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Review

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

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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.

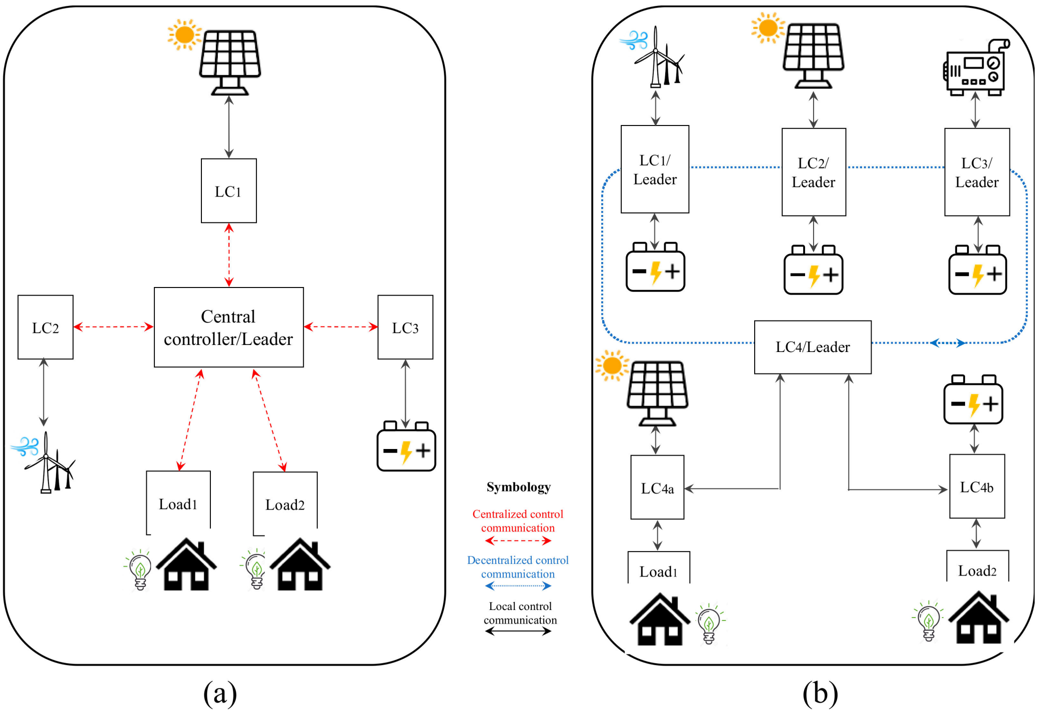

Figure 1. (**a**) Centralized control architecture, (**b**) Decentralized control architecture.

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 nothing 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.

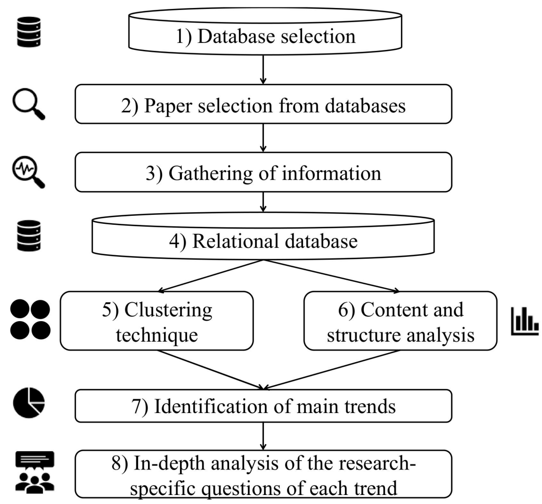

Figure 2. Overview of the proposed procedure.

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).

