data prediction methods and participation in electricity markets.

This review paper contributes to a detailed overview of scientific papers in the field of EMS for prosumers. In addition, this review paper gives an overview of integrated electricity sources, electricity loads, and ESS used by the authors in their works. All this is necessary for the development of a complete EMS model for the prosumer. Furthermore, based on the observed gaps in the review papers, additional special attention will be given to the following:

- Optimization frameworks;
- Methods for predicting electricity generation;
- Methods for predicting electricity consumption;
- Participation in the electricity market.

The rest of the paper is organized as follows: Section 2 shows the prosumer control structure. Section 3 shows the prosumer EMS. The market environment of the prosumer is shown in Section 4. The conclusion is given in Section 5.

2. Methodology

This review paper aims to provide the state of the art of the prosumer EMS, as well as tackle the issues of the direction of future research and where there is room for improvement. Although there are review papers on the topic of the prosumer EMS, this paper fills the gap concerning optimization frameworks. In addition, prediction methods and participation in electricity markets are analyzed in detail.

It can be seen from the above that the scope of this work is an effort made to study all aspects necessary for developing and making an accurate prosumer optimization model that aims to minimize costs or maximize earnings by participating in the electricity market. Therefore, the study of this paper will provide readers (especially those becoming familiar with the area) with a clear view of the current state of EMS for prosumers.

In order to be able to deal with the topic in detail and provide the state of the art of prosumer EMS, this research analyzed recent scientific works that deal with the aforementioned topic. However, the authors focused on searching scientific databases with some limiting factors:

- scientific papers published in the last five years were taken into account, with the exception of highly cited papers with a larger scope published more than five years ago that were also taken into account;
- papers dealing with the development of EMS systems for prosumers and microgrids were taken into account;
- papers dealing with the development of EMS based on ESS, DSM, hybrid EMS and EV were considered;
- review papers on the topics of prosumer EMS, microgrid EMS, input data prediction in optimization problems and the electricity market were taken into account, but also published in the last five years, with the exception of highly cited papers;
- fundamental books of high quality with the topic of RES integration and their impact on the grid were considered;
- other aspects, such as security and communication technologies, were not taken into account.

Research keywords used for searching the scientific literature in the observed area are as follows: prosumer EMS, microgrid EMS, electricity market, demand response programs, electric vehicle, predicting data, prosumer control structure, microgrid control structure, and their combinations.

The presented research concept determined the structure of this review paper as follows:

- a quality and comprehensive overview of the research topic, analysis of review papers published so far, as well as identification of room for improvement and the gap planned to be filled by the current research are presented in the introductory part;
- a detailed overview of the prosumer control structure, EMS with a detailed examination of each aspect and the market environment are presented as a result of the conducted research;
- recommendations, the conclusion and room for improvement are based on a detailed review of scientific papers.

Figure 2 shows a review structure of this study that includes all sections and subsections.

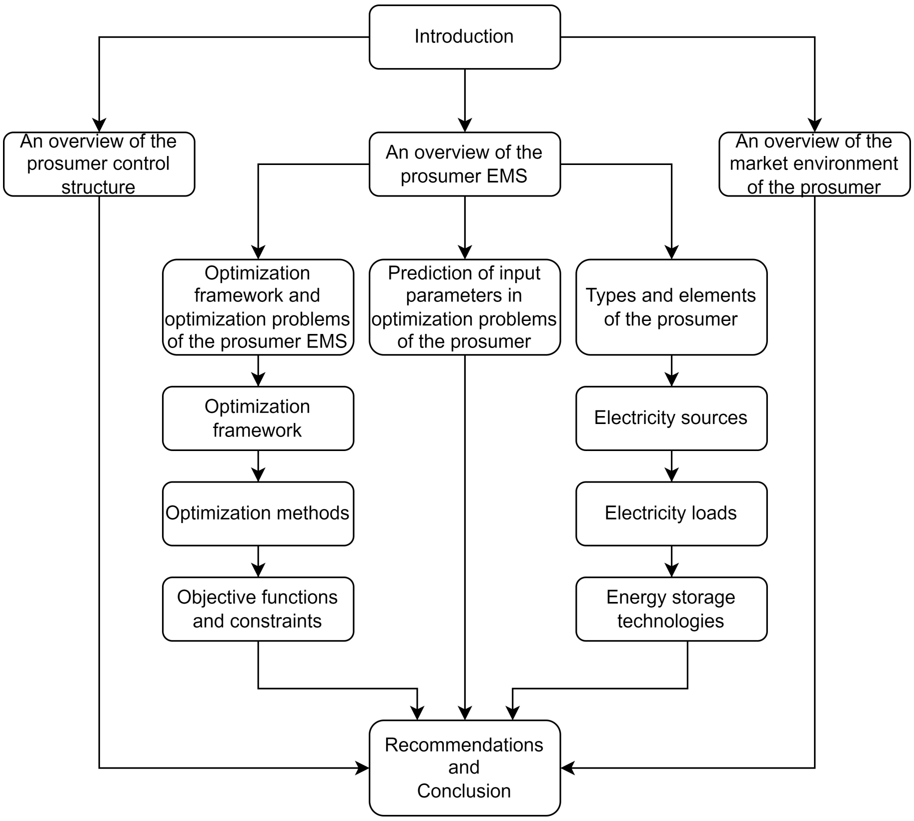

Figure 2. A review structure of the paper includes all section and subsections.

3. An Overview of the Prosumer Control Structure

A review of the scientific literature reveals prosumer control structures that can be roughly divided into centralized and decentralized. Furthermore, by optimally integrating RES into the distribution grid, RES can be integrated as part of a prosumer community or a microgrid.

In the case of prosumers (as a smaller unit), by reviewing scientific papers [58,59,64–74], it can be concluded that a centralized control structure is the most commonly used control structure in the literature. Based on this, each prosumer has an EMS (one central controller) for optimal resource allocation. Additionally, a prosumer EMS allows prosumers to trade within the prosumer community by offering a community offer based on more or less electricity [55,64,65,75–78].

A microgrid can be a controllable unit in relation to the rest of the power system. Accordingly, it must be equipped with an appropriate EMS. There is a problem with the standardization of solutions in the mass exploitation of microgrids, especially in the standardization of their energy management. A microgrid EMS is classified in the scientific literature into two main groups according to a degree of responsibility of each microgrid (element) controller, centralized or decentralized control. Furthermore, as there is no general concept of the architecture of a microgrid EMS due to differences in construction size, types and existing infrastructure, the concept of a microgrid EMS with a hierarchical organization is often encountered in the scientific literature. According to [79], the hierarchical organization represents a local and a central controller and communication system on the following three levels:

- Primary regulation is realized using a fast local controller in control of only one element of the microgrid, be it DG, a controllable load or several aggregated elements;
- Secondary regulation is usually realized using the central controller in control of coordination and supervision of all local controllers;
- Tertiary regulation serves as an intermediary between the central microgrid controller and external agents such as aggregators, grid operators, or electricity market operators.

The evolution in the standardization of the microgrid EMS is evident in the IEEE 2030.7-2017 standard for microgrid controllers, which defines a new microgrid management framework on three levels [80]:

- Lower control functions—regulation of voltage, frequency, active and reactive power at the level of local controllers of each controllable element of the microgrid;
- Essential control functions—operation between on-grid and off-grid mode and vice versa, and energy management;
- Upward control functions—realization of communication with the system operator, market operator, and aggregator, and integration into external information and communication systems.

Primary controllers are realized as one unit (lower control functions), while secondary controllers (essential control functions) and tertiary controllers (upward control functions) are usually realized within an EMS.

In a centralized microgrid EMS, secondary and tertiary regulations are responsible for optimal planning and management of the plant regardless of the operational strategy (economic, environmental, technical, or a combination). In a decentralized system, management capability is distributed to local controllers that are empowered to make their own decisions [79]. A decentralized microgrid EMS is most often implemented using multi-agent systems (MAS).

4. An Overview of a Prosumer EMS

This section provides a detailed overview of a prosumer EMS. An EMS is extremely important because it ensures optimal resource utilization. A review of the scientific literature in the field of optimal energy management at the distribution grid level shows a division in terms of grouping prosumers. According to the literature review, all electricity customers with integrated RES can be grouped into prosumers communities or microgrids. It should be noted that the whole microgrid can be viewed as one prosumer, especially if it is connected to the main grid at a point of common coupling (PCC). According to the reviewed literature, a generalized EMS scheme can be derived as shown in Figure 3.

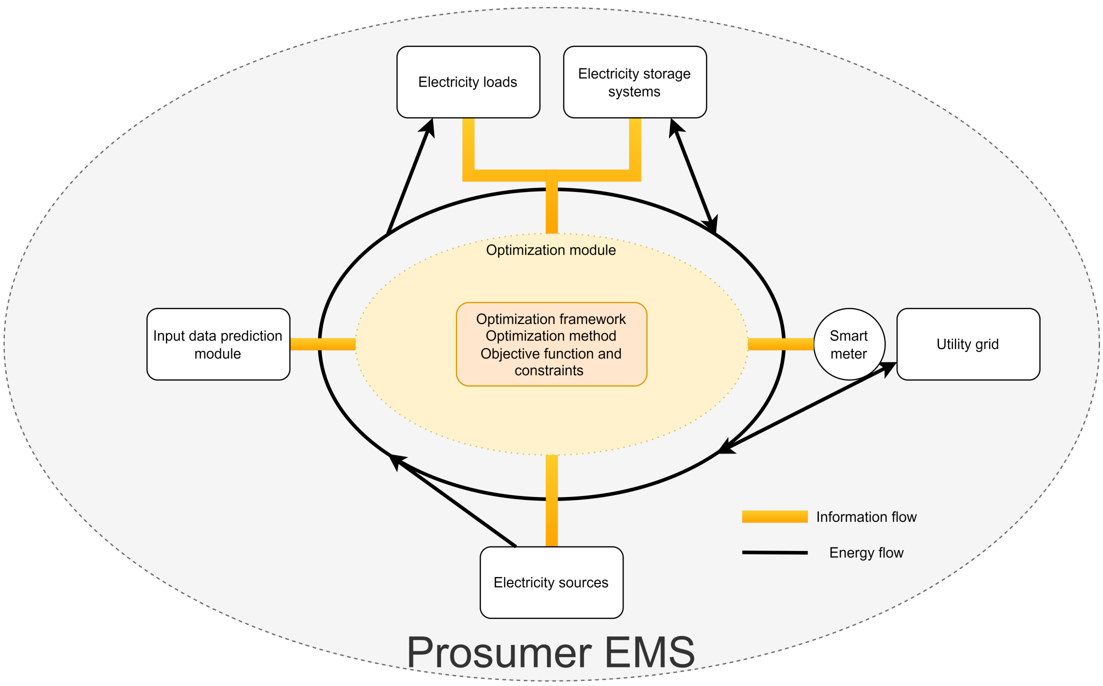

Figure 3. Overview of the prosumer EMS.

In the case of the prosumer community, each prosumer must ensure optimal energy management to maintain distribution grid stability, optimize resource utilization, and ensure savings.

According to [18], the concept of an intelligent home (IH) is a technology that serves prosumers. In addition, according to [18], innovative technologies also raise the level of user comfort by providing security and optimal electricity consumption for a specific future period. Users can control and monitor smart devices using an intelligent home EMS in households (IHEMS). Such system also enables remote control through telecommunication technologies [18]. According to [18], there are many definitions of IH. One of them reads: "The IH concept is the integration of different services within a home by using a common communication system. It assures an economical, secure and comfortable home operation and includes a high degree of intelligent functionality and flexibility". Furthermore, according to [18], each IH should be equipped with an IHEMS that contains hardware, software and a smart meter (SM). The idea is that through an SM, power suppliers can send signals for the current price of electricity to the household, which can be forwarded by the SM to the energy management controller (EMC) (an EMS is a subsystem of the IHEMS). At the same time, the user status can be returned to the power supplier. The EMC is the main part of the IHEMS that is connected via a sensor and actuators with smart devices (SD) in the household and via mobile applications with users [18]. According to [18], the power scheduling problem in an intelligent home (PSPIH) is defined as the allocation, subject to constraints, of resources to objects being placed in space-time in such a way as to minimize the total cost of some set of the resources used. The PSPIH should be implemented with several constraints that can be divided into two basic types:

- hard constraints—must be satisfied in the solution;
- soft constraints—satisfaction in the solution is not essential but desirable.

The PSPIH is an optimization problem whose primary objective is to plan the operation of household appliances to achieve optimal savings, the peak-to-average ratio for energy and customer satisfaction [18]. Most frequently, a short-term energy management schedule is developed for the next 24 h in the future [55,58,67–74]. As mentioned above, the IHEMS contains hardware with the necessary software, communication and connection with SD and often with RES (for optimal energy management of SD and RES). The most common integrated RES are PV and WT, which are most frequently combined with ESS, such as batteries [61]. It is important to note that the PSPIH can be applied to different profiles of prosumers, not necessarily households. According to [61], applications of different solution methods (techniques) to the IHEMS problem can be divided into:

- a rule-based algorithm—used for shifting loads to periods of low prices and reducing peak load;
- artificial intelligence—used for finding optimum maintenance of heat, consumption energy, renewable energy use, turning devices on and off, reducing total energy costs using an artificial neural network (ANN), fuzzy logic control (FL) and an adaptive neuro-fuzzy inference system (ANFIS);
- optimization methods (techniques)—the objective function is the minimization of errors, cost, optimal design and management using classical mathematical and heuristic optimization methods (techniques).

Furthermore, according to [81], biologically inspired algorithms (often called metaheuristic methods) can be divided into:

- evolutionary computing (EC);
- swarm intelligence (SI).

On the other hand, an EMS also ensures optimal planning and management of the microgrid (as already mentioned, a microgrid can be seen as a type of prosumer). An EMS is considered to be any computer system responsible for implementing an operational strategy that generates optimal decisions for each controllable unit within the system to which it is superior and can be applied to the microgrid. The microgrid EMS is most commonly used for short-term planning and management of a microgrid plant with a scheduling horizon of 24 h to several days. Additionally, examples for long-term planning and management of the microgrid plant can be found in the scientific literature, usually on an annual basis [45,82–84]. Such studies are mainly used for optimal planning of the configuration and size of microgrid components.

In [19], the authors generally divide EMS into four basic subsystems:

- human machine interface (HMI) of the operator for monitoring and entering input settings;
- supervisory control and data acquisition (SCADA);
- a module for predicting input data required for optimization based on current and historical measurement data;
- the optimization module responsible for optimal operations by generating decisions for the observed scheduling horizon.

