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Highlights

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- The six aspects of the energy management system optimization of islanded microgrids
- Overview of heuristic algorithms for EMS optimization problem
- Discussion of frameworks for EMS optimization problem in islanded microgrids
- Analysis of uncertainty handling schemes: Deterministic, stochastic, and robust
- Reviewing constraints, cost functions, and time-frames for EMS optimization problem
- Introducing the future trends in energy management system of islanded microgrids

Energy Management System Optimization in Islanded Microgrids: An Overview and Future Trends

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ABSTRACT

Islanded microgrids (IMGs) provide a promising solution for reliable and environmentally friendly energy supply to remote areas and off-grid systems. However, the operation management of IMGs is a complex task including the coordination of a variety of distributed energy resources and loads with an intermittent nature in an efficient, stable, reliable, robust, resilient, and self-sufficient manner. In this regard, the energy management system (EMS) of IMGs has been attracting considerable attention during the last years, especially from the economic and emissions point of view. This paper provides an in-depth overview of the EMS optimization problem of IMGs by systematically analyzing the most representative studies. According to the state-of-the-art, the optimization of energy management of IMGs has six main aspects, including framework, time-frame, uncertainty handling approach, optimizer, objective function, and constraints. Each of these aspects is discussed in detail and an up-to-date overview of the existing EMSs for IMGs and future trends is provided. The future trends include the need for improved models, advanced data analytic and forecasting techniques, performance assessment of real-time EMSs in the whole MG's control hierarchy, fully effective decentralized EMSs, improved communication and cyber security systems, and validations under real conditions. Besides, a comprehensive overview of the widely-used heuristic optimization methods and their application in EMSs of IMGs as well as their advantages and disadvantages are given. It is hoped that this study presents a solid starting point for future researches to improve the EMS of IMGs.

1. Introduction

Nowadays, the population increase around the world and global concerns over environmental problems demand to seek new ways of energy generation, which should either eliminate air pollution or reduce it as much as possible. Besides, energy demand is increasing not only in big cities but also in remote areas where the infrastructure of the current utility does not exist yet. For instance, in 2018, approximately 860 million people around the world lived without access to electricity. Therefore, developing efficient solutions for reliable and environmentally friendly energy supply to remote areas and off-grid systems is of vital importance. Consequently, the interest in renewable energy sources (RESs) has considerably increased during the last years, *e.g.*, the year 2019 was detected as the year with the largest ever-growing of renewable capacity with a total investment of roughly 301.7 billion USD, allocating 47% to solar power and 47% to wind power. Besides, the total renewables power capacity installed in 2019 reached 2588 GW while more than 32 countries rely on RESs for more than 10 GW of their electricity production. Regarding renewable power capacity per inhabitant, Iceland is the global leader, following by Denmark and Sweden [1]. Furthermore, many governments have presented initiatives, like Germany, with a target of 30% and 50% of renewable sharing by 2020 and 2030, respectively; California, USA, with a goal of supplying 33% of its retail power demand by renewables in 2020, among others [2].

However, the increase of RESs utilization might eventually cause instability issues in power systems if the highly uncertain and inertia-less nature of these systems are not managed properly. In this respect, microgrid (MG) concept

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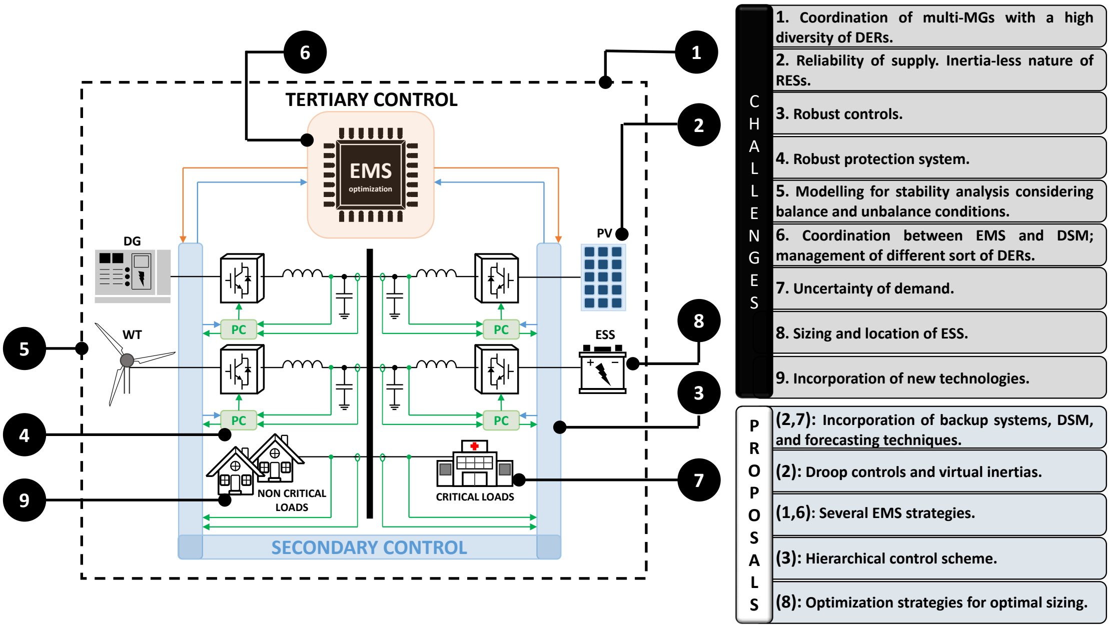