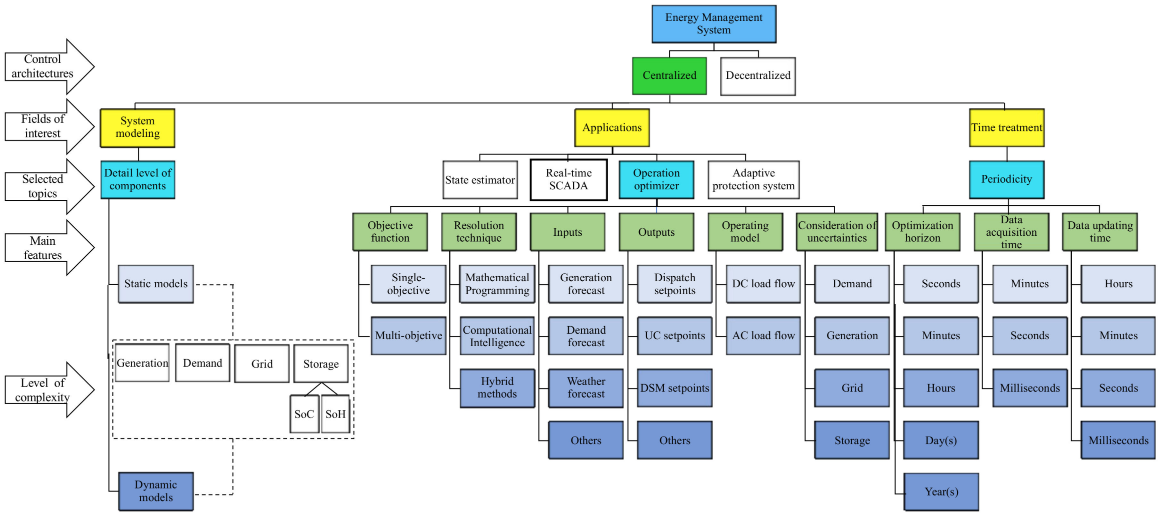

Figure 3. Analysis scheme proposed for the review.

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.

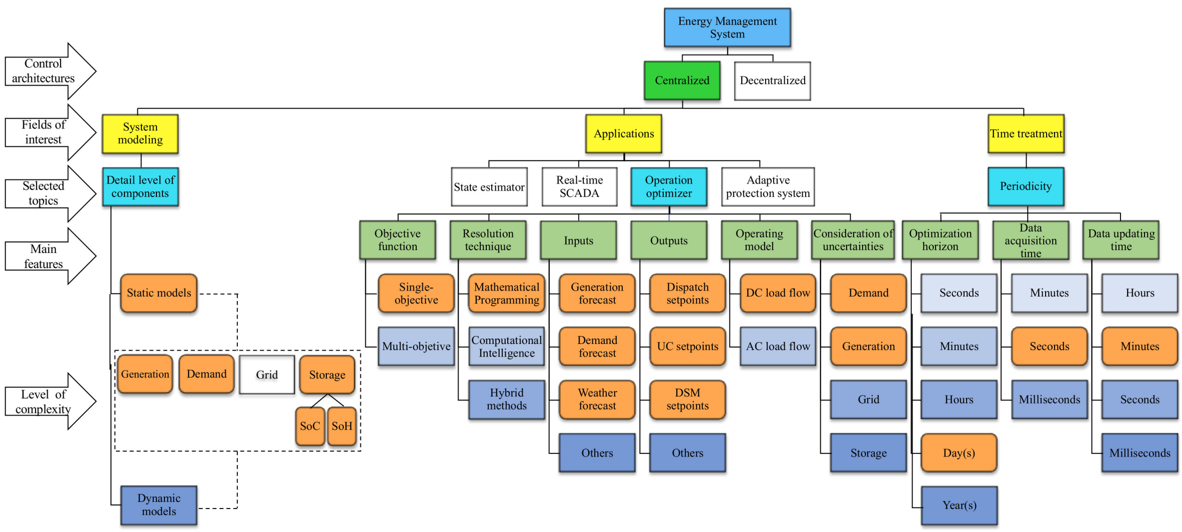

Figure 4. Example of the proposed analysis framework scheme application.

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.

Table 1. Letter code for features and attributes.

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

Table 2. Features and attributes of the distinctive papers selected.

Ref.	A	B	C			D	E	F	G	H	I	J
			MP	CI	HM							
[50]	STM	SOBJ	MILP			OIN	DSET + OOU	DC	DY	DM + GE		MIN
[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.