The main parts of the prosumer EMS are the optimization module and the prediction module for input data shown in Figure 3. EMS modeling is a multidisciplinary problem with many features due to the diversification of possible prosumer design and operation aspects. In order to cover all aspects of the EMS at the same time, a review of the scientific literature was observed from the following aspects:

- The type of the prosumer and the elements the prosumer integrates;
- The market environment in which the prosumer is integrated;
- Methods for predicting input parameters in optimization problems;
- Optimization frameworks and optimization problems of the prosumer EMS.

The prosumer as a concept can be realized in many different topologies and elements, which gives them an advantage. Different prosumer topologies modeled in the literature can be found in the examples of DC (DC prosumer), AC (AC prosumer) and hybrid (AC/DC prosumer) prosumers. Due to the more significant existing infrastructure, the most commonly used type in the literature is AC (AC prosumers). However, each type has its advantages.

One of the main features and advantages of the microgrid as a prosumer is island mode operation, which enables the power supply to local consumers in the event of power supply interruption or a failure in the main electricity grid. Furthermore, although island mode of the microgrid is essential, there are a large number of EMS in the scientific literature that do not model the possibility of island mode operation [26,30,32,37,47,52,85–115].

The optimization module under the EMS must contain models of all prosumer elements together with aspects of prosumer operation. Diversified examples of prosumers with various controlled and uncontrolled elements are found in the scientific literature, such as:

- electricity sources:
  - controllable sources (CS),
  - uncontrollable sources (RES);
- electricity loads:
  - controllable loads (CL),
  - uncontrollable (critical) loads (UL);
- energy storage systems:
  - electrochemical systems (secondary batteries),
  - chemical systems,
  - electrical systems.

4.1. Types and Elements of the Prosumer

4.1.1. Electricity Sources

Electricity power sources can be roughly divided into controllable and uncontrollable sources, as shown in Figure 4. Controllable electricity sources enable the regulation of power output, which usually depends on the primary energy source (fuel) used by the electricity source. Furthermore, controllable electricity sources are often used as additional (backup) power supply systems essential for island mode operation of the microgrid. The following controllable electricity source technologies are most often modeled in the literature:

- generators with an internal combustion engine (usually diesel or petrol) (GWICE) [37,46,96,101,105,111,115–122];
- microturbine (MT) [24,39,46,47,85,92,96,97,103,106–110,112,115,117,119,122–125];
- cogeneration power plants for simultaneous production of electricity and heat (CP) [25,88,92,96,97,100,110,116,123,125–127].

Although different technologies are involved, mathematical models of such elements mainly have the properties of the optimization problem of unit commitment and economic dispatching with the following constraints:

- the minimum/maximum output power of the aggregator (electricity power source);
- the rate of change of the output power or ramp up/down;
- the minimum electricity generation time and the minimum interruption time of electricity generation or the minimum up/down time;
- electricity generation (working time) costs are most often divided into fuel and start-up costs.

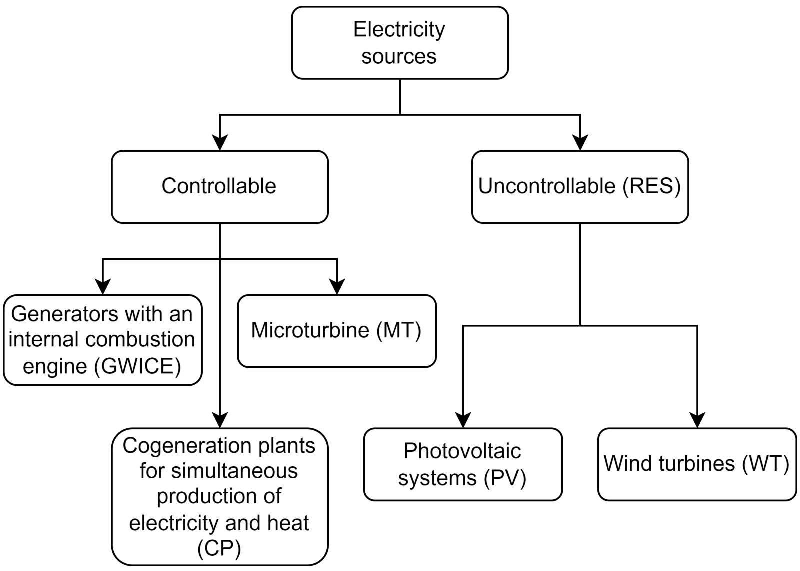

Figure 4. Overview and division of electricity sources

The constraints engaged in the mathematical model depend on the generator type and the installed power of the generator. With a small-size generator, which can be integrated into the microgrid, some constraints can be ignored.

Uncontrollable electricity sources most often involve renewable energy technologies where the power output depends on the availability of primary energy sources (wind speed and solar irradiance). The term uncontrolled refers to the inability to change the output power throughout the range as needed. Photovoltaic systems (PV) and wind turbines (WT) are most commonly used in the scientific literature [26,27,30,32,49,52,55,58,66–74,86,87,89–91,93–95,98,99,114,128,129]. Table 1 shows an overview of the scientific papers with respect to the electricity sources used by the authors in their papers.

4.1.2. Electricity Loads

An unavoidable feature of the prosumer is consumption management. Electricity loads come in a variety of installed power and consumption profiles. A division into controllable and uncontrollable (critical) electricity loads is most frequently used in the scientific literature, as shown in Figure 5.

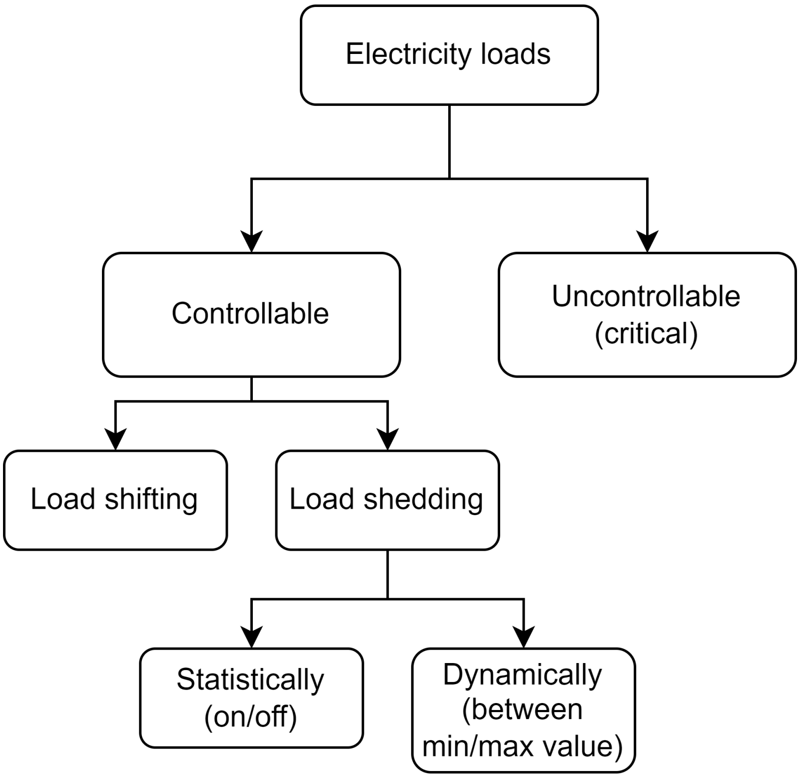

Figure 5. Overview and division of electricity loads.

Controllable electricity loads are mostly not modelled in the EMS. However, various examples are found in the scientific literature that modelled a set of controllable electricity loads (aggregate of loads) or each individually controllable electricity load. In Table 1, a set of controllable electricity loads is indicated by the abbreviation (Aggr). Depending on the modeling method, two effects are achieved when managing the consumption of a set of controllable electricity loads: load shifting and/or load shedding. When modeling controllable electricity loads, the authors believe that the prosumer participates in DRP. In this way, the same effect on the electricity consumption profile of the prosumer is achieved, but with some financial compensation [24,37,39,46,86,96,100,101,105,117–119,121–124,126]. In separate modeling, controllable electricity loads are most often a time-shiftable (Tshift) device that can move its consumption cycle to another time interval [32,96,102,104,107,108,111,112]. Furthermore, examples of statically (on-off) and dynamically (consumption regulation between the minimum and maximum value) controllable electricity loads can be found in the scientific literature, and they are used only in the case of emergency. In Table 1, statically (on-off) and dynamically controllable electricity loads are indicated by the abbreviation (SAD). These electricity loads do not consume the needed energy in their consumption cycle [102,104,108,125,128]. A detailed overview of DRP can be found in the prosumer market environment section.

It is important to note here that EV have great potential for use in DRP because they stand out from other electricity loads due to their high charging power and long charging time. An overview of methods for charging (and discharging) EV connected to the power grid is given in [130] to ensure controlled charging (and discharging) of EV and reduce the impact on the power grid. An optimization algorithm for EV charging based on real-time measurement is presented in [59]. Based on the measurements, peak load avoidance and savings of 60% are achieved compared to uncontrolled EV charging. Optimization models of controlled EV charging (CCEV) in the prosumer environment are presented in [58,66–68,70–73], and these also represent the current direction of the research community and room for improvement.

Uncontrollable electricity loads represent a set of multiple electricity loads (aggregate electricity loads) that require power at every moment of prosumer scheduling and operation. Therefore, the consumption of uncontrollable electricity loads cannot be managed regardless of whether the microgrid in on-grid or off-grid (island) mode.

Table 1 shows an overview of the scientific papers with respect to the electricity loads used by the authors in their papers.

Table 1. Review of the scientific literature with respect to types, elements and modeling of the power electronics converter of prosumers.

Ref.	CS	RES	EV/PHEV	CL	ESS	BPEC	CCCEL	CCADE and LCADP
[85]	MT	PV	No	-	ECS	No	-	Yes
[86]	-	PV	Yes	Aggr	CHS	-	-	-
[26]	-	PV	No	-	ECS	No	-	Yes
[32]	-	PV, WT	No	Tshift	ECS	No	-	Yes
[37]	GWICE	PV, WT	No	Aggr	ECS	No	-	Yes
[52]	-	PV	No	-	ECS	No	-	Yes
[87]	-	PV	No	-	ECS	No	-	Yes
[88]	CP	-	No	-	TS	-	-	-
[89]	-	PV, WT	No	-	ECS	No	-	Yes
[90]	-	PV, WT	No	-	ECS	No	-	Yes
[91]	-	PV	No	-	ECS	-	Yes	Yes
[92]	MT, CP	PV	No	-	ECS	No	-	Yes
[30]	-	PV	No	-	ECS	-	Yes	Yes
[93]	-	PV, WT	No	-	ECS	-	Yes	Yes
[47]	MT	PV	No	-	ECS	No	-	Yes
[94]	-	WT	No	-	ECS	No	-	Yes
[95]	-	PV, WT	No	-	ECS	No	-	Yes
[96]	GWICE, MT, CP	PV, WT	No	Aggr, Tshift	ECS, CHS	-	-	-
[97]	MT, CP	PV	No	-	ECS	No	-	Yes
[98]	-	PV	No	-	ECS	No	-	Yes
[99]	-	PV	No	-	ECS	-	Yes	Yes
[100]	CP	PV	No	Aggr	ECS	No	-	Yes
[101]	GWICE	PV, WT	Yes	Aggr	ECS	No	-	Yes
[102]	-	-	No	Tshift, SAD	ECS	No	-	Yes
[103]	MT	PV, WT	No	-	ECS	No	-	Yes
[104]	-	-	Yes	Tshift, SAD	ECS	No	-	Yes
[105]	GWICE	PV	No	Aggr	ECS	-	-	-
[106]	MT	PV	No	-	ECS	-	-	-
[107]	MT	PV, WT	No	Tshift	ECS	No	-	Yes
[108]	MT	PV, WT	No	Tshift, SAD	ECS	No	-	Yes
[109]	MT	PV, WT	No	-	ECS	No	-	Yes
[110]	MT,CP	PV, WT	No	-	ECS, CHS	No	-	Yes
[111]	GWICE	PV, WT	No	Tshift	ECS	No	-	Yes
[112]	MT	WT	No	Tshift	ECS	No	-	Yes
[113]	-	-	Yes	-	ECS	No	-	Yes
[114]	-	PV, WT	No	-	ECS	No	-	Yes
[115]	GWICE, MT	PV, WT	No	-	ECS, CHS	No	-	Yes
[116]	GWICE, CP	PV, WT	No	-	ECS	-	-	-
[46]	GWICE, MT	PV	No	Aggr	ECS	No	-	Yes
[117]	GWICE, MT	PV, WT	No	Aggr	ECS	No	-	Yes
[118]	GWICE	PV, WT	No	Aggr	ECS	No	-	Yes
[119]	GWICE, MT	PV, WT	No	Aggr	ECS	No	-	Yes
[120]	GWICE	PV, WT	No	-	ECS	No	-	Yes
[121]	GWICE	PV	No	Aggr	ECS	No	-	Yes
[122]	GWICE, MT	PV, WT	No	Aggr	ECS	No	-	Yes
[24]	MT	PV, WT	No	Aggr	ECS	No	-	Yes
[123]	MT, CP	PV, WT	Yes	Aggr	CHS	No	-	Yes
[124]	MT	-	No	Aggr	-	-	-	-
[39]	MT	PV, WT	No	Aggr	ECS	No	-	Yes
[125]	MT, CP	PV, WT	No	SAD	ECS	No	-	Yes
[25]	CP	PV, WT	No	-	ECS	No	-	Yes
[126]	CP	PV	No	Aggr	ECS	No	-	Yes
[127]	CP	-	No	-	TS	No	-	Yes
[128]	-	PV, WT	No	SAD	ECS	No	-	No (CC/CV)

Table 1. *Cont.*

Ref.	CS	RES	EV/PHEV	CL	ESS	BPEC	CCCEL	CCADE and LCADP
[27]	-	PV, WT	No	-	ECS	No	-	Yes
[129]	-	PV	No	-	ECS, CHS	No	-	Yes
[49]	-	PV, WT	No	-	ECS	No	-	No (CC/CV)
[58]	-	PV	Yes	CCEV	-	-	-	-
[66]	-	PV	Yes	CCEV	-	-	-	-
[67]	-	PV	Yes	CCEV, Aggr	ECS	No	-	Yes
[68]	-	-	Yes	CCEV	-	-	-	-
[69]	-	PV, WT	Yes	-	ECS	No	-	Yes
[70]	-	PV	Yes	-	ECS	No	-	Yes
[71]	-	PV	Yes	CCEV	-	-	-	-
[72]	-	PV	Yes	CCEV	ECS	No	-	Yes
[73]	-	PV	Yes	-	ECS	No	-	Yes
[74]	-	PV	Yes	CCEV	ECS	No	-	Yes
[55]	-	PV, WT	No	-	ECS	No	-	Yes

4.1.3. Energy Storage Technologies

Flexibility is essential in an advanced power system, and an increasing number of scientific papers have been published on this topic. An advanced power system would collapse without flexibility, and the reason for that is the unpredictability of electricity generation from RES (especially from wind and sun) and unpredictable demand (especially in relation to EV). That is why this area is of great importance to research. Flexibility is necessary to ensure advanced power systems in the case of the prosumer as well. A flexible power system can be achieved in several ways, the most important of which are:

- energy management;
- energy storage.

