Energy Management Systems for Microgrids: Main Existing Trends in Centralized Control Architectures

Danny Espin-Sarzosa ¹, Rodrigo Palma-Behnke ¹,* and Oscar Núñez-Mata ²

¹ Energy Center, Department of Electrical Engineering, Faculty of Mathematical and Physical Sciences, University of Chile, Santiago 8370451, Chile; despin@ing.uchile.cl
² School of Electrical Engineering, University of Costa Rica, San José 11501, Costa Rica; oscar.nunezmata@ucr.ac.cr
* Correspondence: rodpalma@cec.uchile.cl; Tel.: +56-9576-96810

Received: 11 December 2019; Accepted: 17 January 2020; Published: 22 January 2020

Abstract: This paper presents both an extensive literature review and a qualitative and quantitative study conducted on nearly 200 publications from the last six years (based on international experience and a top-down analysis framework with five classification levels) to establish the main trends in the field of centralized energy management systems (EMS) for microgrids. No systematic trend analyses have been observed in this field in previous literature reviews. EMS attributes for several features such as objective functions, resolution techniques, operating models, integration of uncertainties, optimization horizons, and modeling detail levels are considered for main trend identification. The main contribution of this study is the identification of four specific existing research trends: (i) dealing with uncertainties (comprises 33% of the references), (ii) multi-objective strategy (29%), (iii) traditional paradigm (21%), and (iv) P-Q challenge (17%). Each trend is described and analyzed based on the main drive of these separate research fields. The key challenges and the way to cope with them are described based on the rationality of each trend, the results of previous reviews, and the previous experience of the authors. Overall, finding these main trends, together with a complete paper database and their features, serve as a useful outcome for a better understanding of the current research-specific challenges, opportunities, potential barriers, and open questions regarding the creation of future centralized EMS developments. The traditional numerical analysis is insufficient to identify research trends. Therefore, the need of further analyses based on the clustering approach is emphasized.

Keywords: microgrid; energy management system; centralized control architecture; review; research trends; clustering

1. Introduction

In a microgrid (MG), energy management systems are recognized as control-essential elements in terms of stability, security, and efficiency, as well as power balancing elements in terms of their dependence on operating conditions variability, characterized by the uncertainty caused by power supplies from renewable energy resources (RES) and/or the dynamic behavior of electricity demand. In recent years, literature exhibited a new generation of energy management systems (EMS) approaches for MGs, which aim at dealing with the management of energy in variable operating and technological contexts. However, power flow control and the guarantee of highly reliable and stable MGs are becoming progressively complex [1]. Optimizing the size of the components and adopting an EMS strategy are essential to decreasing the cost of the system and limiting its negative effects [2].

An MG is defined as a self-contained electrical power system consisting of distributed energy resources (DERs), such as distributed generators (DG) and energy storage systems (ESS), and loads (controllable loads in some cases). All the above are considered as a single controllable system [3,4].
An MG can operate in either grid-connected [5–12] or isolated mode [13–21] or both [22]. The presence of more than one DER requires energy flow control from various sources to ensure reliable energy supply, safety, and a minimum-cost operation. Decisions on MGs are made by the EMS. In this sense, EMS are control devices responsible for defining the optimum scheduling of dispatchable units in an MG [23] by using different information about the latter, such as demand forecasting, power generation, energy storage, weather forecasts, energy grid prices, etc. [20]. An EMS can be classified by adopting a top-down approach, starting from general principles and down to developing specific processes models. Consequently, EMS can be classified at the top-level based on whether they have a centralized or decentralized control architecture.

In a centralized control architecture, the main responsibility for microgrid value maximization and the optimization of its operation lies with the EMS/Central controller [24], as shown in Figure 1a. In this figure, the red dashed arrows represent the exchange of information (centralized control communication) among local controllers and the EMS/Central controller, while the solid black arrows refer to the exchanged information (local control communication) among microgrid agents and their local controllers. The EMS uses inputs (weather forecast, load demand, SoC, energy prices, etc.) to perform scheduling and optimization procedures to determine the optimal set points for distributed generation (DG) loads and local controllers (LCs) in the MG.

On the other hand, a decentralized control architecture is shown in Figure 1b. In this figure, the blue dotted arrow represents the communication channel that allows local controllers/leaders to exchange information among them (decentralized control communication), and the black solid arrows, as in Figure 1a, represent the exchanged information among the local controller/leader and either other local controllers or microgrid agents. Each agent or group of agents is self-controlled or controlled by a leader, respectively [25]. For that reason, LC4a and LC4b are managed by LC4/Leader, and LC1, LC2, and LC3 are self-controlled; they can also exchange information among them. The main responsibility is given to competing or collaborating with LCs to optimize their production in order to satisfy the demand and probably provide the possible maximum export to the grid, considering current market prices [24]. A decentralized controller needs a complete local information to run the required control
actions without full awareness of all system parameters [26], i.e., a decentralized approach is mainly based on a local measurement of parameters, such as voltage and frequency values [27]. Control actions are sent to the multiple DER and controllable loads. It is worth noting that the peer-to-peer control concept [28] can be understood as part of the blue dotted line in Figure 1b.

This review paper is focused on centralized EMS architectures, which have been widely used in isolated MGs due to the high level of coordination required among DER units [29,30]. The advantages of a centralized EMS include real-time observability of the whole system and straightforward implementation. Additionally, confidential and private information can be safeguarded inside the central unit. However, from another point of view, those features also mean that the EMS needs to be powerful enough to process a considerable amount of data while making proper decisions. High bandwidth communication is required to exchange information on a timely basis. Moreover, centralized management entails a key risk, i.e., a fault in the central unit may cause the loss of several system functions, including service supply. Low flexibility/expandability is another critical limit of a centralized EMS [31]. To overcome some of these drawbacks, redundancy can be added to the existing control and communication infrastructure which may increase the MG investment cost [32]. On the other hand, in the absence of communication links between the EMS and LCs, the frequency and voltage of the system would be locally kept by the droop control of the units. However, steady-state frequency and voltage deviations from nominal values will be obtained [20,33,34]. Several methods and tools have been proposed to overcome these drawbacks [35–37].

Based on the context above, the authors in [31] have described cases where the use of a centralized control is preferred:

1. Small-scale MGs where centralized information gathering and decision-making with low communication and computation effort can be conducted. All the properties inside the MG have a common goal; therefore, the EMS can operate the MG as a single agent;
2. Military MGs where utmost privacy/confidentiality is required. System configuration is virtually fixed and high flexibility/expandability is not required.

1.1. EMS Review Papers

Thanks to comprehensive research activities on EMS for MGs around the world, many researchers have published review papers that focus on their objective functions, resolution techniques, and uncertainties, among others. For instance, [31] is aimed at summarizing control objectives and associated methodologies. In [38], a comprehensive and critical review of the strategies developed for micro-grid energy management and solution approaches is presented. In [39], a general idea regarding EMS in MGs is provided; EMS connection modes, different strategies, and control techniques are developed; several optimization techniques to lower MGs overall costs and to continuously offset the deviations between generation and demand are applied. In [26], the authors provided insights about the state-of-the-art in energy management as well as generation/consumption prediction issues, practices, and research status. Additionally, this review covers energy management or prediction-related studies of MGs. In [2], a comprehensive review of the proposed approaches is presented. In [40], A. Ahmad Khan et al. present a review on existing optimization objectives, constraints, solution approaches, and tools used in MG energy management. In [41], a literature review on optimal control techniques for energy management and control of an MG is provided. The authors show a classification of the references involved in the design and development of an optimum EMS. This is mainly done by considering the objective functions to be solved as well as the optimization techniques used for solving optimum control issues related to a reliable operation of MGs.

Conclusively, the main review papers in this field focus on the classification and description of specific attributes such as control objectives, forecasting strategies, optimization techniques, and energy management approaches. There are no analyses in previous literature reviews on trends that deal with a consideration of multiple attributes and features in this field.
1.2. Contribution and Structure of this Paper

The main contribution of this study is the identification of specific research trends in the field related to EMS for microgrids, focused on centralized control architectures. To identify these main trends, EMS attributes for various features such as objective functions (e.g., single-objective, multi-objective), resolution techniques (e.g., mathematical programming, computational intelligence), operating model (e.g., DC load flow, AC load flow), integration of uncertainties, optimization horizon, and modeling detail levels are considered in the study. The results show that there is no evidence of a research trend where all EMS development challenges are dealt with simultaneously. Moreover, research proposals are mainly focused on the improvement of specific areas, while making some simplifications in others. Additionally, this work provides a comprehensive review that becomes useful for a better understanding of the current challenges, opportunities, potential barriers, and open questions regarding the creation of future centralized EMS developments.

The path to cope with the challenges identified is described below.

The remaining content in this paper is organized as follows. Section 2 describes the analysis scheme for EMS trend identification. Section 3 presents the numerical results and trends of centralized EMS. Finally, Section 4 shows relevant conclusions and future works on this topic.

2. Analysis Scheme for EMS Trends Identification

2.1. Procedure for the Identification of Main Trends

The literature review identifies a number of review papers regarding EMS development for microgrids. A common approach adopted by previous studies focused on a qualitative analysis based on expert knowledge. In this work, a classification methodology is used that seeks to meet the objectives of both quantitative and qualitative analyses and an identification of the main trends in research papers. The procedure and its main steps are established as follows:

Step (1) Database selection: The database covers a comprehensive review of papers published in the most quoted journals in the field for the last six years (IEEE: Transactions on Power Systems, Smart Grid, Industrial Informatics, Sustainable Energy, Control Systems Technology, Neural Networks and Learning Systems; Elsevier: Applied Energy, Sustainable Energy, Grids and Networks, Energy Conversion and Management, Sustainable Energy Technologies and Assessments, Renewable & Sustainable Energy Reviews, Renewable Energy, Energy, Electric Power Systems Research, Expert Systems with Applications, Energy Reports; IET: Generation, Transmission & Distribution).

Step (2) Paper selection from databases: A group of papers covering the main topics of the selected research field (EMS, microgrid, centralized control, etc.) is gathered by using IEEE Xplore, Google Scholar, ISI Web of Knowledge, and Scopus search engines. Each paper should be analyzed to verify its relationship with the topic related to centralized EMS. This step requires a prior clear understanding of EMS solutions and centralized control architectures. In addition, the reference tree should be followed; therefore, even more papers appeared after following the usual bibliographic search process. This is a key aspect for the methodology used for identifying review papers in the field, as the selection criteria has a direct impact on the quality of the results. This procedure aims at gathering the large majority of the field-related contributions and not only a representative sample.

Step (3) Gathering of information: All the attributes selected from predefined classification levels are searched for and extracted from each paper.

Step (4) Relational database: A relational database is created and populated based on the information from the attributes selected.

Step (5) Clustering technique: Various patterns are identified by means of a Self-Organizing Map (SOM) clustering technique, including the identification of cluster centroids.
Step (6) Content and structure analysis: A statistical analysis is applied to the information of the database created. An analysis of the results is conducted.

Step (7) Identification of main trends: Based on the results of steps (5) and (6) the main trends are identified and analyzed.

Step (8) In-depth analysis of the research-specific questions of each trend: Based on the main trends identified in step (7) and the researcher’s know-how, the research-specific questions and key challenges of each trend can be identified. With this aim, a detailed analysis of the cluster centroids is suggested. Thus, research specific challenges may be identified.

Figure 2 shows an overview of the proposed procedure in this work.

Figure 2. Overview of the proposed procedure.

2.2. Levels for the Classification Framework

Figure 3 summarizes selected attributes and the database structure (steps (3) and (4) in Section 2.1). Five classification levels (each level shown in a different color for a better differentiation between them) are defined as follows:

I. Control Architectures: This level refers to the way an MG is controlled in order to ensure its safe and reliable operation, at minimum cost, among other objectives. To meet these objectives, either centralized or decentralized control architectures can be used. The light green box highlights the centralized control architecture selected as the scope of analysis in this paper. White boxes represent topics out of the paper’s scope but that are also relevant for EMS description.

II. Fields of Interest: The level of yellow boxes presents broader fields for centralized EMS, such as system modeling, EMS application fields, and time treatment in terms of the way different periods of time are used for the acquisition or updating of information.

III. Selected Topics: This level is composed of light blue boxes and presents more details for each field of interest presented at this level. As for “Applications”, four sub-items are identified: state estimator, real-time SCADA, operation optimizer, and adaptive protection system [42]. Regarding time treatment, the focus was on the periodicity (time frames) of EMS processes execution.

IV. Main Features: This level shows the features of the topics that have been selected. As for “Operation Optimizer”, six sub-items are presented (objective function, resolution technique, inputs, outputs, operation model, and the consideration of uncertainties); and, as for “Periodicity”, three sub-items were individualized (optimization horizon, data acquisition time, and data updating time).
V. Level of Complexity: A deeper description of the attributes selected is provided at this final level. The taxonomy is based on the level of complexity of the models and the algorithms used. All the sub-items in this level are colored with different shades of blue according to their increasing and/or decreasing level of complexity (darker shades represent a higher complexity).