Fig. 1: A generic IMG with some current challenges and solutions proposed in the literature. Green lines: primary control communication. Blue lines: secondary control communication. Orange lines: tertiary control communication.

has been attracting the attention of the energy sector during the last two decades. The U.S. Department of Energy defines the MG as *"a group of interconnected loads and distributed energy resources (DERs) within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid, and can operate in grid-connected and island-mode"* [3]. Although a MG can operate in both modes, the islanded configuration is more challenging but also represents a potential solution to electrify remote locations. The islanded microgrids (IMGs) promise is to support energy supply in remote areas, facilitate the large and reliable integration of RESs into the electricity systems, reduce greenhouse gas emissions, and lower energy prices, among others [4]. The main parts of an IMG are the conventional distributed energy resources (CDERs) such as diesel generators (DGs) and micro-turbines (MTs); non-conventional distributed energy resources (NCDERs), which are the renewables; energy storage systems (ESSs), like batteries; and loads, which could be classified as critical, non-critical, or dumping ones [4, 5, 6, 7, 8], see Fig. 1.

However, the high penetration of inertia-less RESs, which are usually electronically linked to the system, brings many challenges to the IMGs in terms of stability, reliability, resiliency, robustness, and operation management optimization. Among the main challenges are the reliability of supply [9]; frequency deviation due to the system low inertia [9, 10]; coordinated operation of multiple MGs [9, 11]; efficient coordination between the energy management system (EMS) and demand side management (DSM) [9]; robust operation of the system; management of multiple DERs with possible conflicting requirements [9, 12]; efficient protection scheme considering the system bi-directional power flow [13]; modelling of system components and processes with the required accuracy [2, 11]; optimal sizing and placement of ESSs [14, 15]; and the reliable and efficient incorporation of new technologies like electric vehicles (EVs) and the Internet of Things (IoT) [16, 17], see Fig. 1.

Therefore, to face these challenges a large variety of control, load management, and energy management systems has been widely proposed. For the control system, hierarchical control architectures are among the most promising techniques in which the control strategies are organized in several levels considering different time scales of MGs operation requirements. The primary control (PC) is the lowest and fastest control level (milliseconds), which usually works with local measurements [18, 19, 20]. The secondary control oversees the primary control operation and its time scale is in the order of a few minutes [6, 11, 18, 19, 20, 21]. The tertiary control is the slowest control level (several minutes) that is responsible to guarantee the long term optimal operation of the MG [11, 19, 20, 21, 22]. Finally, the external agents are responsible for setting MGs operating policies taking into account the external data, such as electricity price and power consumption trends as well as data obtained from the MG site. On the other hand, the load management system (LMS) handles the MG power consumption to reach a predefined goal such as minimizing the MG cost and peak-to-average ratio among others. The actions to change the energy usage pattern can

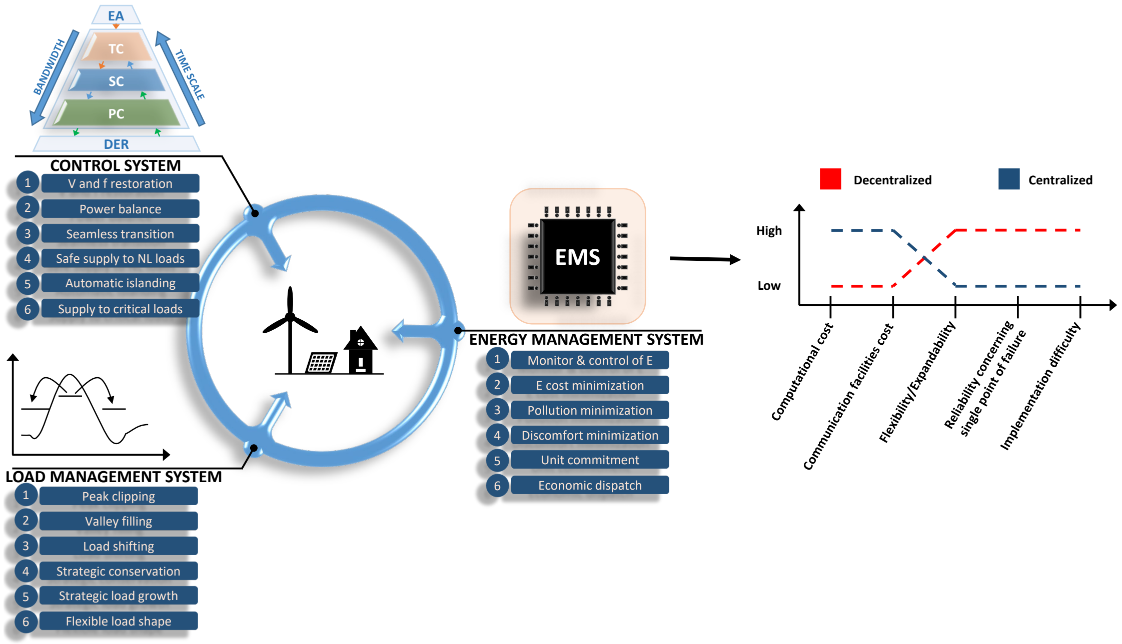

Fig. 2: Control system [18, 21, 26], Load management system [23, 24], and energy management system of IMGs [25].

be executed directly by the LMS or by the MG consumers through financial incentives. The basic techniques applied by the LMSs are based on clipping, filling, modifying, and deferring the loads [23, 24]. Finally, the EMS is dedicated to monitor and manage the energy flow among DERs and loads by scheduling the commitment and power dispatch of each unit to optimize the overall system performance. The MG EMSs can be classified according to their architecture, namely centralized, decentralized, and distributed. The centralized architecture is the simplest to be implemented, but suffers from low reliability, low flexibility, and high computational and infrastructure costs. On the other hand, the decentralized architecture has a high reliability and flexibility while the computational and infrastructure costs are low. However, the implementation difficulty is higher and it might not reach the optimal performance provided by centralized architectures due to the lack of a global view of the system and cooperation among different subsystems. Therefore, the distributed scheme has been used to take advantage of both previous architectures in an attempt to create a reliable and flexible EMS with a low computational cost while having moderate-high levels of infrastructure cost and implementation difficulty [25], see Fig.2.