In comparison with electricity sources and electricity loads, ESS is an element with bi-directional power flows. Two-way power flows allow ESS to act as both a source and a load of electricity, thus ensuring flexibility in operation and balancing between electricity consumption and electricity generation in advanced power systems in the case of the prosumer. In [131], the authors provide an overview of energy storage technologies such as:

- electrical storage (ES)—(i) supercapacitor and (ii) superconducting coil;
- mechanical storage (MS)—(i) pump-accumulation hydropower plant, (ii) compressed air, and (iii) flywheels;
- electrochemical storage (ECS)—(i) secondary batteries and (ii) instantaneous batteries;
- thermochemical storage (TCS)—solar fuel;
- chemical storage (CHS)—fuel cells;
- thermal storage (TS)—(i) low-temperature energy storage and (ii) high-temperature energy tank.

Figure 6 shows a detailed overview and division of energy storage technologies. Mechanical technologies were primarily used in the conventional power system but can be utilized in the advanced power system as well. Other technologies have the potential to be used in the advanced power system, especially stationary battery storage and EV batteries with significant battery capacities and charging and discharging powers, which is possible to conclude from the scientific papers [55,58,64–68,70–74]. ESS optimal sizing and allocation methods are also presented in [131]. Optimal sizing and allocation of ESS are particularly important due to optimal power flows, reduced grid losses and initial investment during building. However, this paper did not observe methods for optimal sizing and allocation.

Electrochemical ESS (secondary batteries) are most commonly used in the microgrid, and more recently, chemical ESS (fuel cells) and electrical ESS (ultracapacitors). The most technologically ready types of electrochemical ESS are lead-acid and lithium-ion batteries. Lead-acid batteries are the most widely used form of energy storage characterized by low cost and ease of recycling, but their disadvantage is the dependence of capacity on the power and depth of discharge, energy density and the use of lead. On the other hand, lithium-ion batteries are the fastest growing battery technology, whose sales doubled between 2013 and 2018. Most of the capacity is installed in EV and consumer devices, and the rest is in stationary battery storage. The main characteristics of lithium-ion batteries are high energy density and high efficiency, high discharge power and a larger number of cycles in the battery life, while they lack safety features due to the high dependence of performance on temperature [132,133]. Table 1 gives an overview of the scientific papers with respect to energy storage technologies and EV or PHEV used by the authors in their papers.

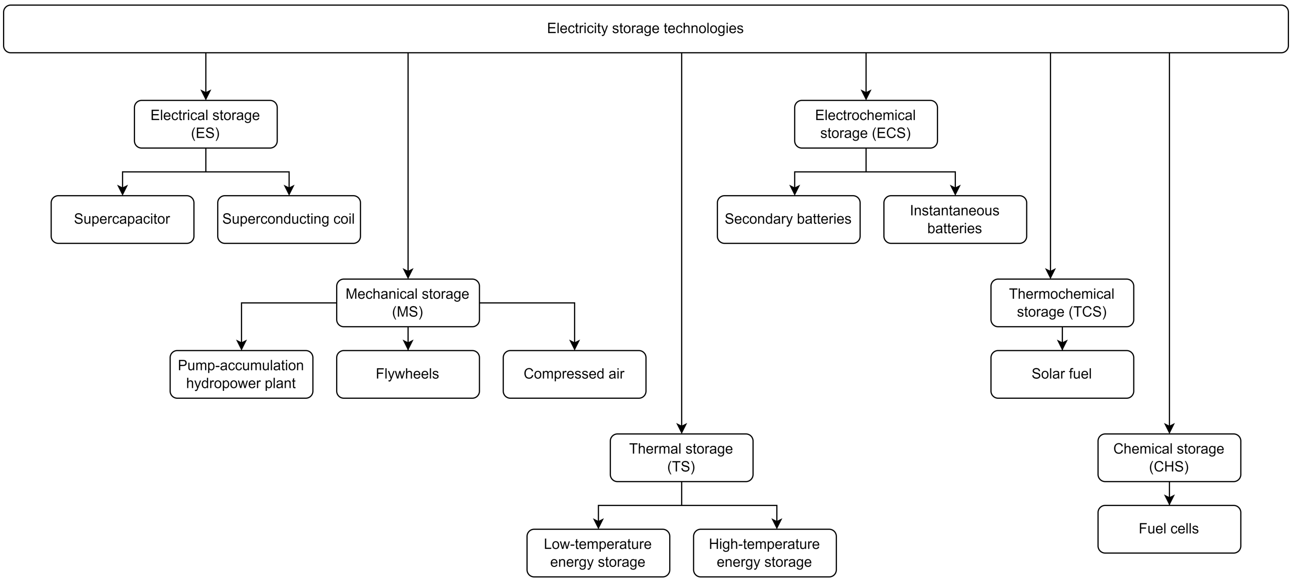

Figure 6. Overview and division of electricity storage technologies.

Technologies of the electrochemical ESS as part of the EMS found in the literature are lead-acid and lithium-ion secondary batteries, which are most frequently used [24–27,30,32,37,39,46,47,49,52,85,87,89–122,125,126,128,129]. Furthermore, examples of electricity management that modeled the fuel cell using stored hydrogen for fuel can be found in the scientific literature [86,96,110,115,123,129]. For more information about new emerging technologies of fuel cells and their performance, we refer the interested reader to [134] and [135], respectively.

A review of the scientific literature on mathematical modeling of a battery ESS shows that simple models are modeled by a large number of simplifications and approximations in which essential features that affect work are neglected. For example, most of the reviewed EMS in the scientific literature neglect modeling of a bidirectional power electronics converter (BPEC) as one of the two basic parts of a battery ESS [24–27,32,37,39,46,47,49,52,85,87,89,90,92,94,95,97,98,100–104,107–115,117–123,125–129]. Examples of research modeling a converter with constant conversion efficiency and constant energy conversion losses are presented in [30,93]. Furthermore, functional dependence of the efficiency on the converter current load as the most accurate interpretation of converter operation is presented in [91,99]. Scientific papers, in which converters with constant conversion efficiency and constant energy conversion losses and functional dependence of the efficiency on the converter current load were considered, are indicated in Table 1 by the abbreviation (CCCEL).

During the review of the scientific literature on the EMS and battery modeling as the second part of the battery ESS, room for improvement was observed. When modeling the battery, researchers model lithium-ion technology with constant charging and discharging efficiency (CCADE) and limit the charging and discharging power to the maximum amount (LCADP) defined by the battery manufacturer [24–27,30,32,37,39,46,47,52,85,87,89–95,97–104,107–115,117–123,125–127,129]. This approach can significantly affect the accuracy of the battery ESS model because it is known that the allowable battery charging power changes during the charging process and depends on various factors, most notably the state of charge of the battery. Furthermore, a review of the scientific literature reveals a small number of examples that limit the charging power of the battery using the constant current/constant voltage (CC/CV) method [49,128]. Table 1 shows an overview of the scientific papers with respect to modeling the power electronics converter and battery charging.

A review of the scientific literature reveals that most papers neglect the power electronics converter when modeling EV battery charging [58,66–74], which is also of particular importance, as already mentioned above, when charging the batteries.

As batteries are electrochemical storage systems, complex degradation processes affected by various stress factors occur during their use. As a result, there is a reduction in performance and operation life, primarily in terms of the ability to charge and discharge and the capacity of the battery. The lifespan of lithium-ion batteries depends on factors that can be divided into operation-dependent and operation-independent [136]. For example, outdoor temperatures, humidity, calendar age and battery health are factors that do not depend on the operation [137]. At the same time, battery cycle depth of discharge, overcharge and over-discharge of the battery, discharge and charge currents, and the average state of charge status are among the factors that depend on battery operation [138]. A review of the scientific literature shows that most EMS do not consider the battery degradation factors, which can affect battery life and the need to reinvest in batteries at high investment costs. However, the authors who consider battery degradation add virtual costs to the objective function, which prevents the frequency of charging and discharging the battery and high discharges of the battery [37,47,93,99,105,114,119,122].

4.2. Prediction of Input Parameters in Prosumer Optimization Problems

Forecasting electricity generation and consumption (especially RES) and electricity prices is important because input parameters directly affect optimization results. One set of input parameters defines one operating point of the optimization problem [139]. The optimization process is performed for a discretized period in the future (a scheduling horizon) which includes a discrete step (an optimization time step) that represents one operating point of the optimization problem. In case the input data for prediction are not satisfactorily predicted, the optimality of the optimization results is questionable because optimization operates based on the value of data expected in the future. It can be concluded from the above that for the optimal result of resource allocation in the future, input data accuracy must be ensured. This reflects one of the EMS characteristics, namely robustness or resilience to uncertainty.

If the electricity consumption and generation (especially from RES) profiles are observed, it can be said that they depend on several often unpredictable parameters. Some of the factors influencing electricity consumption are the characteristics of the consumer whose consumption profile is predicted (households, business sector, industry), the spatial size of the facility whose consumption is observed (distribution area, feeder, neighborhood, street, building, household), user habits (departure/arrival patterns, shifts, working hours), meteorological factors (outdoor temperature, wind speed, air pressure, humidity), the current time of day, type of day (working day, weekend, holiday), and current day in a week, month and year. Meteorological parameters that impact the RES generation profile also depend on many other unpredictable meteorological parameters, which further complicates the forecasting process.

When predicting the profile of electricity consumption and generation from RES plants, two approaches are presented in the scientific literature, i.e. direct and indirect prediction. Direct prediction involves predicting a power consumption or generation profile of the plant, while indirect prediction involves predicting the profile of input physical quantities which power consumption or generation of the plant depends on. Indirect prediction also requires a certain mathematical model that gives the power consumption or generation results. An example of the use of indirect prediction is found in a PV, where solar irradiance and the outside temperature represent mathematical model input data for the numerical calculation of PV output power. Figure 7 shows an overview and division of prediction input parameters in the prosumer optimization problem.

According to [16], electricity generation from solar radiation and speed wind forecasting methods are divided into:

- statistical methods;
- physical methods;
- artificial intelligence methods;
- hybrid methods,

while electricity demand forecasting methods are divided into:

- statistical methods;
- artificial intelligence methods;
- hybrid methods,

where AI and hybrid methods in principle contain the smallest error [16]. Furthermore, according to [140], forecasting methods can be divided into time horizons as:

- very short term (min–h);
- short-term (h–week);
- medium short-term (month–year);
- long-term (over a year).

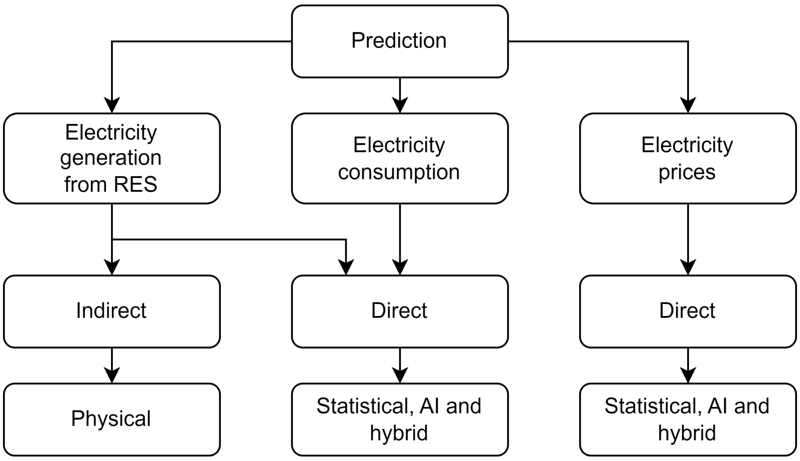

Figure 7. Overview and division of prediction.

In addition, models based on support vector regression (SVR) and ANN proved helpful in rapid change when predicting the generation of a PV power plant [140]. In [141], the authors agree that AI methods have recently dominated the scientific literature.

A large number of methods developed for predicting electricity consumption profiles can be roughly divided into statistical methods and computational intelligence methods, which have dominated lately [142]. Hybrid prediction methods are presented in [143], and these are machine-based learning methods for electricity consumption that the authors claim give the best results and show significant potential for using SVM and ANN. Furthermore, ref. [143] provides an overview of individual electricity consumption predicting methods based on learning, rules, and metaheuristics. In [144], the authors focus on an overview of short-term predicting methods for electricity consumption which they claim are of exceptional importance. Intelligent systems, as the authors call them, are also based on ANN and SVM, with which they achieved the best results.

In addition to predicting electricity generation and consumption, it is essential to predict the price of electricity. In [145], the authors provided a clear overview of statistical methods, deep learning methods and hybrid methods, referring to the accuracy of the methods for day-ahead price prediction in the electricity market. Furthermore, the authors showed the importance of input data when testing prediction methods and developed a toolbox to evaluate new algorithms. Finally, ref. [146] provides an overview of optimization methods in the phase of data set selection and training of ANFIS for the purpose of predicting the price of electricity for the day-ahead electricity market. By applying the optimization method for selecting input data and ANFIS training, significant progress has been achieved in terms of the accuracy of short-term electricity price prediction.