Figure 3. Analysis scheme proposed for the review.

2.3. Main Features and Level of Complexity

The main features of the selected attributes are described in this section (Levels IV and V in Section 2.2):

- **Objective function**

  Two types of objective functions be they single-objective or multi-objective can be considered to formulate an EMS. Firstly, a single-objective function mainly focuses on a minimum-cost operation of the MG. Secondly, a multi-objective function considers different objectives regarding MG operation, such as greenhouse gas reduction, RES maximization, lifetime of batteries, energy purchase costs, maximization of the energy sold to the grid, etc. Objective functions are based on user preferences, geographical area, equipment installed in the MG; MG capacity, government regulations, types of rates, energy storage, and generation [40].

- **Resolution techniques**

  Once the EMS optimization problem is formulated, it requires a solution approach in order to obtain the set points to be used by MG agents. In the literature, the authors solved the resulting EMS optimization problems by means of alternative techniques. The selected solution approach offers key information about the scope and the modeling details of each research work. For example, if the model involves strong non-linearities and uncertainties, the resolution techniques should be able to deal with local optima issues and multiple scenarios. Thus, the techniques were divided into the following three groups:

  (i) **Mathematical programming (MP):** A mathematical programming problem is a special class of decision-making problem where the focus is on an efficient use of limited resources to meet a desired objective [43]. Linear programming and mix-integer programming are examples of MP approaches capable of solving the underlying optimization problem for MG operations. Table A1 summarizes a comprehensive list of MP techniques considered in this study.
(ii) Computational intelligence (CI): Refers to the design and development of algorithms based on biology and linguistics. It has been long-established that CI consists of three main cornerstones, which are neural networks, fuzzy systems and evolutionary computation [44]. Within the last few years, CI has become heavily influenced by nature. Thus, recently new developments have emerged, such as ambient intelligence, artificial life, cultural learning, artificial endocrine networks, social reasoning, and artificial hormone networks. For developing reliable smart systems, CI plays a key role, for example, in games and cognitive development systems. In recent years, Deep Learning has become very popular among researchers, particularly in deep convolutional neural networks. Currently, Deep Learning is considered the principal approach for artificial intelligence (AI) applications [44]. A comprehensive list of the CI techniques capable of solving the EMS optimization problem is presented in Table A2. Furthermore, several authors have proposed their own intelligent algorithm (AA) to solve the EMS problem.

(iii) Hybrid methods (HM): Refers to a combination of methods based on MP and CI. The incorporation of uncertainties in system modeling encourages the use of this approach. The list of the HM approaches considered can be found in Table A3.

It is worth noting that every acronym in the resolution techniques is referenced at least once in the database shown in Tables A4–A10. Consequently, the reader can make a quick search of the description when looking for a specific reference.

- EMS inputs and outputs

Input information is, for example, weather and load demand forecasts, energy prices, state-of-charge (SoC), status of DGs, MG frequency, emissions data, voltage buses, etc.

Outputs are obtained once the optimization process has concluded and sent to the different agents present in the MG. Examples of outputs are unit dispatch setpoints, unit commitment setpoints, demand side management (DSM) setpoints, amount of energy purchased/sold from/to utility, power battery charge/discharge, unit on/off status, signals for MG to operate connected either to the grid or in standalone mode, among other outputs.

- Operating model

This feature shows the type of operation model that the researchers selected to formulate the EMS. It can be either DC load flow or AC load flow. The DC load flow operation model mainly considers the dispatch of active power, while the AC load flow operation model addresses the dispatch of both active and reactive power into the MG. It is important to note that in the proposed definition, the DC approach also considers single node active power dispatch.

- Optimization horizon

In order to address the optimization problem, EMS considers a time frame. This time frame is referred to as optimization horizon or window which can be represented in seconds, minutes, hours, day(s) and year(s), among others. The entire optimization horizon can be divided into time steps. The EMS provides the optimization outputs for each one of them.

- Consideration of uncertainties

Due to RES variability, their uncertainty should be considered in the EMS mathematical model to ensure safe and accurate MG operation. Uncertainties in generation, demand, grid, and storage are identified. Grid uncertainty refers to the price forecasting of the main interconnected system (wholesale market) and its variability.

- Data acquisition time and data updating time
Data acquisition time is the time step during which the EMS obtains input information to perform optimization. For example, the EMS can acquire the data at a step of minutes, seconds, and milliseconds. On the other hand, data updating time is the time step during which the EMS carries out a new optimization process and sends new outputs to MG agents. For instance, the EMS can send new data outputs every hour, minute, or second.

- **Detail level of components**

  The detail level of components refers to the way each MG component (e.g., generation, demand, grid, storage, etc.) is mathematically modeled for their inclusion in the EMS optimization problem. The detail level of components was divided into static models and dynamic models. The static model is a mathematical algebraic equation model usually used for a multiperiod scheme in discrete time steps and it is based on a steady-state description of the system. Dynamic models account for non-periodical time-dependent changes in the system state. Dynamic models are typically represented by differential equations [45,46] to capture the behavior of MG components [47].

  Storage systems are one key component for EMS operation (particularly in isolated applications). More specifically, the use of SoC and/or state-of-health (SoH) corresponds to a relevant modeling aspect.

  For the case of a decentralized EMS, all the attributes of the proposed analysis scheme should be retained. Nevertheless, in contrast to a centralized control architecture, a decentralized approach needs a coordination strategy among all either local controllers or central power processing units [48]. Thus, the analysis scheme of Figure 3 should be broadened to consider the coordination strategy and the attributes of a decentralized control architecture.

### 2.4. Application Case of the Proposed Analysis Scheme

Based on the analysis scheme presented in Section 2.2, a specific application of the classification structure is herein presented for Reference [49]. In this publication, the authors propose “A Microgrid Energy Management System Based on the Rolling Horizon Strategy”. Depending on the attributes found in this paper, the boxes in the analysis framework scheme are highlighted in orange. The result can be observed in Figure 4.

![Figure 4. Example of the proposed analysis framework scheme application.](image-url)

As shown in Figure 4, the proposed analysis scheme is a useful tool in order to extract relevant information from a paper. In each level, the attributes that appear in a specific paper are both selected and highlighted. This approach exhibits advantages when the researchers are interested in classifying a large group of articles. Thus, the proposed analysis scheme is suitable when the aim is to perform a systematic analysis and classification of the state-of-the-art in a selected research field.
3. Results: Attributes and Trends

3.1. Results Obtained from the Proposed Analysis Scheme

A comprehensive review covering papers between the years 2012 and 2018 is conducted by following the proposed analysis scheme (Section 2.1, steps (1) and (2)). Out of a universe of more than 500 papers, 173 were relevant for and applicable to this work, while 125 of them were selected for the database described in steps (3) and (4) from Section 2.1. It is worth noting that the database is not a mere sample of papers in the field but an effort to make a comprehensive identification of contributions. For a better understanding, a letter code for both features and attributes has been assigned in Table 1. For example, letter “A” corresponds to the “detail level of components” (feature), while “STM” refers to static models (attribute). Letter codes assigned in Table 1 are used in Table 2 (except from the acronyms of the other resolution techniques described in Tables A1–A3) for features and attributes extracted from four distinctive papers. Additionally, several summary tables of this complete literature review are shown in Tables A4–A10 in order to provide a quick overview of this research field over the last six years.

It is worth noting that some features or attributes are not mentioned or not discussed if mentioned in some papers. In such case, Table 2 is filled with blank spaces. Consequently, those features or attributes cannot be considered for numerical analysis and trend identification.

| Feature ID | Letter Code | Attribute ID | Letter Code |
|------------|-------------|--------------|-------------|
| Detail level of components | A | Static models | STM |
| |  | Dynamic models | DYM |
| Objective function | B | Single-objective | SOBJ |
| |  | Multi-objective | MOBJ |
| Resolution technique | C | Mathematical programming | MP |
| |  | Computational intelligence | CI |
| |  | Hybrid Methods | HM |
| Inputs | D | Generation forecast | GFO |
| |  | Demand forecast | DFO |
| |  | Weather forecast | WFO |
| |  | Other inputs | OIN |
| Outputs | E | Dispatch setpoints | DSET |
| |  | UC setpoints | UC |
| |  | DSM setpoints | DSM |
| |  | Other outputs | OOU |
| Operating model | F | DC load flow | DC |
| |  | AC load flow | AC |
| Optimization horizon | G | Seconds | SEC |
| |  | Minutes | MIN |
| |  | Hours | HR |
| |  | Day(s) | DY |
| |  | Year(s) | YR |
| Consideration of uncertainties | H | Demand | DM |
| |  | Generation | GE |
| |  | Grid | GR |
| |  | Storage | ST |
| Data acquisition time | I | Minutes | MIN |
| |  | Seconds | SEC |
| |  | Milliseconds | MILI |
| Data updating time | J | Hours | HR |
| |  | Minutes | MIN |
| |  | Seconds | SEC |
| |  | Milliseconds | MILI |
Table 2. Features and attributes of the distinctive papers selected.

| Ref. | A   | B   | C     | D       | E       | F     | G     | H     | I     |
|------|-----|-----|-------|---------|---------|-------|-------|-------|-------|
| [50] | STM | SOBJ| MILP  | IN      | DSET    | OOU   | DC    | DY    | DM    | GE    |
| [51] | STM | MOBJ| MO + FL + ANN | GFO + OIN | DSET | DC | DY | DM | GE |
| [52] | STM | SOBJ| MINLP | GFO + DFO + OIN | OOU | DC | HR |     |     |
| [53] | STM | SOBJ| LO    | OIN    | DSET + DSM | AC | DY | GE |     |     |

3.2. Quantitative Results (Numerical Results Analysis)

Numerical results and quantitative analyses of various features detailed in Table 1 from the database summarized in Tables A4–A10 are presented in this section. Figure 5a shows the distribution of the “resolution techniques” (percentages) used in recent years. The results show that, in general, CI techniques have been used with a higher frequency. Regarding MP approaches, despite MP ability to guarantee global optimal solutions, these have been considered to have a lower frequency than CI techniques. Finally, HM appear as an option to solve the EMS optimization problem. Based on the increasing complexity and new requirements for microgrid operations (cost-effectiveness, reliability, and resilience), HM may gain strength in the future.

On the other hand, Figure 5b shows the results of the objective function types researchers have used to formulate the mathematical optimization problem in EMS. The red line shows that, in general, SOBJ functions have been considered to have a higher frequency than MOBJ functions. This is an expected result for a technology that focuses on main objectives in early development phases. Nevertheless, a minimum-cost operation is not the only objective of an EMS. In fact, authors have
recently considered other objectives to improve MG overall performance, e.g., reduction of polluting gases, maximization of the use of renewable resources, maximization of the useful life of batteries, etc.

Upon the penetration of several DG technologies, electrical vehicles, and controllable loads, the need for a more detailed modeling of system components is a well-known issue in the context of distribution systems. Thus, a proper management of reactive power requirements, minimization of losses, and unsymmetrical operations is required. However, this consideration introduces non-linear equations that increase formulation complexity and computational burden [29]. This can explain that, in recent years, the authors have generally considered the use of DC load flow operating models. In fact, the results in Figure 5c show a predominant use of DC load flow approaches with nearly 85% of the references. In spite of the evidence, the authors expect an increase in AC approaches in the future.

Both SoC and SoH are important features to be considered in the operation of the EMS. Figure 5d shows the results on how these attributes are considered in the EMS mathematical optimization problem. In general, the large majority of the papers (nearly 70% on average) have considered the SoC to be part of the mathematical problem. In contrast, only about 15% of the papers integrate the SoH attribute into the optimization problem. No clear trends could be identified over the years for both attributes.

The high penetration of renewable generation into MGs increases multiple power injection variability. Furthermore, load forecasting uncertainty in MGs is higher compared with bulk power systems. This is explained by a high preponderance of individual loads in total MG loads and the integration of electromobility. The factors described above should be considered in EMS optimization approaches [54,55] to achieve more realistic and cost-effective results. Figure 6 summarizes these results. The orange line (linear regression trend) shows that the consideration of uncertainties into the EMS mathematical problem has increased in recent years. Figure 6a shows that in the years 2017 and 2018, uncertainties were considered in approximately 53% and 41% of the papers, respectively. Additionally, Figure 6b shows the distribution of modeled uncertainties such as generation profile, load forecast, grid electricity prices, and storage SoC. Furthermore, Figure 6b shows that the authors have generally considered the uncertainty in generation and load while storage uncertainty seems to be at an early stage but increasing in importance. Electromobility can be a key driver in this direction [56].

![Figure 6](image-url)

**Figure 6.** (a) Uncertainty trend in recent years, (b) Uncertainty consideration distribution in different microgrid agents.