During the last years, the increasing share of RESs; integration of more ESSs; inclusion of new technologies like EVs and smart devices; need for energy in remote and more extreme environments, *etc.*, have posed serious challenges especially for energy management of IMGs. Hence, the interest for the improvement of EMS as the core of IMGs has been considerably increased to facilitate the incorporation of more RESs into the electricity system in a safe, stable, reliable, robust, optimal, and coordinated way. Specifically, special attention has been paid to the EMS optimization seeking the efficient, economical, and environmentally friendly operation of IMGs. In this respect, review studies dedicated to the EMS optimization of IMGs are quite necessary to help experts on the topic to keep track of the state-of-the-art and devote their efforts to the IMGs unmet requirements. Additionally, this sort of studies are very useful for the new researchers to have a solid starting point. However, the existing review papers on EMSs are more dedicated to classify different energy management techniques without specifying the main aspects of an EMS. Or only a few aspects are covered in their classification. Table 1 provides an overview of recent review papers on EMS of MGs with different aspects used for classification. Besides, it shows whether each study considers a grid-connected or islanded configuration and some remarks are given in the last column. Therefore, to the best of our knowledge, an updated and well-established survey on the EMS optimization of IMGs is still needed. Besides, after a comprehensive literature review of more than one hundred papers dedicated to EMS of IMGs, this paper has identified some of the main aspects that EMSs of any IMG should consider to solve the energy management optimization problem. Namely, the optimization framework, time-frame, objective function (OF), constraints, uncertainty handling technique, and optimizer. Each aspect is discussed in detail in Section 3 with a review of different studies to give a comprehensive

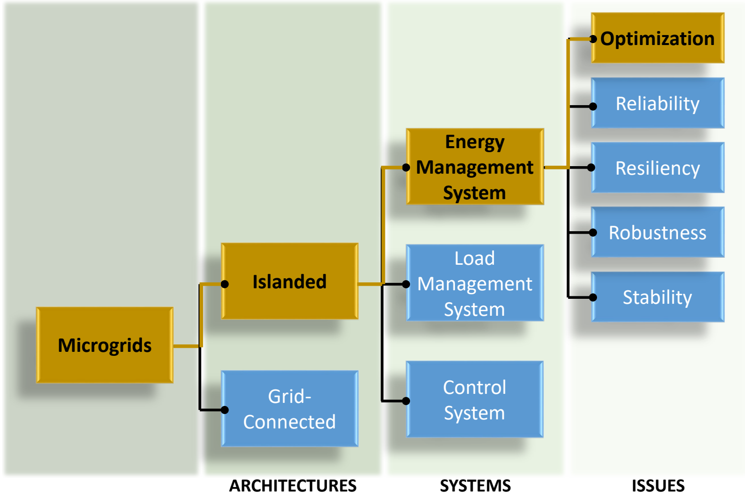

Fig. 3: Classification of issues, systems, and architectures of MGs. The highlighted parts in yellow show the scope of this review.

overview of the EMS optimization problem of IMGs. Fig. 3 highlights the scope of this review paper.

Table 1: An overview of review papers on EMS of MGs. The papers are organized by year of publication and by six main aspects of the EMS of MGs, which are studied in the paper or are part of its classification. The F&O labels the framework and optimizer when they are classified together.

Ref.	Year	C	TF	OF	F	O	F&O	U	GC	IS	Remarks
[12]	2012								✓	✓	Reviewing a list of publications.
[27]	2014								✓	✓	Classification: single user's EMS or utility's EMS. Sub-classification: centralized/distributed. DSM is also classified.
[28]	2015	✓		✓					✓		Brief description of game theory (GT) framework and genetic algorithm (GA) optimizer.
[29]	2015				✓	✓			✓	✓	Classification: centralized/decentralized. Introduction to the framework multi-agent system (MAS). Optimization and OF formulations.
[30]	2015								✓	✓	Reviewing a list of publications. A section about the economical optimization.
[31]	2016	✓		✓			✓		✓	✓	Survey of the EMS features. Detailed tables for OFs and constraints. Summary of software used to solve the EMS problem. Review of real EMSs practices.
[25]	2016						✓		✓	✓	A comparison between centralized/decentralized EMSs. Review of the MAS framework.
[32]	2018	✓		✓		✓			✓	✓	Review of generation/consumption forecasting techniques. Review of MG optimization studies since 2010 to 2016.
[33]	2018	✓		✓			✓	✓	✓	✓	Summary of reviews on EMS. Detailed tables for optimization methods.