It can be concluded that the choice of a particular method depends on several factors, such as the availability of historical data, the length of the forecasting horizon, the accuracy of meteorological data and the desired level of prediction accuracy. Furthermore, a detailed overview of the scientific papers on the prediction of the electricity consumption profile and the profile of input-output (e.g. solar irradiance-power) quantities for the RES plant is given in this paper. Unfortunately, perfectly accurate predictions have been used in [25,27,32,37,46,47,49,52,55,58,67,68,70–74,86–90,92,94–98,102,103,105–107,110–113,115,117–121,123–126,128,129], which is not present in practice. Therefore, the following approach found in the scientific literature is to manually enter deviations from pre-known (measured) profiles of input quantities to increase the reality of the model that has been used in [26,85,99,101,114,116], thus achieving a certain resilience of the EMS to uncertainties in the optimization problem. Furthermore, examples of probabilistic approaches using probability density functions have been used in [24,39,108,109,122]. Probability density functions are generated based on historical data (measurements), which can be used to generate an arbitrary number of profiles and determine the probability of their occurrence.

The following scientific papers show slightly more complex examples of predicting electricity generation and consumption profiles. In [91], the authors use the k-means clustering method, which is a statistical method that utilizes historical data on power and energy of generation from PV systems and electricity consumption to classify by certain types of days and calculate the probabilities of their occurrence. Furthermore, in [30], the authors use two different prediction methods for different prediction horizons. In the higher layer of the EMS, they use ANFIS as an AI method to predict the electricity consumption profile. They also use perfect predictions based on historical data with manual creation deviations in the higher layer to predict generation from PV. In the lower layer of the EMS, they use the adaptive autoregression algorithm (AARA) as a statistical method for predicting generation from PV and the electricity consumption profile. A similar application is seen in [93], where the same authors apply the same AARA for predicting generation from PV and the electricity consumption profile. In [100], the authors use the least-square support vector machine (LSSVM) method as an AI method for predicting generation from PV, while they do not mention any method for predicting consumption. An example of using another statistical method is available in [104], in which the authors use multiple linear regressions with exogenous explanatory variables (MLRWEEV) with a moving average (MA) model. Furthermore, in [108], the authors use the autoregressive integrated moving average (ARIMA) statistical method to predict generation from PV, WT, and electricity consumption profiles. Furthermore, three short-term predicting methods for the real-time electricity price, PV and WT generation, based on a hybrid combination of the K-medoids algorithm and the Elman neural network, are presented in [69]. Predicting profiles of electricity consumption and electricity generation from PV using statistics-based algorithms and predicting EV usage by combining statistics and clustering techniques are presented in [66]. EV usage prediction is also of particular importance, considering the charging power and battery capacity of EVs in relation to overall welfare. There is also room for improvement here.

Table 2 shows an overview of papers with respect to input data prediction.

Table 2. Review of the scientific literature with respect to the optimization framework, optimization method, optimization approach, objective function and other specificities of the optimization problem.

Ref.	Optimization Framework	Optimization Method	Time Step	Scheduling Horizon	Optimization Objectives	Optimization Approach	Prediction of Input Data
[85]	Online	MIQP	1 h	48 h	Technical	Stochastic	Yes
[86]	Offline	LP	1 h	168 h	Economic	Deterministic	No
[26]	Online	QP	30 min	24 h	Technical, Economic	Deterministic	Yes
[32]	Online	MILP	15 min	24 h	Economic	Deterministic	No
[37]	Offline	WOA	1 h	24 h	Economic	Deterministic	No
[52]	Online	HGAFL	15 min	168 h	Economic	Deterministic	No
[87]	Offline	HGAFL	15 min	168 h	Economic	Deterministic	No
[88]	Online	MILP	1 h	20 h	Economic	Deterministic	No
[89]	Online	QP	1 h	24 h	Economic	Deterministic	No
[90]	Online	QP	1 h	24 h	Economic	Deterministic	No
[91]	Online	MILP	15 min	24 h	Economic	Deterministic	Yes
[92]	Online	LP, NLP	15 min	24 h	Environmental, Economic	Deterministic	No
[30]	Online	MILP, RBA	1 min, 15 min	24 h	Economic	Deterministic	Yes
[93]	Online	MILP	1 min, 15 min	24 h	Economic	Deterministic	Yes
[47]	Offline	HDPLP	1 h	24 h	Economic	Deterministic	No
[94]	Offline	NLP	1h	24 h	Economic	Deterministic	No
[95]	Offline	PSO	1h	96 h	Economic	Deterministic	No
[96]	Offline	MINLP	1 h	24 h	Technical, Economic	Deterministic	No
[97]	Offline	MILP	1 h	24 h	Economic	Robust programming	No
[98]	Online	QP	30 min	24 h	Economic	Deterministic	No
[99]	Offline	DP	10 min	24 h	Economic	Deterministic	Yes
[100]	Online	MILP	15 min	6 h	Economic	Deterministic	Yes
[101]	Online	SDP	5 min	24 h	Technical, Economic	Deterministic	Yes
[102]	Offline	MILP	15 min	24 h	Economic	Deterministic	No
[103]	Offline	MINLP, SDP, TMINLPSP	1 h	24 h	Technical, Economic	Deterministic	No
[104]	Online	MILP	1 h	24 h	Economic	Deterministic	Yes
[105]	-	MILP	1 h	24 h	Economic	Deterministic	No
[106]	-	MILP	15 min	24 h	Economic	Deterministic	No
[107]	Offline	MILP	1 min, 10 min, 1 h	24 h	Economic	Deterministic	No
[108]	Offline	MILP	1 h	24 h	Economic	Stochastic	Yes
[109]	Offline	MILP	1 h	24 h	Economic	Stochastic, Robust programming	Yes
[110]	Offline	SQP	1 h	24 h	Economic	Deterministic	No
[111]	Offline	MILP	1 h	24 h	Economic	Deterministic	No
[112]	Online	MILP, MINLP	1 h	24 h	Economic	Robust programming	No
[113]	Online	MILP	15 min	12 h	Economic	Stochastic	No
[114]	Online	QP, MINLP	1h	96 h, 72 h, 48 h, 24 h, 12 h, 6 h	Technical, Economic	Deterministic	Yes
[115]	Online	MILP	1 h, 5 min	24 h	Technical, Economic	Deterministic	No
[116]	Online	MILP	30 min	24 h	Economic	Deterministic	Yes
[46]	Online	PSO	1 h, 1 min	24 h	Economic, Technical, Environmental	Deterministic	No
[117]	Offline	CMISOCP	1 h	24 h	Technical, Economic	Robust programming	No
[118]	Offline	PSO	15 min	24 h	Economic	Deterministic	No
[119]	Online	MILP, QP	30 min, 5 min	24 h	Economic	Deterministic	No
[120]	Offline	NLP	1 h	24 h	Technical, Economic	Stochastic	No
[121]	Offline	MINLP	1 h	24 h	Economic	Deterministic, Stochastic	No
[122]	Online	MILP, NLP	5 min	24 h	Economic	Deterministic	Yes
[24]	Offline	HGAPO	1 h	24 h	Environmental, Economic	Stochastic	Yes
[123]	Online	MILP	1 h	24 h	Economic	Stochastic	No
[124]	Online	SLP	1 h	24 h	Economic	Deterministic	No
[39]	Offline	MILP	1 h	12 h	Economic	Stochastic	Yes
[125]	Offline	GA	15 min	24 h	Environmental, Economic	Deterministic	No
[25]	Offline	MVPA	1 h	24 h	Economic	Deterministic	No

Table 2. *Cont.*

Ref.	Optimization Framework	Optimization Method	Time Step	Scheduling Horizon	Optimization Objectives	Optimization Approach	Prediction of Input Data
[126]	Offline	MIQP	1 h	24 h	Economic	Deterministic	No
[127]	Offline	MILP	5 min	24 h	Economic	Deterministic	No
[128]	Online	MILP	1 h	24 h	Economic	Deterministic	No
[27]	Offline	RBA	1 h	48 h	Economic	Deterministic	No
[129]	Offline	LP, MILP, PSO	1h	24 h	Economic	Deterministic	No
[49]	Online	MILP	1 h	24 h	Economic	Deterministic	No
[58]	Online	MILP, RNN	15 min	24 h	Economic	Deterministic	No
[66]	Online	MILP	15 min, 1 min	168 h	Tehnical	Deterministic	Yes
[67]	Offline	MILP, RBA	15 min	24 h	Economic	Deterministic	No
[68]	Offline	MINLP, GRA	1 h	24 h	Economic	Deterministic	No
[69]	Offline	MILP	15 min	24 h	Economic	Deterministic	Yes
[70]	Offline	NLP	-	24 h	Economic	Deterministic	No
[71]	Offline	MILP	1h	24 h	Economic	Deterministic	No
[72]	Offline	-	1 min	24 h	Economic	Deterministic	No
[73]	Offline	DP	1 h	24 h	Economic	Deterministic	No
[74]	Offline	MILP	1 h	24 h	Economic	Deterministic	No
[55]	Offline	MAS	30 min	24 h	Economic	Deterministic	No

4.3. Optimization Framework and Optimization Problems of the Prosumer EMS

A review of the scientific literature revealed the existence of a wide range of views during modeling. Some views are emphasized, while others are ignored or taken into account to a lesser extent through approximations. The complexity of EMS modeling is the reason for diverse solutions found in the scientific literature. In order to make a comprehensive overview of the areas of optimization frameworks and properties of optimization problems used in the EMS, different points of view will be taken into consideration:

- optimization framework;
- optimization method;
- objective function and constraints.

Figure 8 shows a detailed overview and division of optimization frameworks, optimization methods and objective functions and constraints of optimization problems used in the scientific literature. What follows is a detailed overview of the scientific papers in the field of optimization frameworks and properties of optimization problems used in prosumer EMS.

The optimization model of mixed integer linear programming (MILP) for energy management of prosumer households to minimize the cost and three short-term predicting methods for the real-time electricity price, PV and WT, are presented in [69]. Predictions are based on one of the ANN types and the selection of input data. The authors considered DRP, controlled and uncontrolled loads. The results show that in the case of the prosumer, optimal distribution of resources is mostly affected by RES generation. Furthermore, a smart home EMS containing PV, a battery as electricity storage, EV and different loads related to DRP is presented in [67]. The optimization problem was solved by using MILP to minimize household costs and ensure user comfort, and the algorithm for charging and discharging the battery and extending battery life. Furthermore, an optimization model for EV charging in a residential community with prosumers is presented in [72]. The objective function is to minimize the costs for the required electricity applied to the entire community. In this way, it was achieved that excess electricity generated is stored in batteries, and EV are charged in the evening according to user habits. Moreover, the proposed online model utilizing a recurrent neural network (RNN) to control EV charging and discharging in office buildings is presented in [58]. The results show that by applying the RNN it is possible to determine the optimal solution in milliseconds and significantly reduce the impact of prediction and calculation time compared to the application of MILP optimization. Furthermore, an optimization model for an electric vehicle battery charging and discharging based on predicting electricity consumption and generation using algorithms based on statistics and predicting EV usage by a combination of statistics and clustering techniques is presented in [66]. The objective function is to minimize the exchange of electricity with the grid by applying MILP formulation and a real-time control algorithm.

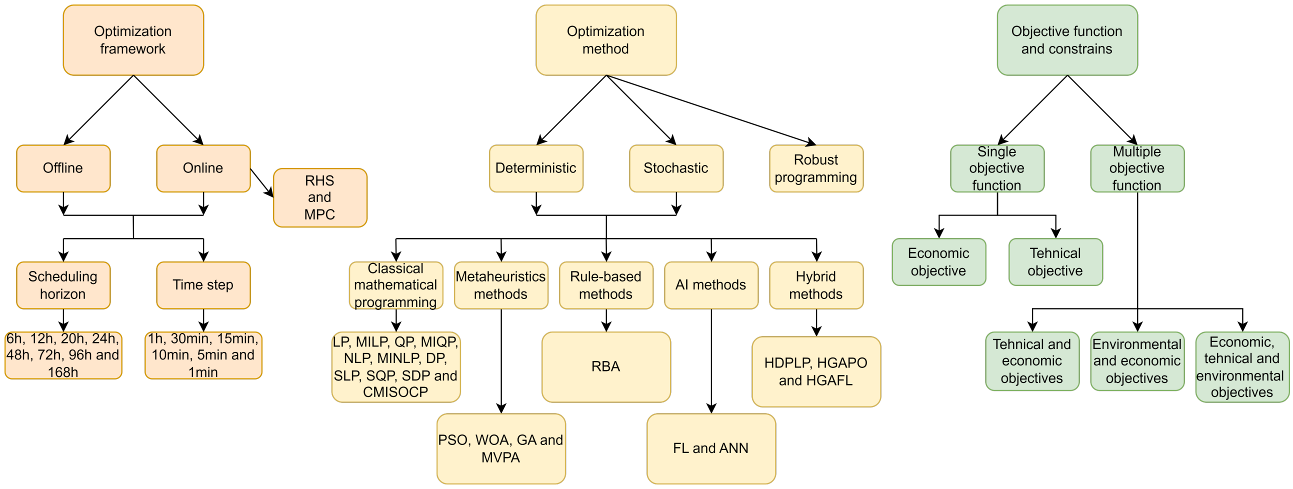

Figure 8. Overview of optimization frameworks, optimization methods, objective functions and constrains of optimization problems.

An optimization model aimed at minimizing the cost of electricity using EV in different locations is presented in [70]. The results show that if EV is used as electricity storage, this is achieved without any influence on the satisfaction and demand for electricity of the user. Furthermore, a low-complexity model of scheduling EV charging and discharging in shared parking is presented in [68]. The objective function is to maximize the profit of all EV users by applying mixed integer nonlinear programming (MINLP), after which the algorithm determines the optimal charging and discharging power for each interval and each EV. A comparison of the usage potential of stationary battery storage and EV battery storage of the prosumer is presented in [73]. More significant savings can be achieved by using an electric vehicle battery in combination with a dynamically programmable algorithm to minimize electricity costs and dependence on the tariff system. An optimization model for EV charging and discharging to minimize the costs of a prosumer who owns a PV is presented in [71]. Significant savings were achieved by applying two-level charging and discharging power compared to one-level charging and discharging power of an EV battery. The optimization model of the prosumer for profit maximization by participating in the energy market is presented in [147]. Ref. [147] also shows the possibility of manipulation of the energy market by the prosumer.

What follows is a detailed overview of the scientific literature with respect to optimization frameworks, optimization methods, objective functions and constraints.