The results of this section help to identify structural research issues from a comprehensive database of research works from past years. Thus, main resolution techniques, objective functions options, load flow types, storage attributes, and the integration of uncertainties were identified. Nevertheless, apart from the uncertainties (Figure 6), it was not possible to identify trends over the period of analysis.
(2012–2018). Moreover, a traditional quantitative analysis could not reveal how these research aspects are related. This situation motivated the following cluster analysis.

### 3.3. Cluster Analysis

The cluster analysis proposed is used in this section to identify additional trends in EMS developments. Only such features holding enough information (see Table 2) are considered for obtaining and analyzing these trends (e.g., detail level of components (A), objective function (B), resolution technique (C), operating model (F), and consideration of uncertainties (H)). More specifically, this identification is performed by using the Kohonen self-organizing maps (SOM) tool. The SOM is a clustering and data visualization technique based on a neural network approach. As with other types of centroid-based clustering, the objective of SOM is to find a group of centroids (reference vectors in SOM terminology) and assign each object in the data group to the centroid that provides the best approximation of that object [57].

To better visualize these trends, the SOM is integrated into RStudio [58]. It associates different colors to each attribute (e.g., red for SOBJ, yellow for MP; etc.) for a general view of the final results. The color code associated to each attribute is shown in Figure 7.

![Figure 7. Attributes considered with their respective associated color.](image)

Four distinctive groups are identified with the aid of the clustering technique. Figure 8 shows the number of papers contained by each group. Each of these groups has its respective features depending on the most common attributes present in the papers from a specific group (see Figure 9). The chart consists of a sequence of equiangular spaces, with each area representing one of the attributes. The data length of every pie is proportional to the magnitude of the attribute (weight) for the data point against the maximum magnitude of the variable across all data points. Furthermore, for every cluster there is a paper with the shortest distance to their representing attribute. This distinctive paper is known as the centroid of the cluster to which it belongs (see Figure 8). Table 2 shows the centroids (papers) for each cluster jointly with a detailed classification of their attributes.

![Figure 8. Number of papers in each cluster.](image)
The following modeling strategies, accordingly EMS trends, are identified based on this combination of attributes (see Figures 8 and 9):

Cluster 1: Dealing with uncertainties: This cluster comprises 33% of the references; therefore, it is the main research trend. Its distinctive feature is the challenge of modeling the uncertainties present in various MG agents (DM, GE, GR) that will impact the performance of the EMS. This is in line with the general idea that uncertainties are becoming an increasingly important issue in MG developments due to DER integration, more active participation of loads, and electromobility. Basic modeling strategies involve static representation of components (STM) and a DC load flow approach. The optimization model corresponds to a SOBJ function, and it is solved by either MP or CI methods. This is a reflection of alternative solution techniques exploration in research proposals. Surprisingly, HMs are not part of this EMS development trend.

As previously mentioned, the centroid of Cluster 1 corresponds to Reference [50] (see Table 2). In this work, a strategy to deal with uncertainties associated with generation and demand is presented. The SOBJ objective function considered is total profit maximization. The optimization problem is formulated by using the MP technique MILP and solved by employing CPLEX. The focus is only on the interchange of active power among power generators, energy storage, energy consumption, and the grid. Thus, DC load flow is considered. Finally, MG components are formulated as STMs (discrete-time formulation). By following step (8) from the proposed procedure, new research-specific challenges in this trend are:

- How to solve further problems entailing higher complexities by combining reactive and proactive techniques and considering the uncertainty of renewable resources and load consumption.
- Guidelines to a simultaneous consideration of different factors (i.e., costs, environmental impact, social aspects, etc.) through the implementation of multi-objective optimization approaches.

Cluster 2: Multi-objective strategy: This cluster contains approximately 29% of the references. This second leading trend addresses a multi-objective approach. For this purpose, three resolution techniques are used for the resulting optimization problem, with a slight predominance of CI approaches. Uncertainties in the fields of DM and GE have been considered on a general basis. In this case, a DC load flow approach is also the basic network modeling approach. Nonetheless, as mentioned in Section 3.2, a predominance of SOBJ approaches in the near future may be expected; a research community with a focus on MOBJ challenges exploring several solution techniques can be clearly identified.

The centroid of Cluster 2 corresponds to Reference [51]. The authors propose a MOBJ framework to minimize operational costs and the environmental impact of an MG. The mathematical problem is solved through FL and ANN, CI techniques used jointly with MP. The problem formulation includes optimum battery scheduling while considering the uncertainties of microgrid DERs and forecasted parameters. The objective functions are only subjected to active power constraints; therefore, a DC load flow is considered.

Based on step (8), research-specific challenges are:
• How a combination of CI and traditional techniques can achieve a clear and important minimization of operation costs, greenhouse gases emissions, and other technical and economic MG-related issues.

• How to achieve a highly accurate forecasting of renewable energy sources by using CI techniques, in order to comply with an efficient MG energy management.

Cluster 3: Traditional paradigm: This third cluster contains approximately 21% of the references. By conceiving a traditional approach for EMS developments, the following options might be selected: SOBJ instead of MOBJ, a deterministic approach instead of focusing on uncertainty modeling, well proven MP approaches, a static representation of components (STM) instead of a DYM approach and finally a focus on active power simulation (DC) vs. an AC paradigm. This is exactly what can be observed in this modeling trend. This type of development can be expected to be very useful for improving current commercial EMS solutions that usually follow a more traditional modeling strategy. The only unexpected feature is a substantial use of HM for the solution techniques. This issue may indicate that most research proposals and innovations in this research group address the migration of traditional MP techniques. This makes use of the advantages of combining CI solutions that constitute HM strategies. In Figure 5a, a positive evolution of this strategy is identified.

The centroid of Cluster 3 is the paper in Reference [52]. In this work, a traditional SOBJ function is used to minimize the total cost of energy. The authors assumed that the voltage level is the same at all MG busses—a DC load flow operating model. MG components are formulated as STMs in a time-discrete formulation resulting in a number of algebraic constraints. Proposed energy management is based on local energy market and allows scheduling MG generation with minimum information shared by the generating units. For EMS optimization, the authors propose a novel algorithm based on a MINLP approach for an MG in islanding mode considering different scenarios. The optimization problem is solved in a GAMS/CONOPT environment.

The following specific challenges were identified in step (8):

• How to enable the owners of the distributed generation units to establish their own strategies to participate in MG generation with minimum information shared between distributed generators. Additionally, comply with consumer’s requirements with a minimum energy cost.

• How to use demand response programs either to avoid or to decrease penalty costs and the amount of unserved power, as well as to improve demand side management.

Cluster 4: The P-Q challenge: This last cluster contains approximately 17% of the references. As mentioned in the previous section, proper management of reactive power requirements, voltage profile, ohmic losses minimization, and unsymmetrical operations are well-known issues in MG developments. Nevertheless, Figure 5c does not identify a clear trend in this field. On the contrary, the cluster analysis was able to extract a trend in this field, where AC modeling is in the core of the solution approaches, together with a predominance of CI-based solution techniques. Additionally, a more deterministic focus in modeling approaches is identified, with the exception of uncertainties in generation (GE). This is the only trend that incorporates STM and some DYM approaches. Additionally, the use of either SOBJ or MOBJ proposals has been identified in this field.

The centroid of Cluster 4 corresponds to Reference [53]. In this study, an online EMS for real-time operation of MGs is presented that considers the power flow and system operational constraints. The SOBJ formulation is to minimize the long-term operational cost, while delivering reliable and high-quality power to customers. Online energy management is modeled as a stochastic optimal power flow (AC load flow model) capable of capturing uncertainties in generation (GE). The EMS problem is solved by the Lyapunov optimization approach (CI).

Finally, Step 8 helps to identify the following research-specific challenges:

• How to properly consider the underlying power distribution network and its associated power flow and system operational constraints in order to achieve control decisions that do not transgress real-world constraints.
• How to develop an intelligent algorithm on the customer side to generate demand requests that allow the EMS to make more accurate operating decisions in the MG.

These papers’ analyses on cluster centroids validate the rationality of cluster descriptions and their main attributes.

3.4. Key Lessons Learned, Key Challenges, and Future Research Directions

The key challenges and the way to cope with them are identified based on the analysis of each trend, the results of previous reviews, and the previous experience of the authors.

Uncertainties in renewables is a topic with an increasing interest to researchers (see Figure 6a) but that is only partially integrated by the research community with a third of research results. It can be envisaged that uncertainties in renewables, demand, and grids will become a common modeling aspect in EMS proposals in the near future. Decentralized solutions will increasingly integrate local renewable sources required by small productive processes (e.g., agriculture, farming, tourism, etc.). Consequently, more complex customer/prosumer behaviors are expected. The modeling of this type of load involves new uncertainties and the need of new simulation strategies that exceeds the traditional ZIP approach (load model that considers constant impedance “Z”, constant current “I”, and constant power “P” components) or a time series analysis.

Some obstacles for the researchers to cope with additional modeling challenges that occur on a simultaneous basis have been identified, e.g., multiple objective functions, full AC network representations, and the application of hybrid solution methods. Each of these combinations constitute new challenges in this research area. In fact, researchers have recently considered introducing more than one objective into the objective functions to enhance overall MG performance (e.g., minimization of operational cost, reduction of polluting gases, maximization of the service life of batteries, etc.). An emerging topic in this field is the integration of dynamic socio-environmental preferences from the local community. The work on the relative weights of the different objective functions is limited, and new consensus strategies resulting from community participation are being developed. Socio-environmental preferences may also be linked to present and future economic costs, which are not only related to the cost of electricity. The integration of all the foregoing is optimal for developing an EMS that considers all real-world constraints while satisfying consumer requirements at the same time. This increase in complexity will impact not only the computational burden of the resulting optimization problems but also the convexity properties of mathematical models, the availability and quality of input data, communication network requirements (bandwidth), cost reduction needs, among others. Based on the specific MG features (size, type and number of technologies, environmental conditions, etc.) a balance and trade-off analysis should be conducted by the researchers in order to develop adequate and practical proposals. Internet of Things (IoT) may play a key role in this area for both the access to a wide range of information sources and types and the cost-effective data acquisition approach. In fact, an important benefit of IoT to microgrids is the ability to control non-critical loads (demand side management), which is the ability to run the microgrid at the lowest possible cost whilst providing the highest possible reliability to provide power to critical loads and improve its flexibility. Moreover, IoT allows the application of DSM in a context of diverse commercial solutions of appliances, a common issue related to MG globally. In this context, more accurate and computationally efficient dynamic models for critical MG components are needed. The centralized approach needs a representation of the critical stability aspects related to operational decisions. The transition between the operation modes is a clear example in the case of isolated operations. The feasibility and impact of each transition should be considered as part of the EMS optimization strategy. Nowadays, this aspect is only considered for specific MG configurations (i.e., failure of the master unit and replacement of a specific predefined back-up unit). This constitutes a barrier for a massive integration of these solutions in everchanging local conditions.

On the other hand, storage systems are one key component for EMS operation. Thus, both SoC and SoH should be fully considered in the EMS mathematical optimization problem. However,
according to the findings from this work, SoH is still not considered on a frequent basis. Consequently, research efforts should focus on developing valid, general, and suitable SoH models to be included in the EMS mathematical problem. Moreover, to consider multiple storage systems in a single, MG.; equivalent storage system approaches or clustering should be considered.

The results have shown that most of these papers hold a high consideration of DC load flow. However, reactive power is also an important part of MG and should be considered in energy management to achieve a reliable and secure system. However, this consideration introduces non-linear equations that increase formulation complexity and computational burden. Therefore, research efforts should focus on developing low complexity and computationally efficient AC load flow models.

To solve the EMS mathematical optimization problem, MP, CI, and HM have been used. CI approaches have advantages in convergence speed and large-scale problem solving compared to MP methods. However, CI techniques may fall into local optima as MG complexity increases. HM approaches that combine the benefits of the above methods have attracted researchers’ attention. Thus, it could be a great opportunity to focus on developing new HM approaches.

The results of this research trend analysis show that there is no evidence of a research cluster where all EMS development challenges were dealt with on a simultaneous basis. In fact, research proposals in every cluster are mainly focused on the improvement of specific areas, while making some simplifications in others. Thus, these proposals can be addressed with the mathematical and computational resources currently available. A clear understanding of each of the four trends identified can be considered a good starting point and guidance for future research contributions. In spite of current proposals imposing some simplifications, they have been accepted for the deployment of EMSs around the world. Thus, they reflect proposals that aim at dealing with specific contexts and practical solutions that can be improved in a number of dimensions, based on the main features and levels of complexity summarized in Section 2.3.

Finally, innovative DSM and storage applications and concepts may play a key role to overcome the current and future challenges faced in the design and solutions of MGs. Thus, more cost-effective, reliable, social, and environmentally compatible solutions are feasible. These opportunities, i.e., key enablers for massive MG integration, have not been properly addressed in the literature.