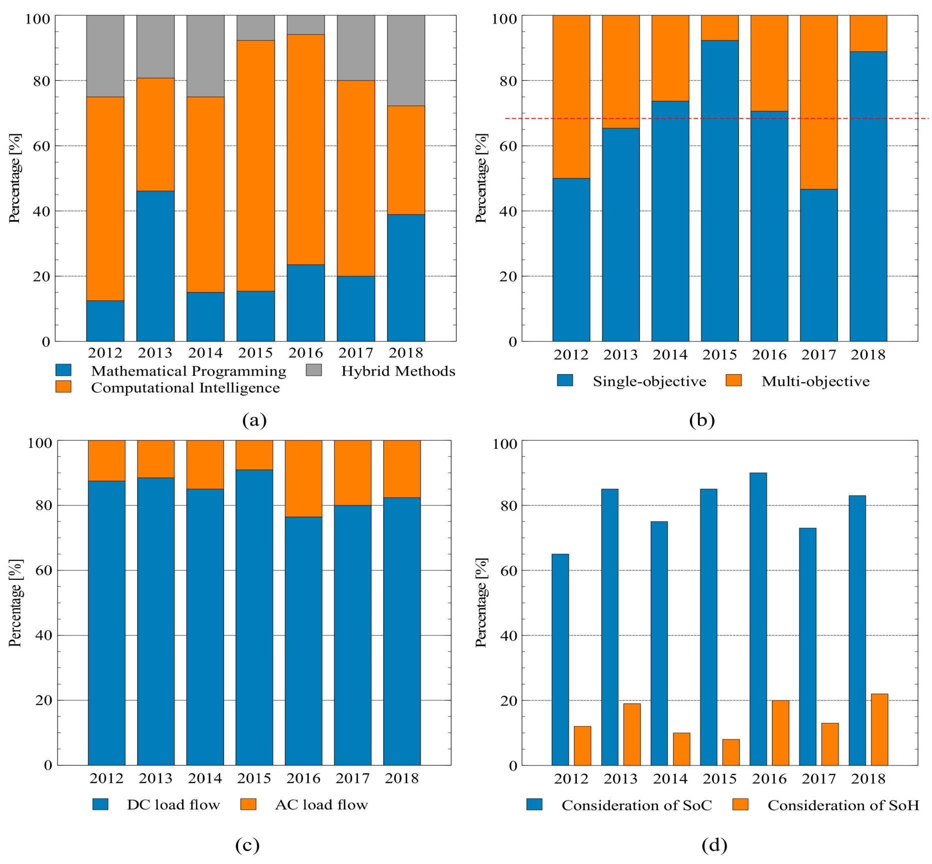

Figure 5. (**a**) Resolution techniques used in recent years, (**b**) Objective function types used in recent years, (**c**) Operating model types used in recent years and (**d**) Consideration of SoC and SoH in storage.

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].