4.3.1. Optimization Framework

Optimization frameworks can be divided into online and offline, Figure 8. Most EMS use an offline optimization approach in which the optimization process is performed only once, i.e. before the beginning of the observed scheduling horizon [24,25,27,37,39,47,55,67–74,86,87,94–97,99,102,103,107–111,117,118,120,121,125–127,129]. Online optimization involves performing the optimization process at every time step or whenever new predicted input data are available. Online optimization achieves greater resilience (adaptability) of the EMS to uncertainty. One of the most commonly used strategies in the scientific literature that implements online optimization is the rolling horizon strategy (RHS), a technique often used in model predictive control (MPC) to minimize the impact of uncertain parameters [26,30,32,46,49,52,85,88–93,98,100,101,104,112–116,119,122–124,128]. MPC is used for discrete control, which means that the amounts of control quantities do not change during the one-time step. Furthermore, examples of papers where the results are corrected to a certain extent with the real-time EMS can be found in the scientific literature in [58,66]. In addition, one more example of rescheduling the optimization result is given in [64]. According to [64], the optimization result obtained on the data from the day-ahead electricity market can be corrected by the data from the intraday electricity market.

As shown in Figure 8, the scientific literature mainly contains the prosumer EMS that has a scheduling horizon length of:

- 24 h (one day) [24–26,30,32,37,46,47,49,55,58,67–74,89–94,96–99,101–112,114–129];
- 6 h [100,114];
- 12 h [39,113,114];
- 20 h [88];
- 48 h [27,85,114];
- 72 h [114];
- 96 h [95,114];
- 168 h (one week) [52,66,86,87].

When analyzing the time steps of prosumer EMS optimization, hourly values are most frequently used in the scientific literature [24,25,27,37,39,46,47,49,68,71,73,74,85,86,88–90,94–97,103–105,107–112,114,115,117,120,121,123,124,126,128,129], which are related to the wholesale energy markets in which hourly values are mostly used for bids to buy or sell. The downside of a one-hour time step can result in not being able to see changes that occur within that time step. Therefore, examples can be found in the scientific literature with 30-min [26,55,98,116,119], 15-min [30,32,52,58,66,67,69,87,91–93,100,102,106,113,118,125], 10-min [99,107], 5-min [101,115,119,122,127] and 1-min [30,46,66,72,93,107] time steps, thus increasing resistance to change, Figure 8.

Table 2 shows a detailed overview of the scientific papers with respect to the optimization framework, the time step and the scheduling horizon.

4.3.2. Optimization Methods

As shown in Figure 8, a review of the scientific literature identifies two primary groups of optimization approaches used in the design of optimization problems, deterministic and stochastic. In the deterministic approach, it is considered that all input parameters into the optimization problem are known with a certain accuracy [25–27,30,32,37,46,47,49,52,55,58,66–74,86–96,98–107,110,111,114–116,118,119,121,122,124–129]. While a stochastic approach includes the property of probability, a stochastic programming approach is most frequently used in the scientific literature to model such optimization problems [24,39,85,108,109,113,120,121,123]. The choice of approach primarily depends on the methods used to predict input parameters of optimization problems. Stochastic approaches use probability density functions that generate an arbitrary number of possible scenarios based on historical data, which are then used in optimization problems. In addition to stochastic programming, examples of robust programming can be found in [97,109,112,117] that also introduce the property of probability into an optimization problem using probability density functions of certain input parameters but have certain features of deterministic optimization approaches.

If optimization methods are observed, a wide range of methods appear in the scientific literature, which can be roughly classified into:

- classical mathematical programming methods;
- methods based on intelligent search of solution space (global optimum approximation methods, metaheuristics);
- rule-based methods;
- multi-agent systems;
- artificial intelligence methods;
- hybrid methods.

The most common methods in the scientific literature are classical mathematical programming methods. Classical mathematical programming belongs to a more extensive set of mathematical optimization methods and is defined as a numerical solution to the problem of minimizing or maximizing a function [139]. The objective function and constraints must have some form for mathematical programming methods to be applied.

The following optimization methods can be found in the scientific literature in relation to classical mathematical modeling of optimization problems:

- linear programming (LP) [86,92,129];
- mixed-integer linear programming (MILP) [30,32,39,49,58,66,67,69,71,74,88,91,93,97, 100,102,104–109,111–113,115,116,119,122,123,127–129];
- quadratic programming (QP) [26,89,90,98,114,119];
- mixed-integer quadratic programming (MIQP) [85,126];
- nonlinear programming (NLP) [70,92,94,120,122];
- mixed-integer nonlinear programming (MINLP) [68,96,103,112,114,121];
- dynamic programming (DP) [73,99];
- sequential linear programming (SLP) [124];
- sequential quadratic programming (SQP) [110];
- semidefinite programming (SDP) [101,103];
- convex mixed-integer second-order cone programming (CMISOCP) [117];
- hybrid methods of using dynamic programming and linear programming (HDPLP) [47];
- transformation of mixed-integer nonlinear programming in semidefinite programming (TMINLPSP) [103];
- other approaches [72].

Examples of methods based on intelligent search of solution space, often called metaheuristic methods (methods of approaching the global optimum), can be found in the scientific literature. These methods are often inspired by phenomena or behaviors in nature. These methods do not require knowledge of the objective function properties but only knowledge of the numerical value of the function, which enables modeling of more realistic optimization problems with fewer approximations. Intelligent space search based methods used in the scientific literature are as follows:

- particle swarm optimization (PSO) [46,95,118,129];
- whale optimization algorithm (WOA) [37];
- genetic algorithm (GA) [125];
- most valuable player algorithm (MVPA) [25];
- hybrid algorithm (combining the genetic algorithm and particle optimization) (HGAPO) [24];
- hybrid algorithm (the genetic algorithm and fuzzy logic) (HGAFL) [52,87];
- greedy algorithm (GRA) [68].

In addition to optimization algorithms, there are rule-based EMS (RBA) in the scientific literature, where the optimization procedure is not used, but decisions are made based on strictly defined conditions or rules [27,30,67]. Furthermore, decentralized EMS are most often implemented using MAS (especially considering the decentralized EMS of the prosumer community and the microgrid) [55]. With metaheuristic methods and RBA, the optimality of optimization results is questionable compared to the methods of classical mathematical programming because these methods are based on obtaining a global solution approach. Currently, more and more researchers are using AI methods [58] or hybrid methods (a combination of several optimization methods) to solve optimization problems [52,87]. Moreover, it has been shown that the use of AI methods can contribute to achieving high accuracy of results in a short time needed to solve the optimization problem [58]. However, with AI methods, it is also possible in some cases to achieve a questionable optimal optimization result compared to classical mathematical methods because it can happen that the system does not know the answer to a new, unexpected condition. As can be concluded from the above, hybrid methods consist of several different optimization methods aimed at achieving greater accuracy of output results and minimizing the time for solving the optimization problem.

Table 2 and Figure 8 show a detailed overview of the scientific papers with respect to optimization approaches and optimization methods.

4.3.3. Objective Functions and Constraints

A review of the scientific literature and a detailed analysis of the prosumer EMS reveals different numbers and types of optimization objectives, Figure 8. Most often it reveals papers with a single objective function [25–27,30,32,37,39,47,49,52,55,58,66–74,85–95,97–124,126–129], while examples with multiple objective functions can be found less frequently [24,46,96,125].

With regard to the optimization objectives to be achieved [148], the following division can be made:

- economic objective [25,27,30,32,37,39,47,49,52,55,58,67–74,86–91,93–95,97–100,102,104–113,116,118,119,121–124,126–129];
- technical objective [66,85];
- a combination of technical and economic objective [26,96,101,103,114,115,117,120];
- a combination of environmental and economic objective [24,92,125];
- a combination of all three objectives, i.e. economic, technical and environmental [46].

Table 2 and Figure 8 show different numbers and types of optimization objectives.

The constraints in the optimization problems depend on the modeled elements and operating aspects, and the form of the constraints depends primarily on the optimization method used. If elements of a prosumer are considered, the most common constraints are physical constraints of the elements. However, in addition to physical constraints, in the case of mathematical programming methods, it is also necessary to define the power balance of the prosumer as a constraint.

5. An Overview of the Prosumer Market Environment

Considering increasing RES integration, much attention is paid to the market aspect. The market aspect observes prosumer profit maximization and/or cost minimization in the electricity market and the ancillary services market. By studying the scientific literature, several mechanisms were observed in terms of the participation of prosumers in the electricity market, such as day-ahead and intraday markets, a (local) flexibility market, multilevel tariffs, Peer to Peer (P2P) (P2P—combined with some new distributive technologies such as Blockchain), and additional participation in DRP.

Electricity billing schemes, either in the direction of energy imported from the grid or energy exported to the grid, are primarily defined per unit of exchanged electricity. Therefore, this profit or cost is regularly included in the objective function of the optimization problem. In the scientific literature, authors observe multi-tariff electricity billing systems, especially for prosumers, as DRP. DRP are defined as measures taken by system operators/aggregators in response to a lack of energy to supply customers in the near future. The aim of these measures is to influence electricity consumption of end-users through different types of programs [149]. From the point of view of the system operator, prosumers have an advantage over classic end-users with controllable loads due to their flexibility in operation which can be activated by controlled loads, controlled sources and ESS. Most research integrates the microgrid into the retail market as an end-user using time-of-use (TOU) or dynamic pricing, also known as RTP. This electricity billing system is an example of a price based on DRP. In multi-tariff systems, most microgrid EMS modeled dual-tariff systems [47,49,92,94,109,114,119,128,129], and examples with a fixed price over time (one tariff) [99,126], three-tariff [97,113,122,126], four-tariff [30,52,93] and seven-tariff systems [89,90] can also be found. Examples of microgrid EMS with dynamic prices where the price changes more often than in multi-tariff systems can be found in [25,27,86,87,95,96,110,114,118,126]. Prices are modeled to reflect the current demand for electricity in the electric power system. In times of high demand, prices are high and vice versa. In the case of the microgrid EMS that uses multi-tariff systems, the same price is applied regardless of the direction of energy exchange (import from the grid or export to the grid). It is important to note that in practice there are generally two different prices, one price for the purchase of electricity and the other price for the sale of electricity to the grid. Examples that take different prices when importing and exporting electricity from and to the grid are available in [37,46,88,91,99,114], which is also applicable to prosumers who have an integrated system for electricity generation from RES connected behind the meter. Furthermore, it is important to note that in practice the retail market is usually encouraged to use one's own (i.e. prosumer's) generated electricity because the price of energy imported from the grid is higher than the price of energy exported to the grid. An example of a detailed cost system of exchanged energy (a microgrid with the power grid) is available in [104] and [71], where several tariff items define the price.

Moreover, as explained in [18], motivation schemes encourage prosumers to reduce electricity consumption during peak loads by shifting consumption to low load periods and distributing electricity consumption over a time horizon. Motivation schemes have been developed based on DRP, and following this, researchers have been interested in and focused on developing DRP [18]. According to [150,151], DRP ensures optimal management (scheduling) of prosumer devices while ensuring user comfort and lowering overall costs, and the aforementioned results in increased savings for the prosumer and benefits for DSO as well. DRP achieve savings by moving the consumption to the interval of lower electricity prices or turning on and off devices, ensuring a reduction in the peak power consumption in the prosumer power grid, and it can additionally be combined with a plant for electricity generation. According to [61], in Europe and the United States, DRP have been widely implemented in order to achieve the above objectives. The classification of DRP according to the United States Department of Energy is shown in Figure 9 [150,151].

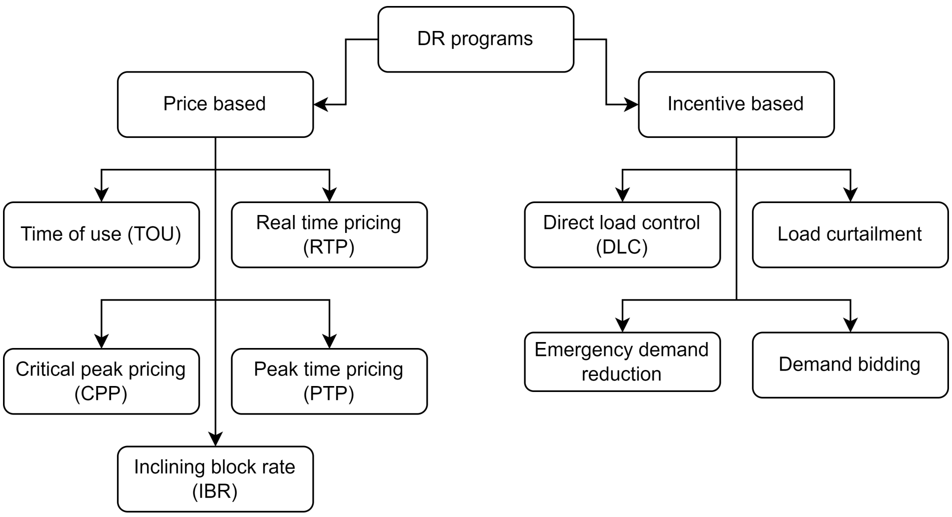

Figure 9. Overview and division of demand response programs.

In the research community, some EMS authors integrate the microgrid into the wholesale market, more precisely into the day-ahead market, where electricity prices for the next day are taken before optimizing the plant for the future period [24,26,39,102,105–107,109,111,115,120,121,123], and microgrids are considered as price takers. In addition to the day-ahead market, some EMS also use intraday market prices in the case of deviations from the planned operation due to uncertainties in relation to various aspects such as future electricity consumption or generation contributing to the optimization problem [100,108,112,116,124].

The application of this market environment largely depends on the legislation that defines the minimum installed power (the microgrid size) required to participate in these forms of the electricity market.

It can be concluded from the above that participation in the wholesale electricity market has been extensively researched and works well in practice. The trend of future research can be concluded from the papers [55,64,65,75,77,78,152], where the solution to the problem of participation of prosumers in the local electricity market within the prosumer community is solved by using P2P services. Furthermore, it is necessary to apply distributed technologies in addition to the P2P service that ensures the recording and secure execution of the transaction, which is presented in [55,76]. A framework for providing flexibility at the local level that allows participants to compete voluntarily in the provision of ancillary services through aggregators is presented in [153]. There is also an increase in the number of scientific papers aimed at integrating the ancillary services market to increase earnings and provide ancillary services to the system [154,155]. Contributions to the provision of ancillary services are, on the one hand, a delay in upgrading the electricity grid, lower costs and an increase in the distribution grid capacity, and on the other hand, a benefit to prosumers, DSO and balance responsible parties (BRP) at the same time [153].