4. Conclusions and Future Works

A review of EMS research trends and their main features is explored in this paper. A brief EMS overview with control architecture types is presented. The quantitative analysis helps to identify some structural aspects in EMS research efforts. Nevertheless, it could not reveal more complex relationships among the main modeling attributes. Therefore, the need of a further analysis based on the clustering approach is emphasized. Upon a cluster analysis, the main trends in the EMS field for microgrids focused on centralized control architectures are discovered. Following a systematic analysis, four main existing research trends are identified: (i) dealing with uncertainties, (ii) multi-objective strategy, (iii) traditional paradigm, and (iv) P-Q challenge. These results prove the existence of active and dynamic research fields in separate research communities where specific research challenges are covered. These trends, together with the entire database of papers, are useful for a better understanding of the current challenges and main open questions in the field of centralized EMS developments. Thus, future research efforts and trends can be developed. The key challenges and the way to cope with them are described based on the rationality of each trend, the results of previous reviews, and the previous experience of the authors. An analysis of cluster centroids that is not cluster-limited is a clear method to identify research-specific challenges. As future work, the authors propose the development of a software tool for the selection of a centralized EMS containing the most appropriate attributes depending on the requirements of each user profile. Additionally, it may be reviewed whether the proposed analysis scheme can become a generally valid classification methodology for other research fields. Finally, since the storage system is a key component in EMS operations, a detailed classification about storage systems becomes a relevant research topic for future improvement options.
Author Contributions: R.P.-B. proposed the initial idea of the investigation. D.E.-S. and O.N.-M. developed the review of the state-of-the-art. Then, together with R.P.-B., they developed the first discussions about the different aspects of the proposed methodology. R.P.-B. and D.E.-S. conceived and designed the strategy for clustering-based data analysis. D.E.-S. developed the clustering analysis. Then, together with R.P.-B., they developed the data analysis and identified the main trends. O.N.-M. made a complete review and edit of the paper before it was submitted. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Chilean Council of Scientific and Technological Research CONICYT-PFCHA/Doctorado Nacional/2017-21171695 and by CONICYT (FONDAP SERC Chile grant number 15110019 and CONICYT/FONDECYT grant number 1181532).

Acknowledgments: The authors would like to thank Chilean Council of Scientific and Technological Research CONICYT for supporting this paper through CONICYT-PFCHA/Doctorado Nacional/2017-21171695. Additionally, this research was supported by SERC Chile FONDAP/CONICYT, grant number 15110019, FONDECYT 1181532 and Ayllu Solar.

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

Appendix A

Table A1. Mathematical programming techniques.

| Acronym | Description                        |
|---------|-----------------------------------|
| LP      | Linear Programming                |
| MILP    | Mixed-Integer Linear Programming  |
| DP      | Dynamic Programming               |
| QP      | Quadratic Programming             |
| MINLP   | Mixed-Integer Non-Linear Programming|
| SLP     | Stochastic Linear Programming      |
| RO      | Robust Optimization               |
| SO      | Stochastic Optimization           |
| MIQCP   | Mixed-Integer Quadratically Constrained Programming |

Table A2. Computational intelligence techniques.

| Acronym | Description                        |
|---------|-----------------------------------|
| GA      | Genetic Algorithms                |
| CQGA    | Chaotic Quantum Genetic Algorithm |
| NSGA    | Nondominated Sorting Genetic Algorithm |
| HGA     | Hierarchical Genetic Algorithm    |
| INIGA   | Isolation Niche Immune Genetic Algorithm |
| FL      | Fuzzy Logic                       |
| MPC     | Model Predictive Control          |
| PSO     | Particle Swarm Optimization       |
| DE      | Differential Evolution            |
| ANN     | Artificial Neural Networks        |
| MACO    | Multi-Layer Ant Colony Optimization |
| ABC     | Ant Bee Colony                    |
| AMFA    | Adaptive Modified Firefly Algorithm |
| IBO     | Interval-Based Optimization       |
| ICA     | Imperialist Competitive Algorithm |
| LO      | Lyapunov Optimization             |
| LHMPC   | Lyapunov Hybrid Model Predictive Control |
| MGSA    | Multi-period Gravitational Search Algorithm |
| NEA     | Niching Evolutionary Algorithm    |
| MBFO    | Modified Bacterial Foraging Optimizaiton |
| ITLBO   | Improved Teaching-Learning-Based Optimization |
| SGSAl   | Self-Adaptive Gravitational Search Algorithm |
| MOMADS  | Multi-Objective Mesh Adaptive Direct Search |
| PCAO    | Parameterized Cognitive Adaptive Optimization |
Table A2. Cont.

| Acronym | Description                                      |
|---------|--------------------------------------------------|
| EADP    | Evolutionary Adaptive Dynamic Programming         |
| RB      | Rule-Based                                        |
| SSOA    | Search Strategy Based On Orthogonal Array         |
| CBPSO   | Chaotic Binary Particle Swarm Optimization        |
| MOPSO   | Multi-Objective Particle Swarm Optimization       |
| EDF     | Event-Driven Framework                            |
| NRSFS   | Non-Dominated Ranking Stochastic Fractal Search   |
| SA      | Simulated Annealing                               |
| D&C     | Divide And Conquer Algorithm                      |
| FSM     | Finite State-Machine                              |

Table A3. Hybrid method’s techniques.

| Acronym | Description                                                                 |
|---------|-----------------------------------------------------------------------------|
| MPC + MILP | Model Predictive Control plus Mixed-Integer Linear Programming              |
| MPC + MIQP | Model Predictive Control plus Mixed-Integer Quadratic Programming          |
| MO + FL + ANN | Multi-Objective Optimization plus Fuzzy Logic and Artificial Neural Networks |
| SM + GA | State Machine Approach plus Genetic Algorithms                              |
| MIP + SBA | Mixed-Integer Programming plus Subgradient-Based Algorithm                   |
| FL + CSA | Fuzzy Logic plus Cuckoo Search Algorithm                                     |
| NMPC + MINLP | Non-Linear Model Predictive Control plus Mixed-Integer Non-Linear Programming |
| MPC + MINLP | Model Predictive Control plus Mixed-Integer Non-Linear Programming           |
| MPC + MIQP + MINLP | Model Predictive Control plus Mixed-Integer Quadratic Programming and Mixed-Integer Non-Linear Programming |
| MPC + MILP + TSSP | Model Predictive Control plus Mixed-Integer Linear Programming and Two-Stage Stochastic Programming |
| MPC + SMILP + NLP | Model Predictive Control plus Stochastic Mixed-Integer Linear Programming and Non-Linear Programming |
| SMPC + DP + EM | Stochastic Model Predictive Control plus Dynamic Programming and Empirical Mean |
| DL + ADP | Deep Learning plus Adaptive Dynamic Programming                            |
| PSO + PDIP | Particle Swarm Optimization plus Primal-Dual Interior Point                 |
| PSO + SQP + FL | Particle Swarm Optimization plus Stochastic Quadratic Programming and Fuzzy Logic |
| LO + MIP | Lyapunov Optimization plus Mixed-Integer Programming                        |
| LP + SA | Linear Programming plus Simulated Annealing                                  |
| MO + GA | Multi-Objective Optimization plus Genetic Algorithms                       |
Appendix B

Table A4. Papers published in 2012.

| Ref. | A    | B     | C         | D                  | E   | F   | G     | H     | I     | J         |
|------|------|-------|-----------|--------------------|-----|-----|-------|-------|-------|-----------|
| [59] | STM  | MOBJ  | ITLBO     | GFO + DFO + OIN   | OOU | DC  | DY    | DM+GE | GR    |            |
| [60] | STM  | MOBJ  | CQGA      | GFO + DFO         | DSET| DC  |       |       |       |            |
| [61] | STM  | SOBJ  | SMPC + DP + EM | GFO + DFO     | DC  |     | HR    | DM+GE |       |            |
| [62] | STM  | SOBJ  | FL       | OIN               | OOU | DC  |       |       |       |            |
| [63] | STM  | MOBJ  | DP       | GFO + DFO + OIN   | UC+OOU| DC  | DY    | MIN   |       |            |
| [64] | STM  | SOBJ  | FL       | OIN               | OOU | DC  |       |       |       |            |
| [65] | STM  | SOBJ  | FL       | OIN               | OOU | DC  |       | MIN   |       |            |
| [66] | STM  | MOBJ  | LP + SA  | GFO + DFO + OIN   | DSET| DC  | DY    | DM+GE | GR    | HR        |
| [67] | STM  | SOBJ  | SGSA     | GFO + DFO + OIN   | DSET+OOU| DC  |       |       |       |            |
| [68] | STM  | MOBJ  | MOMADS   | GFO + DFO + OIN   | OOU | DC  |       |       |       |            |
| [69] | STM  | SOBJ  | MPC + MILP | OIN               | DSET+OOU| DC  |       |       |       |            |
| [70] | STM  | MOBJ  | NEA      | OIN               | DSET| AC  |       |       |       |            |
| [71] | STM  | MOBJ  | SQP + PSO + FL | OIN               | DSET+OOU| DC  | DY    |       |       |            |
| [72] | STM  | SOBJ  | MPC      | OIN               | DSET+OOU| DC  |       |       |       |            |
| [73] | STM  | MOBJ  | AA       | OIN               | DSET| DC  | DY    |       |       |            |
| [74] | STM  | SOBJ  | MINLP    | OIN               | OOU | DC  |       | DM+GE | MILI  |            |
Table A5. Papers published in 2013.

| Ref. | A   | B    | C      | D               | E              | F      | G    | H    | I   | J    |
|------|-----|------|--------|-----------------|----------------|--------|------|------|-----|------|
| [49] | STM | SOBJ | MILP   | GFO + DFO + OIN | DSET + DSM +  | DC     | DY + YR | DM + GE | SEC | MIN |
| [75] | STM | MOBJ | MPC    | GFO + DFO + OIN | DSET           | DC     | HR   | GE   | MIN |
| [76] | STM | SOBJ | AMFA   | GFO + DFO + OIN | DSET           | DC     | DM + GE + GR |
| [77] | STM | SOBJ | MILP   | GFO + DFO + OIN | DSET + DSM     | DC     | DY + YR |
| [78] | STM | SOBJ | FL     | GFO + OIN       | OOU            | DC     |
| [79] | STM | MOBJ | MPC + MIQP | GFO + DFO + OIN | DSET + OOU    | AC     | SEC |
| [80] | STM | MOBJ | MILP   | DFO + OIN       | OOU            | DC     | DY   |
| [81] | STM | SOBJ | QP     | DFO + OIN       | DSET           | DC     |
| [82] | STM | SOBJ | MILP   | GFO + OIN       | DSET + OOU     | DC     | DY   |
| [83] | STM | SOBJ | SM+GA  | OIN             | DSET + OOU     | DC     | HR   |
| [84] | STM | SOBJ | MILP   | OIN             | OOU            | AC     |
| [85] | STM | MOBJ | MINLP  | GFO+DFO+OIN     | OOU            | DC     | HR   |
| [86] | STM | MOBJ | SLP    | GFO + OIN       | DSET           | DC     | DY   | GE   | MIN |
| [87] | STM | MOBJ | MILP   | DFO + OIN       | OOU            | DC     | DY   | HR   |
| [88] | STM | MOBJ | NSGA   | GFO + OIN       | DSET           | DC     | HR   |
| [89] | STM | MOBJ | SO     | GFO + DFO + OIN | DSET           | DC     | DM + GE | HR |
| [90] | STM | SOBJ | FL     | OIN             | OOU            | DC     | HR   |
| [91] | DYM | SOBJ | DP     | OIN             | OOU            | AC     | DY   | MIN |
| [92] | STM | SOBJ | DP     | GFO + OIN       | DSET           | DC     |
| [93] | STM | SOBJ | FL     | GFO + OIN       | DSET + OOU     | DC     | HR   |
| [94] | STM | SOBJ | MPC    | GFO + DFO + OIN | DSET + OOU     | DC     | HR   | MIN |
| [95] | STM | SOBJ | INIGA  | OIN             | DSM            | DC     | DY   |
| [96] | STM | MOBJ | MO + FL + ANN | GFO + OIN | DSET           | DC     | DM + GE |
| [97] | STM | MOBJ | AA     | OIN             | DSET + DSM     | DC     | DY   | DM + GE | MIN |
Table A6. Papers published in 2014.