Continued on next page

Table 1: Review papers regarding EMS optimization (continuation)

Ref.	Year	C	TF	OF	F	O	F&O	U	GC	IS	Remarks
[6]	2019			✓		✓			✓	✓	Classification: Islanded/grid-connected. Counting of papers since 2007 to 2017. Brief table about the application of optimizers.
[34]	2019			✓	✓	✓		✓	✓	✓	Survey of buildings' EMS considering electricity and heat. The uncertainty is categorized as perfect, forecasted, and non-forecasted. The study is mostly dedicated to the multi-objective (MO) optimization. Review of MAS. Classification of OFs and economic models.
[35]	2019	✓		✓			✓	✓	✓	✓	Classification includes four categories for the reserve system utilized. Survey of review papers. Detailed tables of OFs and constraints. Review of MGs configurations and their EMS details.
[36]	2019	✓		✓			✓		✓	✓	Detailed table of optimizers.
[37]	2019	✓					✓		✓	✓	Survey of review papers. A table with some optimizers. Detailed table for each study, highlighting optimizer, contributions, constraints, drawbacks, and OFs. Survey of different software used to solve the optimization problem.
[38]	2020	✓		✓		✓			✓	✓	Details about the integration of renewables from 2007-2017 and their American and European standards. Detailed tables of optimizers. Review of issues and challenges: sizing, cost, placement, and harmonisation of standards for integration of RESs, scheduling, environmental impacts, and safety issues.
[39]	2020			✓		✓			✓	✓	The self-organizing maps technique is used to classify papers. The classification features methods, objectives, power sources. Nine clusters are identified.
[40]	2020								✓	✓	Classification: grid-connected/islanded. A table with characteristics of optimizers.
[41]	2020		✓	✓		✓		✓	✓		Classification regards additionally inputs, outputs, and modelling details. Clustering of papers by using the self organizing maps technique.
[42]	2020	✓		✓						✓	Survey of control variables. The papers are sorted by year from 2004 to 2018. Survey of review papers since 2004 to 2018.
[43]	2020					✓			✓	✓	Brief summary of EMS optimization.

C: Constraints; TF: Time-Frame; F: Framework; U: Uncertainty; O: Optimizer;
GC: Grid-Connected; IS: Islanded; F&O: Framework and optimizer.

This section presented an introduction to MGs and their main systems and current issues. Besides, a survey of review papers conducted from 2012 to 2020 was provided. The rest of the paper is organized as follows. Section 2 presents the systematic literature review (SLR) process conducted in this review paper. Besides, it provides a brief overview of the selecting and analyzing process of the bibliography for this review paper. Afterwards, the main aspects of the energy management optimization of IMGs are comprehensively reviewed in Section 3. Section 4 provides a discussion on the future trends of IMGs. Finally, Section 5 concludes the paper.

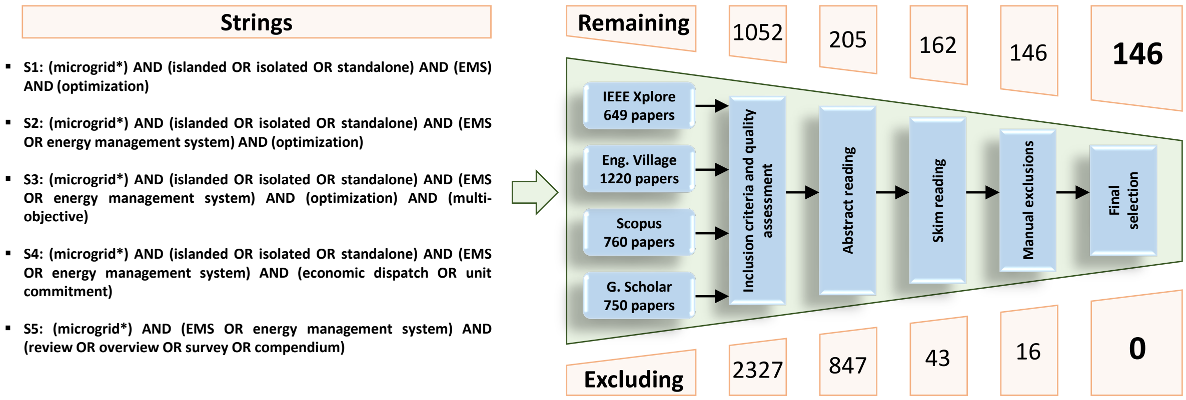

Fig. 4: Searching process for the SLR.

2. Method for Systematic Literature Review

The SLR was developed based on four consecutive steps, namely search, appraisal, synthesis, and analysis (SALSA) [44, 45]. For the first step "search", the scientific databases utilized to find the relevant bibliography were IEEE Xplore, Engineering Village, Scopus, and Google Scholar. Five different searching strings were built *S1, S2, S3, S4, S5*, see Fig. 4. Besides, the search was restricted to the year of publication being between 2000 to 2020 for regular papers and between 2012 to 2020 for the review studies. The total number of publications per string and scientific database is presented in Table 2.

Table 2: Total number of publications for the "search" stage of the SLR (SALSA)

String	S1	S2	S3	S4	S5	Domain	Years[1]
IEEE Xplore	34	313	23	74	205	All metadata	2000 – 2020
Engineering Village	62	637	41	124	356	All fields	2000 – 2020
Scopus	47	353	38	7	315	Title, abstract, keywords	2000 – 2020
Google Scholar[2]	150	150	150	150	150	Anywhere in the article	2000 – 2020

[1]The range was 2012-2020 for S5. [2]Restricted to the first 150 most relevant publications.

The second stage is the "appraisal" where a first screening of the papers is done. The initial papers' selection was done by using inclusion criteria and quality assessment. The inclusion and exclusion criteria are: 1. Include when the title contains most of the searching words comprising the predefined string. 2. Include when the document is not gray literature. 3. Include when the publication is accessible. 4. Exclude when the paper has been selected already. 5. Exclude when the title does not have, or has very few, searching words of the predefined string. The quality assessment at this stage is verifying that the publication is not out of scope of this review study.