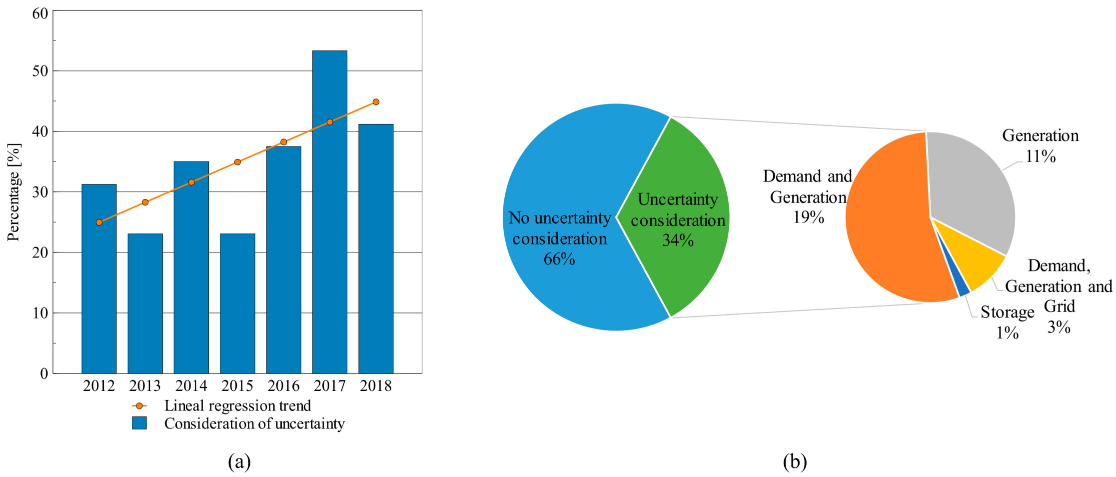

Figure 6. (**a**) Uncertainty trend in recent years, (**b**) Uncertainty consideration distribution in different microgrid agents.

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.

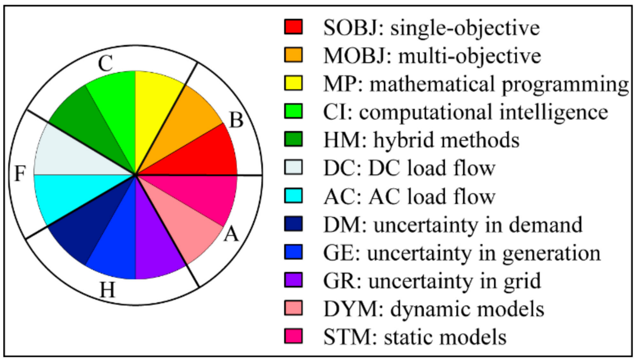

Figure 7. Attributes considered with their respective associated color.

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.

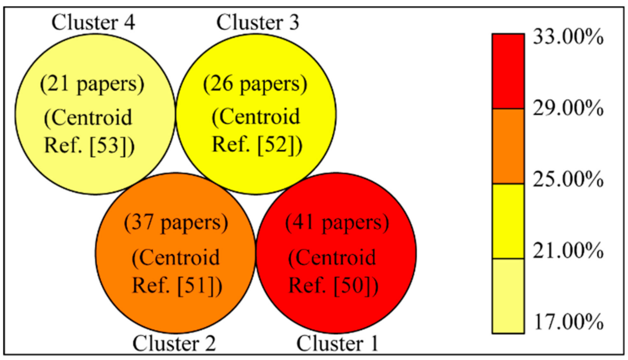

Figure 8. Number of papers in each cluster.

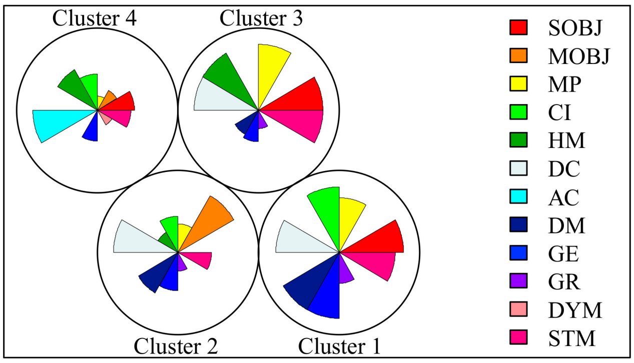

Figure 9. Main attributes of each cluster.

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 5cdoes 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.

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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	Multiperiod Gravitational Search Algorithm
NEA	Niching Evolutionary Algorithm
MBFO	Modified Bacterial Foraging Optimization
ITLBO	Improved Teaching-Learning-Based Optimization
SGSA	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
			MP	CI	HM							
[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			MIN
[67]	STM	SOBJ		SGSA		GFO + DFO + OIN	DSET + OOU	DC	DY	DM + GE+ GR		HR
[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			AC		GE		
[72]	STM	SOBJ		MPC		OIN	DSET + OOU	DC	DY			
[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 + OOU	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				
[52]	STM	SOBJ	MINLP			GFO+DFO+OIN	OOU	DC	HR			
[85]	STM	MOBJ	SLP			GFO + OIN	DSET	DC	DY	GE		MIN
[86]	STM	MOBJ	MILP			DFO + OIN	OOU	DC	DY			HR
[87]	STM	MOBJ		NSGA		OIN	DSET	DC				
[88]	STM	SOBJ			MPC + MIQP	GFO + OIN	DSET	DC	HR			
[89]	STM	MOBJ	SO			GFO + DFO + OIN		DC	HR	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	DSET	DC	DY			
[51]	STM	MOBJ			MO + FL + ANN	GFO + OIN	DSET	DC	DY	DM + GE		
[96]	STM	SOBJ	AA			OIN	DSET + DSM	DC	DY			
[97]	STM	MOBJ			MPC + MILP + TSSP	OIN	DSET + OOU	DC	DY	DM+GE	MIN	

Table A6. Papers published in 2014.