| Ref. | A | B | C       | D       | E       | F       | G       | H       | I       | J       |
|------|---|---|---------|---------|---------|---------|---------|---------|---------|---------|
| [29] | STM| SOB| MPC     | MILP    | GFO     | DFO     | DSET    | AC      | HR      | DY      |
| [98] | STM| SOB| AA      | MPC     | MILP    | DFO     | OIN     | OOU     | DC      | DY      |
| [99] | STM| SOB| AA      | MPC     | MILP    | DFO     | OIN     | OOU     | DC      | DY      |
| [100]| STM| MOB| MPC     | MILP    | DFO     | OIN     | DSET    | OOU     | DC      | HR      |
| [101]| STM| SOB| GA      | MILP    | OIN     | DSET    | OOU     | DC      | DY      | MIN     |
| [102]| STM| SOB| MILP    | OIN     | DSET    | OOU     | DC      | OIN     | DC      | MIN     |
| [103]| DYM| AA  | OIN     | OUU     | DC      | DY      | MIN     |
| [104]| STM| SOB| FL      | OIN     | OOU     | DC      | MIN     |
| [105]| STM| SOB| FL      | OIN     | OOU     | DC      | MIN     |
| [106]| STM| SOB| PSO     | OIN     | OOU     | DC      | MIN     |
| [107]| STM| SOB| FL + CSA| OIN     | DSET    | OOU     | DC      | MIN     |
| [108]| STM| SOB| MIP + SBA| GFO    | DFO     | UC      | DC      | DY      | MIN     |
| [109]| STM| MOB| SO      | GFO     | DFO     | DSET    | OOU     | DC      | DY      |
| [110]| STM| SOB| MINLP   | GFO     | DFO     | OIN     | OOU     | AC      | DY      |
| [111]| STM| SOB| MPC     | MILP    | GFO     | DFO     | OIN     | DSET    | OOU     | DC      | DY      |
| [112]| STM| SOB| MILP    | GFO     | DFO     | OIN     | OOU     | DC      | DY      |
| [113]| STM| MOB| MGSA    | OIN     | DSET    | DC      | DY      |
| [114]| STM| MOB| GA      | DSET    | DC      | DY      |
| [115]| STM| SOB| LP      | DSET    | DC      | DY      |
| [116]| STM| MOB| MBFO    | OIN     | DSET    | OOU     | DC      | DY      |

Table A7. Papers published in 2015.

| Ref. | A | B | C       | D       | E       | F       | G       | H       | I       | J       |
|------|---|---|---------|---------|---------|---------|---------|---------|---------|---------|
| [117]| STM| SOB| MILP    | GFO     | DFO     | UC     | OOU     | DC      | DY      | HR      |
| [50] | STM| SOB| MILP    | OIN     | DSET    | OOU     | DC      | DY      | MIN     |
| [118]| STM| SOB| MPC     | WFO     | OIN     | DSM     | OOU     | DC      | DY      | MIN     |
| [119]| STM| SOB| GA      | OIN     | DSET    | OOU     | DC      | DY      | MIN     |
| [120]| STM| SOB| AA      | GFO     | DFO     | OIN     | DSET    | OOU     | DC      | DY      |
| [121]| DYM| SOB| FL      | OIN     | DSET    | OOU     | DC      | SEC     | MIN     |
| [122]| STM| MOB| DE      | DSET    | DC      | DY      |
| [123]| DYM| SOB| PCAO    | OIN     | OOU     | DC      | MIN     |
| [124]| STM| SOB| FL      | OIN     | OOU     | DC      | MIN     |
| [125]| STM| SOB| ICA     | OIN     | DSET    | OOU     | DC      | DY      |
| [15] | STM| SOB| RB      | OIN     | DSET    | DC      | DY      |
| [126]| STM| SOB| ANN     | OIN     | OOU     | DC      | MIN     |
| [127]| STM| SOB| MPC + SMILP + NLP | GFO + OIN | DSET + UC | AC | DY | GE | MIN |
### Table A8. Papers published in 2016.

| Ref. | A    | B    | C    | D       | E       | F       | G       | H       | I       | J       |
|------|------|------|------|---------|---------|---------|---------|---------|---------|---------|
| [6]  | STM  | MOBJ | SO   | GFO + DFO + OIN | DSM     | DC      | DY      | DM + GE + GR |
| [128]| STM  | SOBJ | LP   | OIN    | OOU     | DC      |  |  |  |  |
| [129]| STM  | MOBJ | EADP | OIN    | OOU     | DC      | MIN     |  |  |  |
| [130]| STM  | SOBJ | IBO  | DSET   | DC      | DY      | DM + GE |  |  |  |
| [131]| STM  | SOBJ | AA   | OIN    | DSET    | DC      | DY      |  |  |  |
| [132]| STM  | MOBJ | AA   | GFO + OIN | DSET    | AC      | HR      |  |  |  |
| [133]| STM  | SOBJ | RB   | OIN    | DSET + DSM | AC      | DY      |  |  |  |
| [134]| STM  | SOBJ | MILP | GFO + DFO | DSET + UC | DC      |  |  |  |  |
| [135]| STM  | SOBJ | FL   | OIN    | OOU     | DC      |  |  |  |  |
| [136]| STM  | SOBJ | NMPC + MINLP | DFO+OIN | OOU     | AC      | MIN | MIN |  |  |
| [142]| STM  | SOBJ | AA   | OIN    | OOU     | DC      |  |  |  |  |
| [143]| STM  | MOBJ | ABC  | OIN    | DSET    | UC + DSM | DC      | DY | DM + GE | MIN |
| [144]| STM  | SOBJ | SSOA | DFO + OIN | DSET + DSM | DC      | DY | DM + GE | MIN |
| [145]| STM  | MOBJ | MPC  | GFO + OIN | DSET + DSM | DC      | DY | GE | MIN |
| [146]| STM  | SOBJ | MACO | OIN    | DSET + DSM + OOU | DC | MIN+DY |  |  |
| [147]| STM  | MOBJ | CBPSO |  | AC      |  | DM + GE |  |  |

### Table A9. Papers published in 2017.

| Ref. | A    | B    | C    | D       | E       | F       | G       | H       | I       | J       |
|------|------|------|------|---------|---------|---------|---------|---------|---------|---------|
| [142]| STM  | SOBJ | EDF  | OOU    | DC      | DY      | ST      | MIN     |  |  |
| [143]| STM  | MOBJ | MPC + MIQP + MINLP | UC + DSM | DC      | DY | DM + GE | MIN |
| [144]| STM  | SOBJ | ABC  | OIN    | DSET    | OOOU    | DC      |  |  |  |
| [145]| STM  | MOBJ | MO + GA | OIN    | OOU     | DC      |  |  |  |  |
| [146]| STM  | SOBJ | AA   | OIN    | OOU     | DC      |  |  |  |  |
| [147]| STM  | MOBJ | NRFS | DFO    | OOI     | DC      |  |  |  |  |
| [148]| STM  | MOBJ | LP + MINLP | GFO + OIN | DSET    | AC | DY | DM + GE | MIN |
| [149]| STM  | MOBJ | HGA  | DFO    | DSET    | AC      |  |  |  |  |
| [150]| STM  | MOBJ | NSGA | GFO    | DC      | DY | GE |  |  |
| [151]| STM  | MOBJ | SA   | DFO    | DC      | DY |  |  |  |  |
| [152]| STM  | MOBJ | D&C  | DFO    | DC      |  |  |  |  |  |
| [153]| STM  | MOBJ | LO   | DFO    | DC      |  |  |  |  |  |
| [154]| STM  | SOBJ | MILP | GFO    | DSET    | DC | DM + GE |  |  |  |
### Table A10. Papers published in 2018.

| Ref. | A      | B      | C          | D          | E    | F    | G    | H    | I   | J     |
|------|--------|--------|------------|------------|------|------|------|------|-----|-------|
| [156] | STM    | SOBJ   | FL + PSO   | DFO + OIN  | OOU  | DC   | DY   |      |     | MIN   |
| [157] | STM    | MOBJ   | AA         | GFO + DFO  | DSET + UC | DC   | DY   | DM + GE |     |       |
| [158] | STM    | SOBJ   | SO + MIQCP | FL         | OIN  | DSET + UC | DC   | HR + DY | MIN |
| [159] | STM    | SOBJ   | RO         | FL         | OIN  | DSET + UC | DC   | DY   | SEC  |
| [160] | STM    | MOBJ   | MOPSO      |            |      |      |      |      |     |       |
| [161] | STM    | MOBJ   |            |            |      |      |      |      |     |       |
| [162] | STM    | SOBJ   | MILP       | GFO + DFO  | OOU  | DC   | HR   | GE   | MILI| MIN   |
| [163] | STM    | SOBJ   | MILP       | GFO + DFO  | DSET + DSM | DC   | DY   |     | HR   |
| [164] | STM    | SOBJ   | SO         | GFO + DFO + OIN | OOU  | AC   | DY   | GE   |     |       |
| [165] | STM    | SOBJ   | DP         | DFO + WFO  | DSET  | DC   | DM + GE |     |     |       |
| [166] | STM    | SOBJ   | PSO + PDIP |            | OIN  | DSET + OOU | AC   | DY   | GE   |     |
| [167] | DYM    | SOBJ   | AA         |            | OIN  |      |      |      |     |       |
| [168] | STM    | SOBJ   | LO + MIP   | GFO + DFO + OIN | DSET + UC | DC   | DY   | DM + GE |     |       |
| [169] | STM    | SOBJ   | DL + ADP   | OIN         | DSET + OIN | DC   |      | MIN  |     |       |
| [170] | STM    | SOBJ   | FSM        | OIN         | DSET  | AC   |      | MILI |     |       |
| [171] | STM    | SOBJ   | MINLP      |            |      |      |      |      |     |       |
| [172] | STM    | SOBJ   | LHMPC      |            |      |      | UC + DSET + OOU | DC   | DY   | MIN  |
| [173] | STM    | SOBJ   | RO + MPC   | GFO + DFO  | DSET  | DC   | DY   | DM + GE | HR |       |
References

1. Torbaghan, S.S.; Blaauwbroek, N.; Kuiken, D.; Gbescu, M.; Hajighasemi, M.; Nguyen, P.; Smit, G.J.; Roggenkamp, M.; Hurink, J. A market-based framework for demand side flexibility scheduling and dispatching. *Sustain. Energy Grids Netw.* 2018, 14, 47–61. [CrossRef]

2. Olatomiwa, L.; Mehkilef, S.; Ismail, M.S.; Moghavvemi, M. Energy management strategies in hybrid renewable energy systems: A review. *Renew. Sustain. Energy Rev.* 2016, 62, 821–835. [CrossRef]

3. Plass, B. Smart microgrids [distributed power generation]. In Proceedings of the 2001 IEEE Power Engineering Society Winter Meeting Conference Proceedings (Cat. No.01CH37194), Columbus, OH, USA, 28 January–1 February 2001; Volume 1, pp. 146–149. [CrossRef]

4. Lasseter, R.H. MicroGrids. In Proceedings of the 2002 IEEE Power Engineering Society Winter Meeting Conference Proceedings (Cat. No.02CH37309), New York, NY, USA, 27–31 January 2002; Volume 1, pp. 305–308. [CrossRef]

5. An, L.N.; Quoc-Tuan, T. Optimal energy management for grid connected microgrid by using dynamic programming method. In Proceedings of the 2015 IEEE Power Energy Society General Meeting, Denver, CO, USA, 26–30 July 2015; pp. 1–5. [CrossRef]

6. 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]

7. Huang, K.; Wang, X.; Yang, L.; Wang, L. Optimal energy management of grid-connected photovoltaic micro-grid. In Proceedings of the 2015 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems, Shenyang, China, 8–12 June 2015; pp. 234–239. [CrossRef]

8. Ma, L.; Liu, N.; Zhang, J.; Tushar, W.; Yuen, C. Energy Management for Joint Operation of CHP and PV Prosumers Inside a Grid-Connected Microgrid: A Game Theoretic Approach. *IEEE Trans. Ind. Inform.* 2016, 12, 1930–1942. [CrossRef]

9. Arcos-Aviles, D.; Pascual, J.; Guinjoan, F.; Marroyo, L.; Sanchis, P.; Marietta, M.P. Low complexity energy management strategy for grid profile smoothing of a residential grid-connected microgrid using generation and demand forecasting. *Appl. Energy* 2017, 205, 69–84. [CrossRef]

10. Mohan, V.; Singh, J.G.; Onsakul, W.; Madhu, M.N.; Reshma Suresh, M.P. Economic and network feasible online power management for renewable energy integrated smart microgrid. *Sustain. Energy Grids Netw.* 2016, 7, 13–24. [CrossRef]

11. Gabbar, H.A.; Zidan, A. Optimal scheduling of interconnected micro energy grids with multiple fuel options. *Sustain. Energy Grids Netw.* 2016, 7, 80–89. [CrossRef]

12. Marino, C.; Quddus, M.A.; Marufuzzaman, M.; Cowan, M.; Bednar, A.E. A chance-constrained two-stage stochastic programming model for reliable microgrid operations under power demand uncertainty. *Sustain. Energy Grids Netw.* 2018, 13, 66–77. [CrossRef]

13. Ismail, M.S.; Moghavvemi, M.; Mahlia, T.M.I. Techno-economic analysis of an optimized photovoltaic and diesel generator hybrid power system for remote houses in a tropical climate. *Energy Convers. Manag.* 2013, 69, 163–173. [CrossRef]

14. Dahmane, M.; Bosche, J.; El-Hajjaji, A.; Dafarivar, M. Renewable energy management algorithm for stand-alone system. In Proceedings of the 2013 International Conference on Renewable Energy Research and Applications, Madrid, Spain, 20–23 October 2013; pp. 621–626. [CrossRef]