Initially, a total of 3379 papers were found by using the predefined searching strings, Table 2. After the first screening, 1052 papers were used for further abstract reading. Then, excluding papers that were not properly studying the EMS in IMGs, resulted in 193 papers. Next, a skim reading of the paper structure, figures, tables, and conclusions was conducted. Thereby, it resulted in 150 papers for further processing. After a full reading, some papers were discarded when the inclusion criteria and quality assessment were not satisfied, resulting in 134 papers finally for further study, Fig. 4.

The third stage of the SALSA is the "synthesis", where the relevant data are extracted and classified for the final "analysis" stage. The features of interest for this study are: Objective function; Optimizer; Strategies compared and/or conditions evaluated; Mathematical models; Validation (simulation, experimentation); Constraints; Resolution; Processing time; Optimization's horizon; kind of data used; Forecasting of energy/load; Architecture; and the uncertainty treatment technique.

At the final stage of the SALSA, named as "analysis", the main features that an EMS in an IMG should consider for optimal energy management were identified and classified.

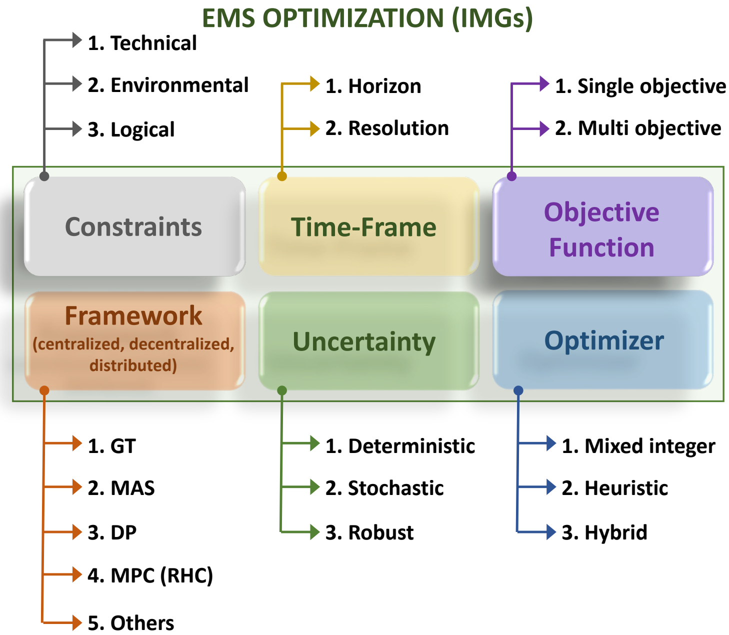

Fig. 5: Main aspects for the EMS optimization problem in IMGs.

3. EMS Optimization Aspects for IMGs

The IMGs have proven their great potential to be a solution for supplying energy to remote locations where the main grid is not available. However, the full adoption of IMGs is still limited due to the high uncertainty that renewables and load demand inherently have. Thereby, intermittent energy resources along with conventional ones and ESSs could solve the problem of uncertainty, up to some extent. Nonetheless, it is imperative to incorporate efficient optimization strategies to reduce the energy cost, the pollution spread, the fuel consumption, *etc.*, while the quality of service is guaranteed. To resolve such a difficulty, it is necessary to form a complete scheme to address the optimization issues. In this paper, the optimization scheme of an IMG is characterized by six significant aspects including the optimization framework, optimization algorithm, uncertainty handling approach, OFs, constraints, and the time-frame, see Fig. 5. Each of these aspects is discussed in this section along with applications on the EMS of IMGs.

3.1. Time-Frame for EMS Optimization

A significant factor for EMS optimization is the time-frame. Basically, the time-frame refers to two essential information: the horizon time in which the optimization is performed, and the time resolution in which the scheduling is carried out. Depending on the application, the time horizon can vary from a few hours to several days (for operation management) [46, 47, 48], to several months or even several years (for maintenance planning, feasibility studies, or planning and sizing of the MGs) [49, 50, 51, 52]. The time resolution commonly ranges from several seconds [46, 47, 53], to one hour [54, 55]. Optimization methods can be also classified as off-line, on-line or real-time. Offline methods are used in cases with complete information or in two-stage decision-making approaches where a second-stage real-time method is used for compensating probable deviations [55, 56]. They can be also used in day-ahead power scheduling for market participation. Real-time control methods which control the system operation in real-time rely on the fast computational, communication, and prediction systems. The goal of these real-time EMSs is to handle forecasting errors in energy availability and load to increase the system reliability [2, 57, 58].

3.2. EMS Optimization Constraints

The high uncertainty in energy availability of NCDERs, as well as the demand uncertainty, especially in islanded systems with high renewable penetration, makes the EMS optimization a non-linear, MO, multi-constraint problem. In fact, the goal of a certain MG could be more than one single objective while is bounded by different sort of constraints. According to the conducted survey, it is possible to classify the constraints of IMGs into technical, environmental, and logical restrictions. Technical constraints correspond to those which limit the physical operation of the MG.