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

Table A7. Papers published in 2015.

Ref.	A	B	C	D	E	F	G	H	I	J
[117]	STM	SOBJ	MILP	GFO + DFO + OIN	UC + OOU	DC	DY			HR
[50]	STM	SOBJ	MILP	OIN	DSET + OOU	DC	DY	DM + GE		MIN
[118]	STM	SOBJ	MPC	WFO+OIN	DSM + OOU	DC				
[119]	STM	SOBJ	GA	OIN		DC	DY			
[120]	STM	SOBJ	AA	GFO + DFO + OIN	OOU		DY			
[121]	DYM	SOBJ	FL	OIN	DSET + OOU	DC	SEC			
[122]	STM	MOBJ	DE		DSET	DC				
[123]	DYM	SOBJ	PCAO	OIN			DY			
[124]	STM	SOBJ	FL	OIN	OOU	DC			MIN	
[125]	STM	SOBJ	ICA	OIN	DSET + OOU	DC		DM + GE		
[15]	STM	SOBJ	RB	OIN	DSET	DC	DY			
[126]	STM	SOBJ	ANN	OIN	OOU	DC				
[127]	STM	SOBJ	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	YR			
[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]		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
[16]	STM	SOBJ		AA		OIN	OOU	DC				
[54]	STM	SOBJ		SSOA				DC		DM + GE		
[137]	STM	SOBJ		MPC		DFO + OIN	DSET + DSM	DC	DY	DM + GE	MIN	
[138]	STM	MOBJ		MPC		GFO + OIN	DSET	DC	DY	GE		MIN
[139]	STM	SOBJ		MACO		OIN	DSET + DSM + OOU	DC	MIN+DY			
[140]	STM	MOBJ		CBPSO				AC		DM + GE		
[141]	STM	SOBJ	MILP					DC	DY			

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	DC	DY	DM + GE		
[145]	STM	MOBJ			MO + GA	OIN	OOU	DC				
[146]	STM	SOBJ	MINLP			GFO + DFO	OOU	DC	DY			
[147]		SOBJ		AA		OIN	OOU	DC				
[148]	STM	MOBJ		NRSFS				DC		DM + GE		
[149]	STM	MOBJ			MPC + MINLP	GFO + OIN	DSET	AC	DY	DM + GE		MIN
[150]	STM	MOBJ		HGA			DSET	AC	DY			
[151]	STM	MOBJ	LP + MILP			GFO + DFO + OIN	DSET + OOU	DC	DY	GE		
[152]	STM	MOBJ		NSGA				DC		GE		
[153]	STM	MOBJ		SA			DSM	DC	DY			
[154]	STM	SOBJ		D&C				DC				
[53]	STM	SOBJ		LO		OIN	DSET + DSM	AC	DY	GE		
[155]	STM	SOBJ	MILP			OIN	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					DC	HR + DY		MIN	
[159]	STM	SOBJ		FL		OIN	OOU	DC	DY		SEC	
[160]	STM	SOBJ	RO				DSET + UC	DC		GEGR		
[161]	STM	MOBJ		MOPSO				DC				
[162]	STM	SOBJ	MILP			GFO + DFO	OOU	DC	HR	GE	MILI	MIN
[163]	STM	SOBJ	MILP			GFO + DFO + OIN	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	OOU					
[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					DC	DY			
[172]	STM	SOBJ		LHMPC		OIN	UC + DSET + OOU	DC	DY			MIN
[173]	STM	SOBJ			RO + MPC	GFO + DFO	DSET	DC	DY	DM + GE		HR

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