15. Dash, V.; Bajpai, P. Power management control strategy for a stand-alone solar photovoltaic-fuel cell–battery hybrid system. *Sustain. Energy Technol. Assess.* 2015, 9, 68–80. [CrossRef]

16. Nasri, S.; Sami, B.S.; Cherif, A. Power management strategy for hybrid autonomous power system using hydrogen storage. *Int. J. Hydrog. Energy* 2016, 41, 857–865. [CrossRef]

17. Chalise, S.; Sternhagen, J.; Hansen, T.M.; Tonkoski, R. Energy management of remote microgrids considering battery lifetime. *Electr. J.* 2016, 29, 1–10. [CrossRef]

18. Amrollahi, M.H.; Bathaei, S.M.T. Techno-economic optimization of hybrid photovoltaic/wind generation together with energy storage system in a stand-alone micro-grid subjected to demand response. *Appl. Energy* 2017, 202, 66–77. [CrossRef]

19. Manbachi, M.; Ordonez, M. AMI-based Energy Management for Islanded AC/DC Microgrids Utilizing Energy Conservation and Optimization. *IEEE Trans. Smart Grid* 2018, 1. [CrossRef]
20. Katiraei, F.; Iravani, R.; Hatzigiorgiou, N.; Dimeas, A. Microgrids management. *IEEE Power Energy Mag.* 2008, 6, 54–65. [CrossRef]

21. Eskandari, M.; Li, L.; Moradi, M.H. Improving power sharing in islanded networked microgrids using fuzzy-based consensus control. *Sustain. Energy Grids Netw.* 2018, 16, 259–269. [CrossRef]

22. Alusio, B.; Dicorato, M.; Forte, G.; Trovato, M. An optimization procedure for Microgrid day-ahead operation in the presence of CHP facilities. *Sustain. Energy Grids Netw.* 2017, 11, 34–45. [CrossRef]

23. Javadi, M.; Marzband, M.; Akorede, M.; Godina, R.; Saad, A.; Pourrezaei, E. A Centralized Smart Decision-Making Hierarchical Interactive Architecture for Multiple Home Microgrids in Retail Electricity Market. *Energies* 2018, 11, 3144. [CrossRef]

24. Hatzigiorgiou, N. *Microgrid: Architectures and Control*, 1st ed.; Wiley-IEEE Press: New Jersey, NY, USA, 2014.

25. Pourbabak, H.; Chen, T.; Su, W. 1-Centralized, Decentralized, and Distributed Control for Energy Internet; Su, W., Huang, A.Q.B.T.-T.E.I., Eds.; Woodhead Publishing: Cambridge, UK, 2019; pp. 3–19. [CrossRef]

26. Rafique, S.F.; Jianhua, Z. Energy management system, generation and demand predictors: A review. *IET Gener. Transm. Distrib.* 2018, 12, 519–530. [CrossRef]

27. Senjyu, T.; Kuninaka, R.; Urasaki, N.; Fujita, H.; Funabashi, T. Power system stabilization based on robust centralized and decentralized controllers. In Proceedings of the 2005 International Power Engineering Conference, Singapore, 29 November–2 December 2005; Volume 2, pp. 905–910. [CrossRef]

28. Almasalma, H.; Engels, J.; Deconinck, G. Peer-to-Peer Control of Microgrids 2017. Available online: https://arxiv.org/pdf/1711.04070.pdf (accessed on 3 January 2020).

29. Olivares, D.E.; Cañizares, C.A.; Kazeneri, M. A Centralized Energy Management System for Isolated Microgrids. *IEEE Trans. Smart Grid* 2014, 5, 1864–1875. [CrossRef]

30. Olivares, D.E.; Cañizares, C.A.; Kazeneri, M. A centralized optimal energy management system for microgrids. In Proceedings of the 2011 IEEE Power and Energy Society General Meeting, Detroit, MI, USA, 24–28 July 2011; pp. 1–6. [CrossRef]

31. Meng, L.; Sanseverino, E.R.; Luna, A.; Dragicevic, T.; Vasquez, J.C.; Guerrero, J.M. Microgrid supervisory controllers and energy management systems: A literature review. *Renew. Sustain. Energy Rev.* 2016, 60, 1263–1273. [CrossRef]

32. Feng, X.; Shekhar, A.; Yang, F.; Hebner, R.E.; Bauer, P. Comparison of Hierarchical Control and Distributed Control for Microgrid Comparison of Hierarchical Control and Distributed Control for Microgrid. *Electr. Power Compon. Syst. Syst.* 2017, 45, 1043–1056. [CrossRef]

33. Olivares, D.E.; Mehrizi-Sani, A.; Etemadi, A.H.; Cañizares, C.A.; Iravani, R.; Kazeneri, M.; Hajimiragha, A.H.; Gomis-Bellmunt, O.; Saeedifard, M.; Palma-Behnke, R.; et al. Trends in Microgrid Control. *IEEE Trans. Smart Grid* 2014, 5, 1905–1919. [CrossRef]

34. Tayab, U.B.; Roslan, M.A.B.; Hwai, L.J.; Kashif, M. A review of droop control techniques for microgrid. *Renew. Sustain. Energy Rev.* 2017, 76, 717–727. [CrossRef]

35. Feng, X. Dynamic balancing for low inertia power systems. In Proceedings of the 2013 IEEE Power & Energy Society General Meeting, Vancouver, BC, Canada, 21–25 July 2013; pp. 1–5. [CrossRef]

36. Hatata, A.Y.; Sedhom, B.E.; El-Saadawi, M.M. A modified droop control method for microgrids in islanded mode. In Proceedings of the 2017 Nineteenth International Middle East Power Systems Conference, Cairo, Egypt, 19–21 December 2017; pp. 728–734. [CrossRef]

37. Katiraei, F.; Iravani, M.R. Power Management Strategies for a Microgrid With Multiple Distributed Generation Units. *IEEE Trans. Power Syst.* 2006, 21, 1821–1831. [CrossRef]

38. 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]

39. Pradhan, S.; Mishra, D.; Maharana, M.K. Energy management system for micro grid pertaining to renewable energy sources: A review. In Proceedings of the 2017 International Conference on Innovative Mechanisms for Industry Applications, Bangalore, India, 21–23 February 2017; pp. 18–23. [CrossRef]

40. Ahmad Khan, A.; Naem, M.; Iqbal, M.; Qaiser, S.; Anpalagan, A. A compendium of optimization objectives, constraints, tools and algorithms for energy management in microgrids. *Renew. Sustain. Energy Rev.* 2016, 58, 1664–1683. [CrossRef]

41. Minchala-Avila, L.I.; Garza-Castañón, L.E.; Vargas-Martínez, A.; Zhang, Y. A Review of Optimal Control Techniques Applied to the Energy Management and Control of Microgrids. *Procedia Comput. Sci.* 2015, 52, 780–787. [CrossRef]
42. Núñez-Mata, O.; Palma-Behnke, R.; Valencia, F.; Mendoza-Araya, P.; Jiménez-Estévez, G. Adaptive Protection System for Microgrids Based on a Robust Optimization Strategy. *Energies* 2018, 11, 308. [CrossRef]
43. Sinha, S.M. *Mathematical Programming: Theory and Methods*. Elsevier Science; Sinha, S.-M., Ed.; Elsevier Inc.: Burlington, NJ, USA, 2006; pp. 1–9. [CrossRef]
44. IEEE Computational Intelligence Society. What is Computational Intelligence? 2018. Available online: https://cis.ieee.org/about/what-is-ci (accessed on 30 May 2019).
45. Dorf, R.C.; Bishop, R.H. *Modern Control Systems*; Pearson Prentice Hall: Upper Saddle River, NJ, USA, 2011.
46. Seborg, D.E.; Mellichamp, D.A.; Edgar, T.F.; Doyle, F.J. *Process Dynamics and Control*; John Wiley & Sons: Hoboken, NJ, USA, 2010.
47. Baimel, D.; Belikov, J.; Guerrero, J.M.; Levron, Y. Dynamic Modeling of Networks, Microgrids, and Renewable Sources in the dq0 Reference Frame: A Survey. *IEEE Access* 2017, 5, 21323–21335. [CrossRef]
48. Nasir, M.; Zaffar, N.A.; Khan, H.A. Analysis on central and distributed architectures of solar powered DC microgrids. In *Proceedings of the 2016 Clemson University Power Systems Conference*, Clemson, SC, USA, 8–11 March 2016; pp. 1–6. [CrossRef]
49. Palma-Behnke, R.; Benavides, C.; Lanas, F.; Severino, B.; Reyes, L.; Llanos, J.; Sáez, D. A Microgrid Energy Management System Based on the Rolling Horizon Strategy. *IEEE Trans. Smart Grid* 2013, 4, 996–1006. [CrossRef]
50. 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]
51. Chaouachi, A.; Kamel, R.M.; Andoulisi, R.; Nagasaka, K. Multiobjective Intelligent Energy Management for a Microgrid. *IEEE Trans. Ind. Electron.* 2013, 60, 1688–1699. [CrossRef]
52. Marzband, M.; Sumper, A.; Dominguez-Garcia, J.L.; Gumara-Ferret, R. Experimental validation of a real time energy management system for microgrids in islanded mode using a local day-ahead electricity market and MINLP. *Energy Convers. Manag.* 2013, 76, 314–322. [CrossRef]
53. Shi, W.; Li, N.; Chu, C.; Gadh, R. Real-Time Energy Management in Microgrids. *IEEE Trans. Smart Grid* 2017, 8, 228–238. [CrossRef]
54. Xiang, Y.; Liu, J.; Liu, Y. Robust Energy Management of Microgrid With Uncertain Renewable Generation and Load. *IEEE Trans. Smart Grid* 2016, 7, 1034–1043. [CrossRef]
55. Theo, W.L.; Lim, J.S.; Ho, W.S.; Hashim, H.; Lee, C.T. Review of distributed generation (DG) system planning and optimisation techniques: Comparison of numerical and mathematical modelling methods. *Renew. Sustain. Energy Rev.* 2017, 67, 531–573. [CrossRef]
56. Ravichandran, A.; Sirouspour, S.; Malyasz, 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]
57. Tan, P.-N.; Steinbach, M.; Kumar, V. *Introduction to Data Mining*, 1st ed.; Pearson: Boston, MA, USA, 2005; Volume 1. [CrossRef]
58. RStudio. RStudio: Integrated Development for R. Available online: http://www.rstudio.com/ (accessed on 3 January 2020).
59. Niknam, T.; Azizipanah-Abarghooee, R.; Narimani, M.R. An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation. *Appl. Energy* 2012, 99, 455–470. [CrossRef]
60. Liao, G.-C. Solve environmental economic dispatch of Smart MicroGrid containing distributed generation system—Using chaotic quantum genetic algorithm. *Int. J. Electr. Power Energy Syst.* 2012, 43, 779–787. [CrossRef]
61. Hooshmand, A.; Poursaeidi, M.H.; Mohammadpour, J.; Malki, H.A.; Grigoriads, K. Stochastic model predictive control method for microgrid management. In *Proceedings of the 2012 IEEE PES Innovative Smart Grid Technologies*, Washington, DC, USA, 16–20 January 2012; pp. 1–7. [CrossRef]
62. Kyriakarakos, G.; Dounis, A.I.; Arvanitis, K.G.; Papadakis, G. A fuzzy logic energy management system for polygeneration microgrids. *Renew. Energy* 2012, 41, 315–327. [CrossRef]
63. Kanchev, H.; Lazarov, V.; Francois, B. Environmental and economical optimization of microgrid long term operational planning including PV-based active generators. In *Proceedings of the 2012 15th International Power Electronics and Motion Control Conference*, Novi Sad, Serbia, 4–6 September 2012; pp. 4–8. [CrossRef]
Erdinc, O.; Elma, O.; Uzunoglu, M.; Selamogullari, U.; Vural, B.; Uger, E.; Boynuegri, A.; Dusmez, S. Experimental performance assessment of an online energy management strategy for varying renewable power production suppression. *Int. J. Hydrogen Energy* 2012, 37, 4737–4748. [CrossRef]

Manjili, Y.S.; Rajaei, A.; Jamshidi, M.; Kelley, B.T. Intelligent decision making for energy management in microgrids with air pollution reduction policy. In Proceedings of the 2012 7th International Conference on System of Systems Engineering, Genova, Italy, 16–19 July 2012; pp. 13–18. [CrossRef]

Enrich, R.; Skovron, P.; Tolos, M.; Torrent-Moreno, M. Microgrid management based on economic and technical criteria. In Proceedings of the 2012 IEEE International Energy Conference and Exhibition, Florence, Italy, 9–12 September 2012; pp. 551–556. [CrossRef]

Niknam, T.; Golestaneeb, F.; Malekpour, A. Probabilistic energy and operation management of a microgrid containing wind/photovoltaic/fuel cell generation and energy storage devices based on point estimate method and self-adaptive gravitational search algorithm. *Energy* 2012, 43, 427–437. [CrossRef]