Among the most common technical constraints used in the current literature by IMGs are power balance, power limits, unbalance limits, state of charge (SOC) and depth of discharge (DOD) limits, voltage limits, power ramping limits, on/off minimum time, operating reserve constraint, limits in the tank diesel volume, controllable load limits, and peak demand constraint. Even though these constraints can be applied not only to islanded but also grid-connected MGs, it should be noticed that some of these constraints are vital for IMGs while they might be omitted in grid-connected mode. Reliability of supply, robustness, resiliency, or even stability of the IMGs can be supported by inclusion of appropriate constraints to their energy management optimization problem. For instance, real-time energy management of an IMG is optimized in [59] while ensuring a stable operation. The EMS performs droop selection and optimizes the generator dispatch every 15 seconds while a droop stability analysis is done off-line. The fuel consumption minimization is achieved by adjusting the droop control gains for real power of each DER. These gains are constrained in a range of values to ensure a stable operation while the droop gains for the reactive power were kept constant due to the low impact on stability. The gains' range were estimated using small-signal stability analysis while the DERs were assumed to be always on. Table 3 gives a summary of several widely-used constraints for EMS optimization of IMGs and the component in which the constraints are commonly applied. Besides, a brief description of each constraint is provided.

Table 3: Physical constraints for EMS optimization of IMGs

Constraint	**CDERs**	**NCDERs**	**Batteries**	**Loads**	**System**	**Brief description**	**Reference**
Power balance[1]					✓	Generation must match consumption. Some exceptions appear with chance-constrained problems. Reactive power is sometimes included.	[2, 5, 7, 47, 53, 57, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76]
Load demand[1]				✓		The actual load is considered higher than the forecasted load.	[60, 77]
Power rate[1]	✓	✓	✓		✓	Manufacturer recommendations about maximum/minimum power.	[2, 5, 7, 47, 53, 57, 60, 61, 62, 64, 65, 66, 67, 68, 69, 71, 72, 73, 74, 76, 78]
Dynamic power rate[1]			✓			Dynamic charging/discharging ratio, in terms of SOC or energy stored in the last step.	[63, 66, 73, 74]
Apparent power[1]	✓				✓	Limits on apparent power of generators, MG lines, or power flow.	[65, 78, 79, 80]
Unbalance[1]	✓					Maximum neutral current on converters interfacing CDERs with MG.	[2]
Voltage level[1]	✓	✓	✓		✓	Limits in DERs terminal voltage and/or power buses.	[2, 7, 65, 79, 81, 82, 83]
Power ramping[1]	✓		✓			Manufacturer recommendations for maximum ramping up/down power.	[2, 55, 56, 57, 58, 62, 65, 73, 74, 76, 79, 84]
On/off min. time[1]	✓					Minimum amount of time that a CDER will keep its on/off state.	[2, 5, 58, 85, 86, 87]
Max. startups and shutdowns[1]	✓					Maximum number of startups/shutdowns in CDERs.	[84, 85, 86]
Power reserve constraint[1]	✓		✓			A reserve of power against sudden changes in load demand and/or energy availability.	[5, 88]
Diesel volume[1]	✓					A minimum level of diesel in the DG tank.	[47, 60, 89]

Table 3: Physical constraints for EMS optimization of IMGs (continuation)

Constraint	CDERs	NCDERs	Batteries	Loads	System	Brief description	Reference
Min. diesel vol. at the end of a period[1]	✓					A minimum level of diesel at the end of a period in the DG tank.	[47]
Peak demand[1]				✓	✓	Preventing a peak demand higher than the current MG generation capacity.	[7]
Excess of generation[1]					✓	Allocating the excess of generation to ESS, dump loads, and demand response (DR) system.	[58, 64, 73, 74]
Controllable load limits[1]				✓		Limits on the controllable loads power, energy (deferrable loads), or a maximum percentage of interruption at each time-step.	[53, 60, 65, 68, 76, 79, 84, 90]
SOC limits[1]			✓			Manufacturer recommendations about SOC limits in batteries and fuel cells (FCs).	[2, 7, 47, 53, 57, 60, 62, 65, 66, 67, 68, 69, 70, 72, 73, 74, 75, 76, 79]
Initial and/or final SOC[1]			✓			Minimum SOC level at the beginning/end of a period.	[7, 47, 57, 65, 66, 68, 72, 79, 81, 91]
DOD and/or max. number of daily operations[1]			✓			Limits on number of operations during a day and/or maximum DOD in batteries.	[72, 84]
Amount of pollution[2]	✓					Bounds on the maximum allowable pollution emissions to atmosphere. Sometimes the pollution produced by the main grid is also considered in grid-connected MGs.	[92, 93, 94]
Avoid conflict[3]	✓		✓			Auxiliary terms for avoiding conflicts between variables.	[2, 7, 47, 55, 56, 60, 76, 84]

1: Technical. 2: Environmental. 3: Logical.

3.3. EMS Objective Functions

The OF corresponds to the optimization goal, which normally includes minimization of the MG cost and pollutant emissions among others, see Table 4. Besides, the OF can be expressed as a single or multiple function while it can be restricted by different constraints, see subsection 3.2. Furthermore, constrained OFs can be transformed to unconstrained ones by considering the restrictions as penalization terms in the OF [72]. A brief summary, of widely-used cost functions in IMGs is given in Table 5.