A detailed analysis of the markets in Europe, North America and Australia with respect to barriers and the potential for RES integration is presented in [156]. The authors agree that in the future the analysis should include 5-min bids, co-optimization of electricity and balance services, the intraday market as a rescheduling of day-ahead market operation, a higher degree of deregulation and better adaptation to various market participants. Ref. [157] presents room for improvement and challenges of the EU electricity market and electricity grid with an increase in the share of electricity from RES. In terms of rapid implementation and a supplement to the electricity grid and the electricity market, the authors recommend the application of AI and Blockchain technology.

Furthermore, in [158], the authors agree that the energy transition in the European Union countries is in progress, and that formal and legal regulations define its scope, while its effectiveness is defined by the position of decision makers legitimized by public support for a certain type of challenge. Finally, the authors note that this research is an important complementary element dedicated to RES market development analysis in Poland and the Baltic countries related to individual RES dimensions [158]. The research results show that an increase in social awareness determines the popularization of RES in individuals [158].

It can be concluded that all aforementioned prosumer market participation methods require an EMS.

6. Recommendations for Future Work

Based on the contribution of this review paper, there is room for improvement in several aspects.

- Optimization problems lack detailed models of EVs that encompass different types of energy management during the charging/discharging process and predict their usage patterns.
- EVs, PV systems and ESS are almost always interfaced with power converters that are regularly left out in optimization models.
- For detailed battery models, it is necessary to consider the amount of charging and discharging power, which is not equal in the entire range but depends on various factors and, most notably, on the state of charge of the battery.
- Input data such as RES generation, load, and market prices into optimization models rarely use exact prediction methods.
- Participation of prosumers in new market mechanisms, especially the local market environments, and detailed modeling of DRP must be further developed and improved.
- Optimization frameworks play a very important role in alleviating the uncertainty associated with RES generation, load and market prices that influence the optimality of the solution. High volatility of RES generation and loads demands higher temporal resolution of the optimization time step, especially when participating in emerging electricity markets.

The recommendations for the authors refer to the development of more detailed optimization models considering room for improvement given above. Such optimization models would give highly accurate results and be resilient to uncertainties.

7. Conclusions

A large number of scientific papers have been observed in the scientific community to solve optimal management of prosumer electricity. The problems that arise when integrating RES into the household premises, the importance of increasing power system flexibility and ensuring optimal energy management are explained in this paper. In order to present the current state of development of the prosumer EMS, it is necessary to look at several aspects that make up an EMS. This paper provides an overview of the current scientific literature with regard to different organizational and control structures of prosumers, types and elements of prosumers, prediction of input data, optimization frameworks, optimization methods, objective functions and their constraints, and the market environment. On the other hand, this research did not cover other aspects, such as security and communication technologies. Furthermore, the overview of review papers has shown that these studies did not analyze optimization frameworks and input data prediction, which is becoming increasingly important in the future. The significance of optimization frameworks comes from the influence of RES generation and consumption, which also results in the adjustment of electricity market participation with higher temporal resolution as DRP and resilience to uncertainties. Because of that, this paper provides a detailed review of scientific papers with respect to optimization frameworks used by the authors. In addition, the review of scientific papers focused on the development of each part of the EMS and the part that the authors mostly neglect. The review process results show that the authors develop simpler optimization models without taking into account functional dependencies of individual parameters which they replace with constant values. In this paper, gaps and room for improvement are described in detail in each section giving clear guidelines for future work.

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References

1. Kyoto Protocol. Available online: https://unfccc.int/kyoto_protocol (accessed on 5 September 2022).
2. Paris Agreement. Available online: https://unfccc.int/process-andmeetings/the-paris-agreement/the-paris-agreement (accessed on 5 September 2022).
3. Climate Action—2030 Climate & Energy Framework. Available online: https://www.consilium.europa.eu/en/policies/climate-change/2030-climate-and-energy-framework (accessed on 5 September 2022).
4. 2050 Energy Strategy. Available online: https://ec.europa.eu/clima/policies/strategies/2050_en (accessed on 6 September 2022).
5. Clean Energy for All Europeans Package. Available online: https://ec.europa.eu/energy/topics/energy-strategy/cleanenergy-all-europeansen (accessed on 6 September 2022).

6. Energy Performance of Buildings Directive. Available online: https://ec.europa.eu/energy/topics/energy-efficiency/energy-efficient-buildings/energy-performance-buildingsdirectiveen (accessed on 7 September 2022).
7. Renewable Energy Directive. Available online: https://ec.europa.eu/energy/topics/renewableenergy/renewable-energy-directive/overviewen (accessed on 7 September 2022).
8. Energy Efficiency Directive. Available online: https://ec.europa.eu/energy/topics/energyefficiency/targets-directive-and-rules/energy-efficiencydirectiveen (accessed on 7 September 2022).
9. Governance of the Energy Union. Available online: https://ec.europa.eu/info/energyclimate-change-environment/implementation-eucountries/energy-and-climate-governance-andreporting/national-energy-and-climate-plans_en (accessed on 7 September 2022).
10. Electricity Regulation. Available online: https://energy.ec.europa.eu/topics/marketsand-consumers/market-legislation/electricity-marketdesign_en (accessed on 8 September 2022).
11. Electricity Directive. Available online: https://eur-lex.europa.eu/legalcontent/EN/TXT/?uri=uriserv:OJ.L_.2019.158.01.0125.01.ENG&toc=OJ:L:2019:158:TOC (accessed on 8 September 2022).
12. Risk Preparedness. Available online: https://energy.ec.europa.eu/topics/energy-security/security-electricity-supply_en (accessed on 8 September 2022).
13. ACER. Available online: https://european-union.europa.eu/institutions-law-budget/institutions-and-bodies/institutions-and-bodies-profiles/agency-cooperation-energy-regulators-acer_en (accessed on 8 September 2022).
14. Žnidarec, M.; Šljivac, D.; Topić, D. Influence of Distributed Generation from Renewable Energy Sources on Distribution Network Hosting Capacity. In Proceedings of the 2017 6th International Youth Conference on Energy (IYCE), Budapest, Hungary, 21–24 June 2017. [CrossRef]
15. Bollen, M.H.J.; Hassan, F. *Integration of Distributed Generation in the Power System*; John Wiley & Sons: Hoboken, NJ, USA, 2011; pp. 1–528. [CrossRef]
16. Rafique, S.F.; Jianhua, Z. Energy management system, generation and demand predictors: A review. *IET Gener. Transmiss. Distrib.* **2018**, *12*, 519–530. [CrossRef]
17. Katiraei, F.; Iravani, R.; Hatziargyriou, N.; Dimeas, A. Microgrids management. *IEEE Power Energy Mag.* **2008**, *6*, 54–65. [CrossRef]
18. Makhadmeh, S.N.; Khader, A.T.; Al-Betar, M.A.; Naim, S.; Abasi, A.K.; Alyasseri, Z.A.A. Optimization methods for power scheduling problems in smart home: Survey. *Renew. Sustain. Energy Rev.* **2019**, *115*, 109362. [CrossRef]
19. Zia, M.F.; Elbouchikhi, E.; Benbouzid, M. Microgrids energy management systems: A critical review on methods, solutions, and prospects. *Appl. Energy* **2018**, *222*, 1033–1055. [CrossRef]
20. Iria, J.; Soares, F. Real-time provision of multiple electricity market products by an aggregator of prosumers. *Appl. Energy* **2019**, *255*, 113792. [CrossRef]
21. Iria, J.; Soares, F.; Matos, M. Optimal bidding strategy for an aggregator of prosumers in energy and secondary reserve markets. *Appl. Energy* **2019**, *238*, 1361–1372. [CrossRef]
22. Yazdani-Damavandi, M.; Neyestani, N.; Shafie-khah, M.; Contreras, J.; Catalao, J.P.S. Strategic Behavior of Multi-Energy Players in Electricity Markets as Aggregators of Demand Side Resources Using a Bi-Level Approach. *IEEE Trans. Power Syst.* **2017**, *33*, 397–411. [CrossRef]
23. Knežević, G.; Maligec, M.; Golub, V.; Topić, D. The optimal utilization of the battery storage for a virtual prosumer participating on a day-ahead market. In Proceedings of the 2020 International Conference on Smart Systems and Technologies (SST), Osijek, Croatia, 14–16 October 2020. [CrossRef]
24. Sedighizadeh, M.; Esmaili, M.; Jamshidi, A.; Ghaderi, M.H. Stochastic multi-objective economic environmental energy and reserve scheduling of microgrids considering battery energy storage system. *Int. J. Electr. Power Energy Syst.* **2019**, *106*, 1–16. [CrossRef]
25. Ramli, M.A.; Bouchekara, H.; Alghamdi, A.S. Efficient Energy Management in a Microgrid with Intermittent Renewable Energy and Storage Sources. *Sustainability* **2019**, *11*, 3839. [CrossRef]
26. Ratnam, E.L.; Weller, S.R. Receding horizon optimization-based approaches to managing supply voltages and power flows in a distribution grid with battery storage co-located with solar PV. *Appl. Energy* **2018**, *210*, 1017–1026. [CrossRef]
27. Nayak, C.K.; Kasturi, K.; Nayak, M.R. Economical management of microgrid for optimal participation in electricity market. *J. Energy Storage* **2019**, *21*, 657–664. [CrossRef]
28. Boussetta, M.; Motahhir, S.; Bachtiri, R.E.; Allouhi, A.; Khanfara, M.; Chaibi, Y. Design and Embedded Implementation of a Power Management Controller for Wind-PV-Diesel Microgrid System. *Int. J. Photoenergy* **2019**, *2019*, 1–16. [CrossRef]
29. García Vera, Y.E.; Dufo-López, R.; Bernal-Agustín, J.L. Energy Management in Microgrids with Renewable Energy Sources: A Literature Review. *Appl. Sci.* **2019**, *9*, 3854. [CrossRef]
30. Elkazaz, M.; Sumner, M.; Thomas, D. Real-Time Energy Management for a Small Scale PV-Battery Microgrid: Modeling, Design, and Experimental Verification. *Energies* **2019**, *12*, 2712. [CrossRef]
31. Shayeghi, H.; Shahryari, E.; Moradzadeh, M.; Siano, P. A Survey on Microgrid Energy Management Considering Flexible Energy Sources. *Energies* **2019**, *12*, 2156. [CrossRef]
32. Silvente, J.; Kopanos, G.M.; Pistikopoulos, E.N.; Espuña, A. A rolling horizon optimization framework for the simultaneous energy supply and demand planning in microgrids. *Appl. Energy* **2015**, *155*, 485–501. [CrossRef]

33. Shahryari, E.; Shayeghi, H.; Mohammadi-ivatloo, B.; Moradzadeh, M. An improved incentive-based demand response program in day-ahead and intra-day electricity markets. *Energy* **2018**, *155*, 205–214. [CrossRef]
34. Aghajani, G.; Shayanfar, H.; Shayeghi, H. Presenting a multi-objective generation scheduling model for pricing demand response rate in micro-grid energy management. *Energy Convers. Manag.* **2015**, *106*, 308–321. [CrossRef]
35. Rabiee, A.; Sadeghi, M.; Aghaeic, J.; Heidari, A. Optimal operation of microgrids through simultaneous scheduling of electrical vehicles and responsive loads considering wind and PV units uncertainties. *Renew. Sustain. Energy Rev.* **2016**, *57*, 721–739. [CrossRef]
36. Alharbi, W.; Raahemifar, K. Probabilistic coordination of microgrid energy resources operation considering uncertainties. *Electr. Power Syst. Res.* **2015**, *128*, 1–10. [CrossRef]
37. Mohammadjafari, M.; Ebrahimi, R.; Darabad, V.P. Optimal Energy Management of a Microgrid Incorporating a Novel Efficient Demand Response and Battery Storage System. *J. Electr. Eng. Technol* **2020**, *15*, 571–590. [CrossRef]
38. Zhao, B.; Xue, M.; Zhang, X.; Wang, C.; Zhao, J. An MAS based energy management system for a stand-alone microgrid at high altitude. *Appl. Energy* **2015**, *143*, 251–261. [CrossRef]
39. Talari, S.; Yazdaninejad, M.; Haghifam, M.R. Stochastic-based scheduling of the microgrid operation including wind turbines, photovoltaic cells, energy storages and responsive loads. *IET Gener. Transm. Distrib* **2015**, *9*, 1498–1509. [CrossRef]
40. Pourmousavi, S.A.; Nehrir, M.H.; Sharma, R.K. Multi-Timescale Power Management for Islanded Microgrids Including Storage and Demand Response. *IEEE Trans. Smart Grid* **2015**, *6*, 1185–1195. [CrossRef]
41. Sfikas, E.; Katsigiannis, Y.; Georgilakis, P. Simultaneous capacity optimization of distributed generation and storage in medium voltage microgrids. *Int. J. Electr. Power Energy Syst.* **2015**, *67*, 101–113. [CrossRef]
42. Karavas, C.S.; Kyriakarakos, G.; Arvanitis, K.G.; Papadakis, G. A multi-agent decentralized energy management system based on distributed intelligence for the design and control of autonomous polygeneration microgrids. *Energy Convers. Manag.* **2015**, *103*, 166–179. [CrossRef]
43. Alavi, S.A.; Ahmadian, A.; Aliakbar-Golkar, M. Optimal probabilistic energy management in a typical micro-grid based-on robust optimization and point estimate method. *Energy Convers. Manag.* **2015**, *95*, 314–325. [CrossRef]
44. Marzband, M.; Ghadimi, M.; Sumper, A.; Domínguez-García, J.L. Experimental validation of a realtime energy management system using multi-period gravitational search algorithm for microgrids in islanded mode. *Appl. Energy* **2014**, *128*, 164–174. [CrossRef]
45. Azaza, M.; Wallin, F. Multi objective particle swarm optimization of hybrid micro-grid system: A case study in Sweden. *Energy* **2017**, *123*, 108–118. [CrossRef]
46. López-Santiago, D.M.; Caicedo, E.F. Optimal management of electric power in microgrids under a strategic multi-objective decision-making approach and operational proportional adjustment. *IET Gener. Transm. Distrib.* **2019**, *13*, 4473–4481. [CrossRef]
47. Et-Taoussi, M.; Ouadi, H.; Chakir, H.E. Hybrid optimal management of active and reactive power flow in a smart microgrid with photovoltaic generation. *Microsyst. Technol.* **2019**, *25*, 4077–4090. [CrossRef]
48. Tenfen, D.; Finardi, E.C. A mixed integer linear programming model for the energy management problem of microgrids. *Electr. Power Syst. Res.* **2015**, *122*, 19–28. [CrossRef]
49. Luna, A.C.; Diaz, N.L.; Graells, M.; Vasquez, J.C.; Guerrero, J.M. Mixed-Integer-Linear-Programming-Based Energy Management System for Hybrid PV-Wind-Battery Microgrids: Modeling, Design, and Experimental Verification. *IEEE Trans. Power Electron.* **2017**, *32*, 2769–2783. [CrossRef]
50. Marzband, M.; Azarinejadian, F.; Savaghebi, M.; Guerrero, J.M. An Optimal Energy Management System for Islanded Microgrids Based on Multiperiod Artificial Bee Colony Combined With Markov Chain. *IEEE Syst. J.* **2017**, *11*, 1712–1722. [CrossRef]
51. Chalise, S.; Sternhagen, J.; Hansen, T.M.; Tonkoski, R. Energy management of remote microgrids considering battery lifetime. *Electr. J.* **2016**, *29*, 1–10. [CrossRef]
52. Leonori, S.; Paschero, M.; Mascioli, F.M.F.; Rizzi, A. Optimization strategies for Microgrid energy management systems by Genetic Algorithms. *Appl. Soft Comput.* **2020**, *86*, 105903. [CrossRef]
53. Dou, C.; Lv, M.; Zhao, T.; Ji, Y.; Li, H. Decentralised coordinated control of microgrid based on multiagent system. *IET Gener. Transm. Distrib.* **2015**, *9*, 2474–2484. [CrossRef]
54. Dehghanpour, K.; Colson, C.; Nehrir, H. A Survey on Smart Agent-Based Microgrids for Resilient/Self-Healing Grids. *Energies* **2017**, *10*, 620. [CrossRef]
55. Luo, F.; Dong, Z.Y.; Liang, G.; Murata, J.; Xu, Z. A Distributed Electricity Trading System in Active Distribution Networks Based on Multi-Agent Coalition and Blockchain. *IEEE Trans. Power Syst.* **2019**, *34*, 4097–4108. [CrossRef]
56. Wang, T.; He, X.; Deng, T. Neural networks for power management optimal strategy in hybrid microgrid. *Neural Comput. Appl.* **2017**, *31*, 2635–2647. [CrossRef]
57. Venayagamoorthy, G.K.; Sharma, R.K.; Gautam, P.K.; Ahmadi, A. Dynamic Energy Management System for a Smart Microgrid. *IEEE Trans. Neural Netw. Learn. Syst.* **2016**, *27*, 1643–1656. [CrossRef]
58. Zhou, H.; Zhou, Y.; Hu, J.; Yang, G.; Xie, D.; Xue, Y.; Nordström, L. LSTM-Based Energy Management for Electric Vehicle Charging in Commercial-Building Prosumers. *J. Mod. Power Syst. Clean Energy* **2021**, *9*, 1205–1216. [CrossRef]
59. Simolin, T.; Rauma, K.; Järventausta, P.; Rautiainen, A. Optimised controlled charging of electric vehicles under peak power-based electricity pricing. *IET Smart Grid* **2020**, *3*, 751–759. [CrossRef]