Mohamed, F.A.; Koivo, H.N. Multiobjective optimization using Mesh Adaptive Direct Search for power dispatch problem of microgrid. *Int. J. Electr. Power Energy Syst.* 2012, 42, 728–735. [CrossRef]

Kriett, P.O.; Salani, M. Optimal control of a residential microgrid. *Energy* 2012, 42, 321–330. [CrossRef]

Conti, S.; Nicolosi, R.; Rizzo, S.A.; Zeineldin, H.H. Optimal Dispatching of Distributed Generators and Storage Systems for MV Islanded Microgrids. *IEEE Trans. Power Deliv.* 2012, 27, 1243–1251. [CrossRef]

Khorrampel, B.; Raoofat, M. Optimal stochastic reactive power scheduling in a microgrid considering voltage drop scheme of DGs and uncertainty of wind farms. *Energy* 2012, 45, 994–1006. [CrossRef]

Valverde, L.; Bordons, C.; Rosa, F. Power management using model predictive control in a hydrogen-based microgrid. In Proceedings of the IECON 2012-38th Annual Conference on IEEE Industrial Electronics Society, Montreal, QC, Canada, 25–28 October 2012; pp. 5669–5676. [CrossRef]

Mohamed, A.; Salehi, V.; Mohammed, O. Real-Time Energy Management Algorithm for Mitigation of Pulse Loads in Hybrid Microgrids. *IEEE Trans. Smart Grid* 2012, 3, 1911–1922. [CrossRef]

Zhang, X.; Sharma, R.; Ho, Y. Optimal energy management of a rural microgrid system using multi-objective optimization. In Proceedings of the 2012 IEEE PES Innovative Smart Grid Technologies, Washington, DC, USA, 16–20 January 2012; pp. 1–8. [CrossRef]

Hooshmand, A.; Asghari, B.; Sharma, R. A novel cost-aware multi-objective energy management method for microgrids. In Proceedings of the 2013 IEEE PES Innovative Smart Grid Technologies Conference, Washington, DC, USA, 24–27 February 2013; pp. 1–6. [CrossRef]

Mommadi, S.; Mozafari, B.; Solimani, S.; Niknam, T. An Adaptive Modified Firefly Optimisation Algorithm based on Hong’s Point Estimate Method to optimal operation management in a microgrid with consideration of uncertainties. *Energy* 2013, 51, 339–348. [CrossRef]

Alharbi, W.; Bhattacharya, K. Demand response and energy storage in MV islanded microgrids for high penetration of renewables. In Proceedings of the 2013 IEEE Electrical Power & Energy Conference, Halifax, NS, Canada, 21–23 August 2013; pp. 1–6. [CrossRef]

Chen, Y.; Wu, Y.; Song, C.; Chen, Y. Design and Implementation of Energy Management System with Fuzzy Control for DC Microgrid Systems. *IEEE Trans. Power Electron.* 2013, 28, 1563–1570. [CrossRef]

Falahi, M.; LotfiFard, S.; Ehsani, M.; Butler-Purry, K. Dynamic Model Predictive-Based Energy Management of DG Integrated Distribution Systems. *IEEE Trans. Power Deliv.* 2013, 28, 2217–2227. [CrossRef]

Bracco, S.; Denti, G.; Siri, S. Economic and environmental optimization model for the design and the operation of a combined heat and power distributed generation system in an urban area. *Energy* 2013, 55, 1014–1024. [CrossRef]

Modiri-Delshad, M.; Koohi-Kamali, S.; Taslimi, E.; Kaboli, S.H.A.; Rahim, N.A. Economic dispatch in a microgrid through an iterated-based algorithm. In Proceedings of the 2013 IEEE Conference on Clean Energy and Technology, Lankgkawi, Malaysia, 18–20 November 2013; pp. 82–87. [CrossRef]

Zhang, D.; Shah, N.; Papageorgiou, L.G. Efficient energy consumption and operation management in a smart building with microgrid. *Energy Convers. Manag.* 2013, 74, 209–222. [CrossRef]

Feroldi, D.; Degliuomini, L.N.; Basualdo, M. Energy management of a hybrid system based on wind–solar power sources and bioethanol. *Chem. Eng. Res. Des.* 2013, 91, 1440–1455. [CrossRef]

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]
85. Cardoso, G.; Stadler, M.; Siddiqui, A.; Marnay, C.; DeForest, N.; Barbosa-Póvoa, A.; Ferrão, P. Microgrid reliability modeling and battery scheduling using stochastic linear programming. *Electr. Power Syst. Res.* 2013, 103, 61–69. [CrossRef]

86. Malysz, P.; Sirouspour, S.; Emadi, A. MILP-based rolling horizon control for microgrids with battery storage. In Proceedings of the IECON 2013-39th Annual Conference of the IEEE Industrial Electronics Society, Vienna, Austria, 10–13 November 2013; pp. 2099–2104. [CrossRef]

87. Zhao, B.; Zhang, X.; Chen, J.; Wang, C.; Guo, L. Operation Optimization of Standalone Microgrids Considering Lifetime Characteristics of Battery Energy Storage System. *IEEE Trans. Sustain. Energy* 2013, 4, 934–943. [CrossRef]

88. García, F.; Bordons, C. Optimal economic dispatch for renewable energy microgrids with hybrid storage using Model Predictive Control. In Proceedings of the IECON 2013-39th Annual Conference of the IEEE Industrial Electronics Society, Vienna, Austria, 10–13 November 2013; pp. 7932–7937. [CrossRef]

89. Nguyen, D.T.; Le, L.B. Optimal energy management for cooperative microgrids with renewable energy resources. In Proceedings of the 2013 IEEE International Conference on Smart Grid Communications, Vancouver, BC, Canada, 21–24 October 2013; pp. 678–683. [CrossRef]

90. García, P.; Torreglosa, J.P.; Fernández, L.M.; Jurado, F. Optimal energy management system for stand-alone wind turbine/photovoltaic/hydrogen/battery hybrid system with supervisory control based on fuzzy logic. *Int. J. Hydrogen Energy* 2013, 38, 14146–14158. [CrossRef]

91. Levron, Y.; Guerrero, J.M.; Beck, Y. Optimal Power Flow in Microgrids With Energy Storage. *IEEE Trans. Power Syst.* 2013, 28, 3226–3234. [CrossRef]

92. Babazadeh, H.; Gao, W.; Wu, Z.; Li, Y. Optimal energy management of wind power generation system in islanded microgrid system. In Proceedings of the 2013 North American Power Symposium, Manhattan, KS, USA, 22–24 September 2013; pp. 1–5. [CrossRef]

93. Mohamed, A.; Mohammed, O. Real-time energy management scheme for hybrid renewable energy systems in smart grid applications. *Electr. Power Syst. Res.* 2013, 96, 133–143. [CrossRef]

94. García, F.; Bordons, C. Regulation service for the short-term management of renewable energy microgrids with hybrid storage using Model Predictive Control. In Proceedings of the IECON 2013-39th Annual Conference of the IEEE Industrial Electronics Society, Vienna, Austria, 10–13 November 2013; pp. 7962–7967. [CrossRef]

95. Liao, G. The optimal economic dispatch of smart Microgrid including Distributed Generation. In Proceedings of the 2013 International Symposium on Next-Generation Electronics, Kaohsiung, Taiwan, 25–26 February 2013; pp. 473–477. [CrossRef]

96. Marzband, M.; Sumper, A.; Ruiz-Álvarez, A.; Domínguez-García, J.L.; Tomaioagá, B. Experimental evaluation of a real time energy management system for stand-alone microgrids in day-ahead markets. *Appl. Energy* 2013, 106, 365–376. [CrossRef]

97. Parisio, A.; Glielmo, L. Stochastic Model Predictive Control for economic/environmental operation management of microgrids. In Proceedings of the 2013 European Control Conference, Zurich, Switzerland, 17–19 July 2013; pp. 2014–2019. [CrossRef]

98. Bracco, S.; Delfino, F.; Pampararo, F.; Robba, M.; Rossi, M. A mathematical model for the optimal operation of the University of Genoa Smart Polygeneration Microgrid: Evaluation of technical, economic and environmental performance indicators. *Energy* 2014, 64, 912–922. [CrossRef]

99. Parisio, A.; Rikos, E.; Glielmo, L. A Model Predictive Control Approach to Microgrid Operation Optimization. *IEEE Trans. Control. Syst. Technol.* 2014, 22, 1813–1827. [CrossRef]

100. Prodan, I.; Zio, E. A model predictive control framework for reliable microgrid energy management. *Int. J. Electr. Power Energy Syst.* 2014, 61, 399–409. [CrossRef]

101. Elsied, M.; Oukour, A.; Gualous, H.; Hassan, R.; Amin, A. An advanced energy management of microgrid system based on genetic algorithm. In Proceedings of the 2014 IEEE 23rd International Symposium on Industrial Electronics, Istanbul, Turkey, 1–4 June 2014; pp. 2541–2547. [CrossRef]

102. Malysz, P.; Sirouspour, S.; Emadi, A. An Optimal Energy Storage Control Strategy for Grid-connected Microgrids. *IEEE Trans. Smart Grid* 2014, 5, 1785–1796. [CrossRef]

103. Karami, N.; Moubayed, N.; Outbib, R. Energy management for a PEMFC–PV hybrid system. *Energy Convers. Manag.* 2014, 82, 154–168. [CrossRef]
104. Kumar, T.P.; Subrahmanyam, N.; Sydulu, M. Fuzzy controlled power management strategies for a grid connected hybrid energy system. In Proceedings of the 2014 IEEE PES T&D Conference and Exposition, Chicago, IL, USA, 14–17 April 2014; pp. 1–5. [CrossRef]

105. Roiné, L.; Therani, K.; Manjili, Y.S.; Jamshidi, M. Microgrid energy management system using fuzzy logic control. In Proceedings of the 2014 World Automation Congress, Waikoloa, HI, USA, 3–7 August 2014; pp. 462–467. [CrossRef]

106. Kumar, R.H.; Ushakumari, S. Optimal management of islanded microgrid using binary particle swarm optimization. In Proceedings of the 2014 International Conference on Advances in Green Energy, Thrivananthapuram, India, 17–18 December 2014; pp. 251–257. [CrossRef]

107. Berrazouane, S.; Mohammedi, K. Parameter optimization via cuckoo optimization algorithm of fuzzy controller for energy management of a hybrid power system. Energy Convers. Manag. 2014, 78, 652–660. [CrossRef]

108. Zhao, B.; Shi, Y.; Dong, X.; Luan, W.; Bornemann, J. Short-Term Operation Scheduling in Renewable-Powered Microgrids: A Duality-Based Approach. IEEE Trans. Sustain. Energy 2014, 5, 209–217. [CrossRef]

109. Zakariazadeh, A.; Jadid, S.; Siano, P. Smart microgrid energy and reserve scheduling with demand response using stochastic optimization. Int. J. Electr. Power Energy Syst. 2014, 63, 523–533. [CrossRef]

110. Su, W.; Wang, J.; Roh, J. Stochastic Energy Scheduling in Microgrids With Intermittent Renewable Energy Resources. IEEE Trans. Smart Grid 2014, 5, 1876–1883. [CrossRef]

111. Parisio, A.; Rikos, E.; Tzamalis, G.; Gielmo, L. Use of model predictive control for experimental microgrid optimization. Appl. Energy 2014, 115, 37–46. [CrossRef]

112. Khodaei, A. Microgrid Optimal Scheduling With Multi-Period Islanding Constraints. IEEE Trans. Power Syst. 2014, 29, 1383–1392. [CrossRef]

113. Marzband, M.; Ghadimi, M.; Sumer, A.; Domínguez-García, J.L. Experimental validation of a real-time energy management system using multi-period gravitational search algorithm for microgrids in islanded mode. Appl. Energy 2014, 128, 164–174. [CrossRef]

114. Zhao, B.; Zhang, X.; Li, P.; Wang, K.; Xue, M.; Wang, C. Optimal sizing, operating strategy and operational experience of a stand-alone microgrid on Dongfushan Island. Appl. Energy 2014, 113, 1656–1666. [CrossRef]

115. Faxas-Guzmán, J.; García-Valverde, R.; Serrano-Luján, L.; Urbina, A. Priority load control algorithm for optimal energy management in stand-alone photovoltaic systems. Renew. Energy 2014, 68, 156–162. [CrossRef]

116. Motevassel, M.; Seifi, A.R. Expert energy management of a micro-grid considering wind energy uncertainty. Energy Convers. Manag. 2014, 83, 58–72. [CrossRef]

117. Mazzola, S.; Astolfi, M.; Macchi, E. A detailed model for the optimal management of a multigood microgrid. Appl. Energy 2015, 154, 862–873. [CrossRef]

118. Bruni, G.; Cardiner, S.; Mulone, V.; Rocco, V.; Spagnolo, F. A study on the energy management in domestic micro-grids based on Model Predictive Control strategies. Energy Convers. Manag. 2015, 102, 50–58. [CrossRef]