Table 4: Widely-used objective functions for energy management optimization of IMGs

OF	Reference
Minimizing operation cost.	[2, 47, 53, 55, 56, 60, 62, 65, 71, 75, 81, 88, 89, 95, 96, 97]
Minimizing generation cost.	[4, 54, 58, 64, 66, 73, 74, 77, 79, 90, 98, 99, 100, 101]

Table 4: Widely-used objective functions for energy management optimization of IMGs (continuation)

OF	Reference
Optimizing battery sizing and/or minimizing fuel consumption.	[5, 49, 57, 67, 70, 78]
Minimizing operation cost and/or minimizing emission.	[46, 61, 72, 76, 82, 85, 92, 102, 103]
Minimizing operation cost, minimizing emission and minimizing dump energy.	[84]
Minimizing operation cost and minimizing charging cost (customer perception).	[7]
Minimizing power ramping in DGs.	[65]

Table 5: Cost functions for EMS optimization of IMGs

Item	Sort of cost function	Reference
NCDER	• Operation, maintenance, and profits.	[62]
CDER	• Fuel consumption. • Constant startup cost. • Constant shutdown cost. • Variable startup cost with time in which the DER has been off. • Variable startup/shutdown cost with starting-up duration. • Oil consumption. • Emission of pollutants.	[2, 7, 46, 47, 54, 57, 60, 61, 62, 66, 71, 72, 75, 76, 78, 79, 82, 84, 85, 86, 87, 102]
Investment, operation and maintenance (OM)	• Operation and maintenance cost during the entire time horizon. • Hourly operation and maintenance cost. • Initial investment cost.	[5, 61, 71, 72, 75, 82, 84, 104, 105, 106]
Batteries	• Total cost per day. • State of health. • Operation, maintenance, and profits. • DOD and SOC. • Degradation. • Replacement cost. • Charging EV battery.	[5, 7, 48, 60, 62, 76, 79, 88, 91, 107]

Table 5: Cost functions for EMS optimization of IMGs (continuation)

Item	Sort of cost function	Reference
Penalty terms	• Unused energy. • Interrupting or deferring a load. • Losses in lines by Joule effect. • Violating power ramp rates of DGs. • When batteries are not fully charged. • When SOC is lower than certain level. • Pollutant emissions.	[46, 47, 48, 55, 58, 60, 61, 64, 65, 72, 73, 74, 79, 81, 82, 84, 98, 101, 102]

3.4. EMS Optimization Framework

The proposed optimization frameworks for EMS of IMGs are based on three architectures: centralized, where all the information is gathered and processed in a central unit; decentralized, where the information of each unit is gathered locally and processed relying completely on local information; and distributed, which is a combination of the aforementioned architectures, where the data is gathered locally and shared with the neighbours. Widely-used optimization frameworks applying to EMS of IMGs are the GT approach, MAS, dynamic programming (DP), rolling horizon control (RHC) (model predictive control (MPC)), and others in which are included hybrid approaches. This subsection is devoted to introducing these frameworks and their application in IMGs' EMS.

3.4.1. Dynamic Programming

DP is an optimization framework proposed by Bellman in the mid 1950s, which splits a multi-stage decision-making problem into a sequence of simpler subproblems and thus, results in a computational time reduction [108, 109]. The DP framework for operation optimization of islanded and grid-connected MGs has been widely addressed [57, 110, 111, 112]. For instance, in [57], the SOC of batteries is quantized in each time-step (between its limits) during the whole time horizon. The links between one step and the next one are weighted with a cost depending on the economic dispatch (ED) of the CDERs. The task is to find the cheapest path between the beginning and the end of the desired time horizon. The results show the superiority over the traditional day-ahead ED technique. In [85], an advanced DP algorithm is applied for energy scheduling in an IMG. Two scenarios are tested with and without the use of ESS. The results show roughly 8.5% lower daily cost when ESS is used. In [113], a stochastic-DP technique is applied to the EMS optimization of an islanded house-MG. The time-variant Markov process is used to model the photovoltaic (PV) generated power and the problem is formulated as a RHC. The strategy is compared with a rule-based algorithm in two different scenarios. The simulated and experimental results show the stochastic-DP superiority.

For reducing the processing time, the implementation of DP+portryagin's maximum principle (PMP) is proposed in [66]. The combination of these methods is applied to EMS of an IMG and compared with the mixed integer linear programming (MILP) and non-linear programming (NLP) by simulation, using real data. The results show the superiority of DP+PMP regarding processing time, which is less than one second (about 0.5 seconds) and a reduction in generation cost compared with the MILP technique. The proposed method does not require any kind of linearization but discretization.

3.4.2. Game Theory

GT is a mathematical framework for modelling the interaction between independent individuals with their own strategies, working for reaching their particular objectives [114]. GT is mainly split into two categories of non-cooperative and cooperative games, where the Nash equilibrium is one possible solution concept [115]. The nature of GT gives the possibility to use it in a fully distributed energy management system (DEMS). In [116], centralized and distributed configurations are compared, analyzing the processing time while the number of homes in a MG goes up. It is shown that the distributed configuration outperforms hugely the centralized one when the number of homes increases. Nevertheless, since convergence is hard to guarantee in GT, especially with plug-and-play members, authors in [62] have proposed to use an enhanced algorithm, GT-potential game (PG), and according to them, the convergence and global power balance is guaranteed. Another attempt for ensuring convergence is done by [114], where

GT-PG is applied along with a multi-objective hybrid genetic algorithm (MOHGA) to seek the Nash equilibrium point. The optimization goal is to minimize the total production cost of MGs and the results are compared with the results of multi-objective sequential quadratic programming (MOSQP), multi-objective mesh adaptive direct search (MOMADS), and multi-objective genetic algorithm (MOGA). Regarding accuracy, MOHGA is the best, but in terms of the processing time, MOSQP is the fastest. Moreover, authors in [86] compare a modified GT-based EMS for environmental-economic operation optimization with the same aforementioned strategies. Three scenarios are considered where the first two are related to the island configuration of MGs. The results approve the superiority of MO-GT in terms of accuracy.