60. Alam, M.S.; Arefifar, S.A. Energy Management in Power Distribution Systems: Review, Classification, Limitations and Challenges. *IEEE Access* **2019**, *7*, 92979–93001. [CrossRef]
61. Shareef, H.; Ahmed, M.S.; Mohamed, A.; Al Hassan, E. Review on Home Energy Management System Considering Demand Responses, Smart Technologies, and Intelligent Controllers. *IEEE Access* **2018**, *6*, 24498–24509. [CrossRef]
62. Zafar, R.; Mahmood, A.; Razzaq, S.; Ali, W.; Naeem, U.; Shehzad, K. Prosumer based energy management and sharing in smart grid. *Renew. Sustain. Energy Rev.* **2018**, *82*, 1675–1684. [CrossRef]
63. Sami, M.S.; Abrar, M.; Akram, R.; Hussain, M.M.; Nazir, M.H.; Khan, M.S.; Raza, S. Energy Management of Microgrids for Smart Cities: A Review. *Energies* **2021**, *14*, 5976. [CrossRef]
64. Zepter, J.M.; Lüth, A.; Crespo del Granado, P.; Egging, R. Prosumer integration in wholesale electricity markets: Synergies of peer-to-peer trade and residential storage. *Energy Build.* **2019**, *184*, 163–176. [CrossRef]
65. Lüth, A.; Zepter, J.M.; Crespo del Granado, P.; Egging, R. Local electricity market designs for peer-to-peer trading: The role of battery flexibility. *Appl. Energy* **2018**, *229*, 1233–1243. [CrossRef]
66. Giordano, F.; Ciocia, A.; Leo, P.D.; Mazza, A.; Spertino, F.; Tenconi, A.; Vaschetto, S. Vehicle-to-Home Usage Scenarios for Self-Consumption Improvement of a Residential Prosumer with Photovoltaic Roof. *IEEE Trans. Ind. Appl.* **2020**, *56*, 2945–2956. [CrossRef]
67. Hou, X.; Wang, J.; Huang, T.; Wang, T.; Wang, P. Smart Home Energy Management Optimization Method Considering Energy Storage and Electric Vehicle. *IEEE Access* **2019**, *7*, 144010–144020. [CrossRef]
68. Mehrabi, A.; Kim, K. Low-Complexity Charging/Discharging Scheduling for Electric Vehicles at Home and Common Lots for Smart Households Prosumers. *IEEE Trans. Consum. Electron.* **2018**, *64*, 348–355. [CrossRef]
69. Koltsaklis, N.; Panapakidis, I.P.; Pozo, D.; Christoforidis, G.C. A prosumer model based on smart home energy management and forecasting techniques. *Energies* **2021**, *14*, 1724. [CrossRef]
70. Zhong, Q.W.; Buckley, S.; Vassallo, A.; Sun, Y.Z. Energy cost minimization through optimization of EV, home and workplace battery storage. *Sci. China Technol. Sci.* **2018**, *61*, 761–773. [CrossRef]
71. Mišljenović, N.; Stanić, M.; Knežević, G.; Jakab, J. Optimal maintenance of the electric vehicle battery storage level in prosumer power network. In Proceedings of the 30th International Conference on Organization and Technology of Maintenance (OTO 2021), Osijek, Croatia, 10–10 December 2021. [CrossRef]
72. Gong, H.; Ionel, D.M. Optimization of aggregated EV power in residential communities with smart homes. In Proceedings of the 2020 IEEE Transportation Electrification Conference and Expo (ITEC), Chicago, IL, USA, 23–26 June 2020. [CrossRef]
73. Bjarghov, S.; Korpas, M.; Zaferanlouei, S. Value comparison of EV and house batteries at end-user level under different grid tariffs. In Proceedings of the 2018 IEEE International Energy Conference (ENERGYCON), Limassol, Cyprus, 3–7 June 2018. [CrossRef]
74. Knežević, G.; Mišljenović, N.; Radić, N.; Brandis, A. The optimal use of stationary battery storage in a prosumer power system. In Proceedings of the 2022 7th International Conference on Smart and Sustainable Technologies (SpliTech), Split/Bol, Croatia, 5–8 July 2022. [CrossRef]
75. Morstyn, T.; Farrell, N.; Darby, S.J.; McCulloch, M.D. Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants. *Nat. Energy* **2018**, *3*, 94–101. [CrossRef]
76. Aloqaily, M.; Boukerche, A.; Bouachir, O.; Khalid, F.; Jangsher, S. An energy trade framework using smart contracts: Overview and challenges. *IEEE Netw.* **2020**, *34*, 119–125. [CrossRef]
77. Tushar, W.; Saha, T.K.; Yuen, C.; Morstyn, T.; McCulloch, M.D.; Poor, H.V.; Wood, K.L. A motivational game-theoretic approach for peer-to-peer energy trading in the smart grid. *Appl. Energy* **2019**, *243*, 10–20. [CrossRef]
78. Zia, M.F.; Benbouzid, M.; Elbouchikhi, E.; Muyeen, S.M.; Techato, K.; Guerrero, J.M. Microgrid transactive energy: Review, architectures, distributed ledger technologies, and market analysis. *IEEE Access* **2020**, *8*, 19410–19432. [CrossRef]
79. Vandoorn, T.L.; Vasquez, J.C.; Kooning, J.D.; Guerrero, J.M.; Vandevelde, L. Microgrids: Hierarchical Control and an Overview of the Control and Reserve Management Strategies. *IEEE Ind. Electron. Mag.* **2013**, *7*, 42–55. [CrossRef]
80. *IEEE 2030.7–2017*; Standard for the Specification of Microgrid Controllers. IEEE: Piscataway, NJ, USA, 2018. [CrossRef]
81. Nguyen, T.H.; Nguyen, L.V.; Jung, J.J.; Agbehadji, I.E.; Frimpong, S.O.; Millham, R.C. Bio-inspired approaches for smart energy management: State of the art and challenges. *Sustainability* **2020**, *12*, 1–24. [CrossRef]
82. Bashir, A.A.; Lehtonen, M. Day-Ahead Rolling Window Optimization of Islanded Microgrid with Uncertainty. In Proceedings of the 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Sarajevo, Bosnia and Herzegovina, 21–25 October 2018. [CrossRef]
83. Contreras, S.F.; Cortes, C.A.; Myrzik, J.M. Multi-Objective Probabilistic Power Resources Planning for Microgrids with Ancillary Services Capacity. In Proceedings of the 2018 Power Systems Computation Conference (PSCC), Dublin, Ireland, 11–15 June 2018. [CrossRef]
84. Contreras, S.F.; Cortes, C.A.; Myrzik, J.M.A. Optimal microgrid planning for enhancing ancillary service provision. *J. Mod. Power Syst. Clean Energy* **2019**, *7*, 862–875. [CrossRef]
85. Zachar, M.; Daoutidis, P. Energy management and load shaping for commercial microgrids coupled with flexible building environment control. *J. Energy Storage* **2018**, *16*, 61–75. [CrossRef]
86. Panwar, L.K.; Konda, S.R.; Verma, A.; Panigrahi, B.K.; Kumar, R. Operation window constrained strategic energy management of microgrid with electric vehicle and distributed resources. *IET Gener. Transmiss. Distrib.* **2017**, *11*, 615–626. [CrossRef]

87. Leonori, S.; Santis, E.D.; Rizzi, A.; Mascioli, F.F. Optimization of a microgrid energy management system based on a Fuzzy Logic Controller. In Proceedings of the IECON 2016—42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 23–26 October 2016. [CrossRef]
88. Kopanos, G.M.; Pistikopoulos, E.N. Reactive Scheduling by a Multiparametric Programming Rolling Horizon Framework: A Case of a Network of Combined Heat and Power Units. *Ind. Eng. Chem. Res.* **2014**, *53*, 4366–4386. [CrossRef]
89. Choi, S.; Min, S.W. Optimal scheduling and operation of the ESS for prosumer market environment in grid-connected industrial complex. In Proceedings of the 2017 IEEE Industry Applications Society Annual Meeting, Cincinnati, OH, USA, 1–5 October 2017. [CrossRef]
90. Choi, S.; Min, S.W. Optimal scheduling and operation of the ESS for prosumer market environment in grid-connected industrial complex. *IEEE Trans. Ind. Appl.* **2018**, *54*, 1949–1957. [CrossRef]
91. Ciornei, I.; Albu, M.; Sanduleac, M.; Rodriguez-Diaz, E.; Guerrero, J.; Vasquez, J.C. Real-time optimal scheduling for prosumers resilient to regulatory changes. In Proceedings of the 2018 IEEE International Energy Conference (ENERGYCON), Limassol, Cyprus, 3–7 June 2018. [CrossRef]
92. Delfino, F.; Ferro, G.; Robba, M.; Rossi, M. An Energy Management Platform for the Optimal Control of Active and Reactive Powers in Sustainable Microgrids. *IEEE Trans. Ind. Appl.* **2019**, *55*, 7146–7156. [CrossRef]
93. Elkazaz, M.; Sumner, M.; Thomas, D. Energy management system for hybrid PV-wind-battery microgrid using convex programming, model predictive and rolling horizon predictive control with experimental validation. *Int. J. Electr. Power Energy Syst.* **2020**, *115*, 105483. [CrossRef]
94. Gabash, A.; Li, P. Active-Reactive Optimal Power Flow in Distribution Networks With Embedded Generation and Battery Storage. *IEEE Trans. Power Syst.* **2012**, *27*, 2026–2035. [CrossRef]
95. Hossain, M.A.; Pota, H.R.; Squartini, S.; Abdou, A.F. Modified PSO algorithm for real-time energy management in grid-connected microgrids. *Renew. Energy* **2019**, *136*, 746–757. [CrossRef]
96. Karimi, H.; Jadid, S. Optimal energy management for multi-microgrid considering demand response programs: A stochastic multi-objective framework. *Energy* **2020**, *195*, 116992. [CrossRef]
97. Luo, Z.; Gu, W.; Wu, Z.; Wang, Z.; Tang, Y. A robust optimization method for energy management of CCHP microgrid. *J. Mod. Power Syst. Clean Energy* **2017**, *6*, 132–144. [CrossRef]
98. Paul, T.G.; Hossain, S.J.; Ghosh, S.; Mandal, P.; Kamalasadan, S. A Quadratic Programming Based Optimal Power and Battery Dispatch for Grid-Connected Microgrid. *IEEE Trans. Ind. Appl.* **2018**, *54*, 1793–1805. [CrossRef]
99. Riffonneau, Y.; Bacha, S.; Barruel, F.; Ploix, S. Optimal Power Flow Management for Grid Connected PV Systems With Batteries. *IEEE Trans. Sustain. Energy* **2011**, *2*, 309–320. [CrossRef]
100. Parisio, A.; Rikos, E.; Tzamalis, G.; Glielmo, L. Use of model predictive control for experimental microgrid optimization. *Appl. Energy* **2014**, *115*, 37–46. [CrossRef]
101. Zou, H.; Wang, Y.; Mao, S.; Zhang, F.; Chen, X. Online Energy Management in Microgids Considering Reactive Power. *IEEE Internet Things J.* **2019**, *6*, 2895–2906. [CrossRef]
102. Vukasovic, M.; Vukasovic, B. Modeling optimal deployment of smart home devices and battery system using MILP. In Proceedings of the 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Turin, Italy, 26–29 September 2017. [CrossRef]
103. Bahrami, S.; Wong, V.W.S. Security-Constrained Unit Commitment for AC-DC Grids With Generation and Load Uncertainty. *IEEE Trans. Power Syst.* **2018**, *33*, 2717–2732. [CrossRef]
104. Ottesen, S.O.; Tomasgard, A. A stochastic model for scheduling energy flexibility in buildings. *Energy* **2015**, *88*, 364–376. [CrossRef]
105. Amicarelli, E.; Tran, T.Q.; Bacha, S. Optimization algorithm for microgrids day-ahead scheduling and aggregator proposal. In Proceedings of the 2017 IEEE Int. Conf. on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), Milan, Italy, 6–9 June 2017. [CrossRef]
106. Bella, A.L.; Farina, M.; Sandroni, C.; Scattolini, R. Microgrids aggregation management providing ancillary services. In Proceedings of the 2018 European Control Conference (ECC), Limassol, Cyprus, 12–15 June 2018. [CrossRef]
107. Majzoobi, A.; Khodaei, A. Application of microgrids in providing ancillary services to the utility grid. *Energy* **2017**, *123*, 555–563. [CrossRef]
108. Shen, J.; Jiang, C.; Liu, Y.; Wang, X. A Microgrid Energy Management System and Risk Management Under an Electricity Market Environment. *IEEE Access* **2016**, *4*, 2349–2356. [CrossRef]
109. Wang, J.; Zhong, H.; Tang, W.; Rajagopal, R.; Xia, Q.; Kang, C.; Wang, Y. Optimal bidding strategy for microgrids in joint energy and ancillary service markets considering flexible ramping products. *Appl. Energy* **2017**, *205*, 294–303. [CrossRef]
110. Pei, W.; Du, Y.; Xiao, H.; Shen, Z.; Deng, W.; Yang, Y. Optimal operation of microgrid with photovoltaics and gas turbines in demand response. In Proceedings of the 2014 International Conference on Power System Technology, Chengdu, China, 20–22 October 2014. [CrossRef]
111. Shen, J.; Jiang, C.; Liu, Y.; Qian, J. A Microgrid Energy Management System with Demand Response for Providing Grid Peak Shaving. *Electr. Power Compon. Syst.* **2016**, *44*, 843–852. [CrossRef]
112. Aboli, R.; Ramezani, M.; Falaghi, H. Joint optimization of day-ahead and uncertain near real-time operation of microgrids. *Int. J. Electr. Power Energy Syst.* **2019**, *107*, 34–46. [CrossRef]