119. Provata, E.; Kolokotsa, D.; Papantoniou, S.; Pietrini, M.; Giovannelli, A.; Romiti, G. Development of optimization algorithms for the Leaf Community microgrid. Renew. Energy 2015, 74, 782–795. [CrossRef]

120. Pascual, J.; Barricarte, J.; Sanchis, P.; Marroyo, L. Energy management strategy for a renewable-based residential microgrid with generation and demand forecasting. Appl. Energy 2015, 158, 12–25. [CrossRef]

121. Zhao, H.; Wu, Q.; Wang, C.; Cheng, L.; Rasmussen, C.N. Fuzzy logic based coordinated control of battery energy storage system and dispatchable distributed generation for microgrid. J. Mod. Power Syst. Clean. Energy 2015, 3, 422–428. [CrossRef]

122. Wang, S.; Fan, X.; Han, L.; Ge, L. Improved Interval Optimization Method Based on Differential Evolution for Microgrid Economic Dispatch. Electr. Power Compon. Syst. 2015, 43, 1882–1890. [CrossRef]

123. Baldi, S.; Karagevrekis, A.; Michalidis, I.T.; Kosmatopoulos, E.B. Joint energy demand and thermal comfort optimization in photovoltaic-equipped interconnected microgrids. Energy Convers. Manag. 2015, 101, 352–363. [CrossRef]

124. Arcos-Aviles, D.; Pascual, J.; Marroyo, L.; Sanchis, P.; Guinjoan, F.; Marietta, M.P. Optimal Fuzzy Logic EMS design for residential grid-connected microgrid with hybrid renewable generation and storage. In Proceedings of the 2015 IEEE 24th International Symposium on Industrial Electronics, Buzios, Brazil, 3–5 June 2015; pp. 742–747. [CrossRef]
125. Nikmehr, N.; Najafi-Ravadanegh, S. Optimal operation of distributed generations in micro-grids under uncertainties in load and renewable power generation using heuristic algorithm. *IET Renew. Power Gener.* 2015, 9, 982–990. [CrossRef]

126. Brka, A.; Kothapalli, G.; Al-Abdeli, Y.M. Predictive power management strategies for stand-alone hydrogen systems: Lab-scale validation. *Int. J. Hydrogen Energy* 2015, 40, 9907–9916. [CrossRef]

127. Olivares, D.E.; Lara, J.D.; Cañizares, C.A.; Kazernani, M. Stochastic-Predictive Energy Management System for Isolated Microgrids. *IEEE Trans. Smart Grid* 2015, 6, 2681–2693. [CrossRef]

128. Sohn, J. Generation Applications Package for Combined Heat Power in On-Grid and Off-Grid Microgrid Energy Management System. *IEEE Trans. Smart Grid* 2015, 6, 59–75. [CrossRef]

129. 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]

130. Karki, R.S.; Chanana, S. Energy management system for local energy market in microgrid consisting fuel cell. In Proceedings of the 2016 7th India International Conference on Power Electronics, Patiala, India, 17–19 November 2016; pp. 1–6. [CrossRef]

131. Guo, L.; Liu, W.; Li, X.; Liu, Y.; Jiao, B.; Wang, W.; Wang, C.; Li, F. Energy Management System for Stand-Alone Wind-Powered-Desalination Microgrid. *IEEE Trans. Smart Grid* 2016, 7, 1079–1087. [CrossRef]

132. Almada, J.B.; Leão, R.P.S.; Sampaio, R.F.; Barroso, G.C. A centralized and heuristic approach for energy management of an AC microgrid. *Renew. Sustain. Energy Rev.* 2016, 60, 1396–1404. [CrossRef]

133. Sohn, J. Generation Applications Package for Combined Heat Power in On-Grid and Off-Grid Microgrid Energy Management System. *IEEE Trans. Smart Grid* 2016, 4, 3444–3453. [CrossRef]

134. Athari, M.H.; Ardehali, M.M. Operational performance of energy storage as function of electricity prices for on-grid hybrid renewable energy system by optimized fuzzy logic controller. *Renew. Energy* 2016, 85, 890–902. [CrossRef]

135. Minchala-Avila, L.I.; Garza-Castañon, L.; Zhang, Y.; Ferrer, H.J.A. Optimal Energy Management for Stable Operation of an Islanded Microgrid. *IEEE Trans. Ind. Inform.* 2016, 12, 1361–1370. [CrossRef]

136. Valencia, F.; Sáez, D.; Collado, J.; Avila, F.; Marquez, A.; Espinosa, J.J. Robust Energy Management System Based on Interval Fuzzy Models. *IEEE Trans. Control. Syst. Technol.* 2016, 24, 140–157. [CrossRef]

137. Valencia, F.; Collado, J.; Sáez, D.; Marin, L.G. Robust Energy Management System for a Microgrid Based on a Fuzzy Prediction Interval Model. *IEEE Trans. Smart Grid* 2016, 7, 1486–1494. [CrossRef]

138. Marzband, M.; Yousefnejad, E.; Sumper, A.; Domínguez-García, J.L. Real time experimental implementation of optimum energy management system in standalone Microgrid by using multi-layer art colony optimization. *Int. J. Electr. Power Energy Syst.* 2016, 75, 265–274. [CrossRef]

139. Li, P.; Xu, D.; Zhou, Z.; Lee, W.; Zhao, B. Stochastic Optimal Operation of Microgrid Based on Chaotic Binary Particle Swarm Optimization. *IEEE Trans. Smart Grid* 2016, 7, 66–73. [CrossRef]

140. Anglani, N.; Oriti, G.; Colombini, M. Optimized energy management system to reduce fuel consumption in remote military microgrids. In Proceedings of the 2016 IEEE Energy Conversion Congress and Exposition, Milwaukee, WI, USA, 18–22 September 2016; pp. 1–8. [CrossRef]

141. Michelson, D.; Mahmood, H.; Jiang, J. A Predictive Energy Management System Using Pre-Emptive Load Shedding for Islanded Photovoltaic Microgrids. *IEEE Trans. Ind. Electron.* 2017, 64, 5440–5448. [CrossRef]

142. Solanki, B.V.; Bhattacharya, K.; Cañizares, C.A. A Sustainable Energy Management System for Isolated Microgrids. *IEEE Trans. Sustain. Energy* 2017, 8, 1507–1517. [CrossRef]

143. Marzband, M.; Azarnejadian, F.; Savaghebi, M.; Guerrero, J.M. An Optimal Energy Management System for Islanded Microgrids Based on Multi-period Artificial Bee Colony Combined With Markov Chain. *IEEE Syst. J.* 2017, 11, 1712–1722. [CrossRef]

144. Leonori, S.; Paschero, M.; Rizzi, A.; Mascioli, F.M.F. An optimized microgrid energy management system based on FIS-MO-GA paradigm. In Proceedings of the 2017 IEEE International Conference on Fuzzy Systems, Naples, Italy, 9–12 July 2017; pp. 1–6. [CrossRef]

145. Kang, Y.; Yu, H.; Wang, J.; Qin, W. Day-ahead microgrid energy management optimization scheduling scheme. In Proceedings of the 2017 IEEE Conference on Energy Internet and Energy System Integration, Beijing, China, 26–28 November 2017; pp. 1–6. [CrossRef]
147. Borase, P.B.; Akolkar, S.M. Energy management system for microgrid with power quality improvement. In Proceedings of the 2017 International Conference on Microelectronic Devices, Circuits and Systems, Vellore, India, 10–12 August 2017; pp. 1–6. [CrossRef]

148. Aznavi, S.; Fajri, P.; Benidris, M.; Falahati, B. Hierarchical droop controlled frequency optimization and energy management of a grid-connected microgrid. In Proceedings of the 2017 IEEE Conference on Technologies for Sustainability, Phoenix, AZ, USA, 12–14 November 2017; pp. 1–7. [CrossRef]

149. Solanki, B.V.; Raghurajan, A.; Bhattacharya, K.; Cañizares, C.A. Including Smart Loads for Optimal Demand Response in Integrated Energy Management Systems for Isolated Microgrids. *IEEE Trans. Smart Grid* 2017, 8, 1739–1748. [CrossRef]

150. Lu, T.; Wang, Z.; Ai, Q.; Lee, W. Interactive Model for Energy Management of Clustered Microgrids. *IEEE Trans. Ind. Appl.* 2017, 53, 1739–1750. [CrossRef]

151. Sukumar, S.; Mokhils, H.; Mokhilef, 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]

152. Sarshar, J.; Moosapour, S.S.; Joorabian, M. Multi-objective energy management of a micro-grid considering uncertainty in wind power forecasting. *Energy* 2017, 139, 680–693. [CrossRef]

153. Nwulu, N.I.; Xia, X. Optimal dispatch for a microgrid incorporating renewables and demand response. *Renew. Energy* 2017, 101, 16–28. [CrossRef]

154. Tushar, M.H.K.; Assi, C. Optimal Energy Management and Marginal-Cost Electricity Pricing in Microgrid Network. *IEEE Trans. Ind. Inform.* 2017, 13, 3286–3298. [CrossRef]

155. Nosratabadi, S.M.; Modarresi, J. Stochastic energy management in a practical smart microgrid in Davarzani-Iran considering demand response with wind and PV power scenarios. In Proceedings of the 2017 Smart Grid Conference, Tehran, Iran, 20–21 December 2017; pp. 1–7. [CrossRef]

156. Youssef, T.A.; Hariri, M.E.; Elsayed, A.T.; Mohammed, O.A. A DDS-Based Energy Management Framework for Small Microgrid Operation and Control. *IEEE Trans. Ind. Inform.* 2018, 14, 958–968. [CrossRef]

157. Romero-Quete, D.; Cañizares, C.A. An Affine Arithmetic-Based Energy Management System for Isolated Microgrids. *IEEE Trans. Smart Grid* 2018, 1. [CrossRef]

158. 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]

159. Arcos-Aviles, D.; Pascual, J.; Marroyo, L.; Sanchis, P.; Guinjoan, F. Fuzzy Logic-Based Energy Management System Design for Residential Grid-Connected Microgrids. *IEEE Trans. Smart Grid* 2018, 9, 530–543. [CrossRef]

160. Guo, Y.; Zhao, C. Islanding-Aware Robust Energy Management for Microgrids. *IEEE Trans. Smart Grid* 2018, 9, 1301–1309. [CrossRef]

161. Aghajani, G.; Ghadimi, N. Multi-objective energy management in a micro-grid. *Energy Rep.* 2018, 4, 218–225. [CrossRef]

162. 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]

163. Li, Z.; Xu, Y. Optimal coordinated energy dispatch of a multi-energy microgrid in grid-connected and islanded modes. *Appl. Energy* 2018, 210, 974–986. [CrossRef]

164. Ghasemi, A.; Enayatzaere, M. Optimal energy management of a renewable-based isolated microgrid with pumped-storage unit and demand response. *Renew. Energy* 2018, 123, 460–474. [CrossRef]

165. Moradi, H.; Esfahanian, M.; Ahtabi, A.; Zilouchian, A. Optimization and energy management of a standalone hybrid microgrid in the presence of battery storage system. *Energy* 2018, 147, 226–238. [CrossRef]

166. Goroohi Sardou, I.; Zare, M.; Azad-Farsani, E. Robust energy management of a microgrid with photovoltaic inverters in VAR compensation mode. *Int. J. Electr. Power Energy Syst.* 2018, 98, 118–132. [CrossRef]

167. Julian, A.L.; Oriti, G.; Ji, C.; Zanchetta, P. Single-Phase Energy Management System Operating in Islanding Mode With Repetitive Control and Active Damping. *IEEE Trans. Ind. Appl.* 2018, 54, 5163–5172. [CrossRef]

168. Hu, W.; Wang, P.; Gooi, H.B. Toward Optimal Energy Management of Microgrids via Robust Two-Stage Optimization. *IEEE Trans. Smart Grid* 2018, 9, 1161–1174. [CrossRef]

169. Wu, N.; Wang, H. Deep learning adaptive dynamic programming for real time energy management and control strategy of micro-grid. *J. Clean Prod.* 2018, 204, 1169–1177. [CrossRef]

170. Wang, J.; Zhao, C.; Pratt, A.; Baggu, M. Design of an advanced energy management system for microgrid control using a state machine. *Appl. Energy* 2018, 228, 2407–2421. [CrossRef]
171. Chamandoust, H. Economic Scheduling of Microgrid Based on Energy Management and Demand Response. *Electr. Control Commun. Eng*. 2018, 14, 100–107. [CrossRef]

172. Olama, A.; Mendes, P.R.C.; Camacho, E.F. Lyapunov-based hybrid model predictive control for energy management of microgrids. *IET Gener. Transm. Distrib*. 2018, 12, 5770–5780. [CrossRef]

173. Zhang, Y.; Fu, L.; Zhu, W.; Bao, X.; Liu, C. Robust model predictive control for optimal energy management of island microgrids with uncertainties. *Energy* 2018, 164, 1229–1241. [CrossRef]

© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).