113. Ravichandran, A.; Sirouspour, S.; Malysz, P.; Emadi, A. A Chance-Constraints-Based Control Strategy for Microgrids with Energy Storage and Integrated Electric Vehicles. *IEEE Trans. Smart Grid* **2018**, *9*, 346–359. [CrossRef]
114. Ju, C.; Wang, P.; Goel, L.; Xu, Y. A Two-Layer Energy Management System for Microgrids with Hybrid Energy Storage Considering Degradation Costs. *IEEE Trans. Smart Grid* **2018**, *9*, 6047–6057. [CrossRef]
115. Zhang, Z.; Wang, J.; Ding, T.; Wang, X. A Two-Layer Model for Microgrid Real-Time Dispatch Based on Energy Storage System Charging/Discharging Hidden Costs. *IEEE Trans. Sustain. Energy* **2017**, *8*, 33–42. [CrossRef]
116. Holjevac, N.; Capuder, T.; Zhang, N.; Kuzle, I.; Kang, C. Corrective receding horizon scheduling of flexible distributed multi-energy microgrids. *Appl. Energy* **2017**, *207*, 176–194. [CrossRef]
117. Giraldo, J.S.; Castrillon, J.A.; Lopez, J.C.; Rider, M.J.; Castro, C.A. Microgrids Energy Management Using Robust Convex Programming. *IEEE Trans. Smart Grid* **2019**, *10*, 4520–4530. [CrossRef]
118. Manbachi, M.; Ordonez, M. AMI-Based Energy Management for Islanded AC/DC Microgrids Utilizing Energy Conservation and Optimization. *IEEE Trans. Smart Grid* **2019**, *10*, 293–304. [CrossRef]
119. Yang, F.; Feng, X.; Li, Z. Advanced Microgrid Energy Management System for Future Sustainable and Resilient Power Grid. *IEEE Trans. Ind. Appl.* **2019**, *55*, 7251–7260. [CrossRef]
120. Silani, A.; Yazdanpanah, M.J. Distributed Optimal Microgrid Energy Management With Considering Stochastic Load. *IEEE Trans. Sustain. Energy* **2019**, *10*, 729–737. [CrossRef]
121. Martinez-Ramos, J.L.; Marano-Marcolini, A.; Garcia-Lopez, F.P.; Almagro-Yravedra, F.; Onen, A.; Yoldas, Y.; Khiat, M.; Ghomri, L.; Fragale, N. Provision of Ancillary Services by a Smart Microgrid: An OPF Approach. In Proceedings of the 2018 International Conference on Smart Energy Systems and Technologies (SEST), Seville, Spain, 10–12 September 2018. [CrossRef]
122. Jiang, Q.; Xue, M.; Geng, G. Energy Management of Microgrid in Grid-Connected and Stand-Alone Modes. *IEEE Trans. Power Syst.* **2013**, *28*, 3380–3389. [CrossRef]
123. Farsangi, A.S.; Hadayeghparast, S.; Mehdinejad, M.; Shayanfar, H. A novel stochastic energy management of a microgrid with various types of distributed energy resources in presence of demand response programs. *Energy* **2018**, *160*, 257–274. [CrossRef]
124. Gomes, M.H.; Saraiva, J.T. Allocation of reactive power support, active loss balancing and demand interruption ancillary services in MicroGrids. *Electr. Power Syst. Res.* **2010**, *80*, 1267–1276. [CrossRef]
125. Deckmyn, C.; de Vyver, J.V.; Vandoorn, T.L.; Meersman, B.; Desmet, J.; Vandevelde, L. Day-ahead unit commitment model for microgrids. *IET Gener. Transm. Distrib.* **2017**, *11*, 1–9. [CrossRef]
126. Jin, M.; Feng, W.; Marnay, C.; Spanos, C. Microgrid to enable optimal distributed energy retail and end-user demand response. *Appl. Energy* **2018**, *210*, 1321–1335. [CrossRef]
127. Wang, H.; Good, N.; Cesena, E.A.M.; Mancarella, P. Co-optimization of a Multi-Energy Microgrid Considering Multiple Services. In Proceedings of the 2018 Power Systems Computation Conference (PSCC), Dublin, Ireland, 11–15 June 2018. [CrossRef]
128. Luna, A.C.; Meng, L.; Diaz, N.L.; Graells, M.; Vasquez, J.C.; Guerrero, J.M. Online Energy Management Systems for Microgrids: Experimental Validation and Assessment Framework. *IEEE Trans. Power Electron.* **2018**, *33*, 2201–2215. [CrossRef]
129. Sukumar, S.; Mokhlis, H.; Mekhilef, S.; Naidu, K.; Karimi, M. Mix-mode energy management strategy and battery sizing for economic operation of grid-tied microgrid. *Energy* **2017**, *118*, 1322–1333. [CrossRef]
130. Solanke, T.U.; Ramachandaramurthy, V.K.; Yong, J.Y.; Pasupuleti, J.; Kasinathan, P.; Rajagopalan, A. A review of strategic charging–discharging control of grid-connected electric vehicles. *J. Energy Storage* **2020**, *28*, 101193. [CrossRef]
131. Das, C.K.; Bass, O.; Kothapalli, G.; Mahmoud, T.S.; Habibi, D. Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality. *Renew. Sustain. Energy Rev.* **2018**, *91*, 1205–1230. [CrossRef]
132. Díaz-González, F.; Sumper, A.; Bellmunt, O. *Energy Storage in Power Systems*; John Wiley & Sons: Hoboken, NJ, USA, 2016; pp. 1–320. [CrossRef]
133. U.S. Department of Energy. *Energy Storage Grand Challenge: Energy StorageMarket Report*; Technical Report; U.S. Department of Energy: Washington, DC, USA, 2020.
134. Corigliano, O.; Pagnotta, L.; Fragiacomo, P. On the Technology of Solid Oxide Fuel Cell (SOFC) Energy Systems for Stationary Power Generation: A Review. *Sustainability* **2022**, *14*, 15276. [CrossRef]
135. Fragiacomo, P.; De Lorenzo, G.; Corigliano, O. Intermediate temperature solid oxide fuel cell/electrolyzer towards future large-scale production. In Proceedings of the International Conference on Industry 4.0 and Smart Manufacturing (ISM 2019), Rende Italy, 20–22 November 2019. [CrossRef]
136. Xu, B.; Zhao, J.; Zheng, T.; Litvinov, E.; Kirschen, D.S. Factoring the Cycle Aging Cost of Batteries Participating in Electricity Markets. *IEEE Trans. Power Syst.* **2018**, *33*, 2248–2259. [CrossRef]
137. Kassem, M.; Bernard, J.; Revel, R.; Pélissier, S.; Duclaud, F.; Delacourt, C. Calendar aging of a graphite/LiFePO4 cell. *J. Power Sources* **2012**, *208*, 296–305. [CrossRef]
138. Vetter, J.; Novák, P.; Wagner, M.; Veit, C.; Möller, K.C.; Besenhard, J.; Winter, M.; Wohlfahrt-Mehrens, M.; Vogler, C.; Hammouche, A. Ageing mechanisms in lithium-ion batteries. *J. Power Sources* **2005**, *147*, 269–281. [CrossRef]
139. Ölvander, J. A Survey of Multiobjective Optimization in Engineering Design. Technical Report, Department of Mechanical Engineering, Linköping University. Linköping, Germany, 2000.
140. Das, U.K.; Tey, K.S.; Seyedmahmoudian, M.; Mekhilef, S.; Idris, M.Y.I.; Van Deventer, W.; Horan, B.; Stojcevski, A. Forecasting of photovoltaic power generation and model optimization: A review. *Renew. Sustain. Energy Rev.* **2018**, *81*, 912–928. [CrossRef]

141. Ahmed, A.; Khalid, M. A review on the selected applications of forecasting models in renewable power systems. *Renew. Sustain. Energy Rev.* **2019**, *100*, 9–21. [CrossRef]
142. Fallah, S.; Ganjkhani, M.; Shamshirband, S.; wing Chau, K. Computational Intelligence on Short-Term Load Forecasting: A Methodological Overview. *Energies* **2019**, *12*, 393. [CrossRef]
143. Mamun, A.A.; Sohel, M.; Mohammad, N.; Haque Sunny, M.S.; Dipta, D.R.; Hossain, E. A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models. *IEEE Access* **2020**, *8*, 134911–134939. [CrossRef]
144. Jahan, I.S.; Snasel, V.; Misak, S. Intelligent systems for power load forecasting: A study review. *Energies* **2020**, *13*, 6105. [CrossRef]
145. Lago, J.; Marcjasz, G.; De Schutter, B.; Weron, R. Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark. *Appl. Energy* **2021**, *293*, 116983. [CrossRef]
146. Pourdaryaei, A.; Mohammadi, M.; Karimi, M.; Mokhlis, H.; Illias, H.A.; Kaboli, S.H.A.; Ahmad, S. Recent development in electricity price forecasting based on computational intelligence techniques in deregulated power market. *Energies* **2021**, *14*, 6104. [CrossRef]
147. Ramyar, S.; Liu, A.L.; Chen, Y. Power Market Model in Presence of Strategic Prosumers. *IEEE Trans. Power Syst.* **2020**, *35*, 898–908. [CrossRef]
148. Hatziargyriou, N. (Ed.) *Microgrids: Architectures and Control*; John Wiley & Sons: Hoboken, NJ, USA, 2014; pp. 1–344.
149. Mohagheghi, S.; Stoupis, J.; Wang, Z.; Li, Z.; Kazemzadeh, H. Demand Response Architecture: Integration into the Distribution Management System. In Proceedings of the 2010 First IEEE International Conference on Smart Grid Communications, Gaithersburg, MD, USA, 4–6 October 2010. [CrossRef]
150. Yan, X.; Ozturk, Y.; Hu, Z.; Song, Y. A review on price-driven residential demand response. *Renew. Sustain. Energy Rev.* **2018**, *96*, 411–419. [CrossRef]
151. Jordehi, A.R. Optimisation of demand response in electric power systems, a review. *Renew. Sustain. Energy Rev.* **2019**, *103*, 308–319. [CrossRef]
152. Oureilidis, K.; Malamaki, K.N.; Gallos, K.; Tsitsimelis, A.; Dikaiakos, C.; Gkavanoudis, S.; Cvetkovic, M.; Mauricio, J.M.; Ortega, J.M.M.; Ramos, J.L.M.; et al. Ancillary services market design in distribution networks: Review and identification of barriers. *Energies* **2020**, *13*, 917. [CrossRef]
153. Olivella-Rosell, P.; Lloret-Gallego, P.; Munné-Collado, Í.; Villafafila-Robles, R.; Sumper, A.; Ottessen, S.Ø.; Rajasekharan, J.; Bremdal, B.A. Local flexibility market design for aggregators providing multiple flexibility services at distribution network level. *Energies* **2018**, *11*, 822. [CrossRef]
154. Gomez-Gonzalez, M.; Hernandez, J.; Vera, D.; Jurado, F. Optimal sizing and power schedule in PV household-prosumers for improving PV self-consumption and providing frequency containment reserve. *Energy* **2020**, *191*, 116554. [CrossRef]
155. Zhou, Y.; Wu, J.; Song, G.; Long, C. Framework design and optimal bidding strategy for ancillary service provision from a peer-to-peer energy trading community. *Appl. Energy* **2020**, *278*, 115671. [CrossRef]
156. Pavic, I.; Beus, M.; Pandzic, H.; Capuder, T.; Stritof, I. Electricity markets overview—Market participation possibilities for renewable and distributed energy resources. In Proceedings of the 2017 14th International Conference on the European Energy Market (EEM), Dresden, Germany, 6–9 June 2017. [CrossRef]
157. Crasta, C.; Agabus, H.; Palu, I. EU electricity market design issues and solutions for increased RES penetration. In Proceedings of the 2020 17th International Conference on the European Energy Market (EEM), Stockholm, Sweden, 16–18 September 2020. [CrossRef]
158. Chomać-Pierzecka, E.; Sobczak, A.; Urbańczyk, E. RES Market Development and Public Awareness of the Economic and Environmental Dimension of the Energy Transformation in Poland and Lithuania. *Energies* **2022**, *15*, 5461. [CrossRef]