3.4.3. Multi-Agent Systems

Multi-agent optimization framework is based on the interaction, bargaining, and coordination of a number of agents (different MG's components for example) for achieving a common goal, following the rules and regulations [117]. Nevertheless, to consider the agents as intelligent entities, they need to have mainly four features: autonomy, reactive skills, proactive skills, and social skills [115, 118]. This framework is successfully applied to EMS of grid-connected and IMGs in different studies [119, 120, 121]. The MAS process flow is basically a negotiation among different agents. For instance, in [119, 120], the administrator agent first gathers the information of each agent and energy prices, then calls for proposals to other agents. Next, considering the power balance, the administrator makes (or not) a call for proposal to the storage elements, and the power balance is evaluated. Afterwards, the administrator agent accepts or rejects agents' proposals. The accepted proposals must be implemented. The final stage is to send the reports to the administrator by each agent and this cycle is repeated [119, 120]. Worthy to mention that MAS in distributed configuration has several advantages over the centralized architecture; firstly, all the units can operate almost autonomously without the need for processing large amount of data resulting in reducing the computational time; secondly, higher flexibility for plug-and-play operations will be achieved. However, one disadvantage of the MAS distributed architecture is the weaker cooperation between units in comparison with the centralized configuration [122].

3.4.4. Rolling Horizon Control

Finding the current instantaneous solution of an optimization problem by using an online finite horizon open loop optimal control is called RHC or MPC [56]. One advantage of RHC is replacing a close-loop control problem with a simpler open-loop control problem using an initial state [123]. Thereby, the current decision will be affected by the predicted future conditions. Using this technique, the unit commitment (UC) and ED decisions are made at every time-step with updated data to reduce the potential errors in inaccurate models and forecasting data [124, 125]. In [53], as an attempt to enhance the traditional RHC, it is proposed to split the RHC process into three stages. The first stage is related to finding the optimal ED of DERs and non-critical loads. Secondly, the switching state of the non-critical loads are optimized. The last stage is devoted to fine tuning of the power in each DER. The control procedure is repeated every 15 minutes and it is shown that similar simulation results can be achieved with both zero and large forecasting errors. In [126], energy management of an IMG is optimized using two coordinated layers, namely an schedule layer and a dispatch layer. The former schedules the state and power of each DER with an economical perspective in the whole horizon while the latter adjusts the decisions taken by the schedule layer in each step considering technical aspects like power flow and voltage limits. The power balance is maintained by the dispatch layer using the power reserve allocated by the schedule layer to each DER. Besides, a DSM is considered. The main goal is to keep a reliable power supply with the minimum operation cost. The proposed technique was simulated in a generic MG while different levels of forecasting error were considered. The results indicate a lower satisfaction rate of the load by increasing the forecasting error. In [84], it is proposed to apply the RHC strategy together with robust optimization (RO) for optimal ED, considering the uncertainties in energy availability of RESs and power demand. The problem is solved using mixed integer non-linear programming (MINLP) and simulation results are provided for both grid-connected and IMGs. On the other hand, in [127] it is proposed to relax the DG's binary variables to reduce the complexity of the RHC solved with MILP. The simulation results show a decrement of the computational burden without largely degrading the accuracy in comparison with the traditional RHC in an IMG. The best results are obtained when the relaxation starts after five hours in the horizon window. In [128], the RHC is applied along with proposed thermal models and MILP is used to find the solution every 15 minutes. The simulation results show a considerable reduction in the total cost of the energy in two different scenarios while it is compared with an EMS without considering any thermal modelling.

3.4.5. Hybrid Frameworks

In [118], to show the superiority of DEMS over centralized configuration, the MAS framework is combined with GT for the multi-agent coordination and ED service of a DEMS in a grid-connected MG, using simulation environment and Tioman Island as a study case. Furthermore, four scenarios are analyzed with and without disturbances in energy availability and load demand. The results are compared with a centralized EMS, showing the superiority of the distributed approximation. Moreover, the authors report a shorter processing time by using the distributed scheme. Another work, which also uses the MAS approach along with the GT (MAS-GT) for EMS optimization is given in [115]. A Greek island is considered as a MG and simulation studies are performed for two scenarios with low and high renewable energy availability. Furthermore, the proposed configuration is compared with a DEMS based on MAS-fuzzy cognitive maps (FCM). The results show the superiority of the MAS-GT framework over the MAS-FCM. Moreover, RHC is proposed along with the GT framework for a real-time DSM in [129]. In [113], RHC and stochastic-DP are used to formulate the EMS problem of a home-MG.

3.5. Uncertainty Treatment for EMS Optimization

In an IMG, there are different sources of uncertainty like the available energy of RESs, consumer demand, electricity price, and so on that need to be dealt with through efficient uncertainty handling techniques. The EMS optimization can be carried out employing deterministic approximations relying on accurate forecast systems, *e.g.*, the RHC or MPC strategy [60]. However, the uncertainty is not explicitly taken into account in these methods and therefore, their outcome strongly depends on the accuracy of the forecasting strategy. Another way to address the uncertainty is by using stochastic approximations, which need assumptions about the probability distribution function of uncertain parameters [7], for instance in scenario-based and chance-constrained optimization methods that might lead to poor performance in case the precise knowledge of the uncertainty is not available. The energy management uncertainty can be also handled through RO techniques, which do not need the specific probability distribution for the random variables, but requires an assumption for the uncertainty bounds [55, 84].

The RO scheme is widely applied for EMS of IMGs. In [55], the EMS of an IMG is split into two stages. The first stage is a robust UC on an hourly basis while the second stage is an optimal power flow (ED) every five minutes considering penalty terms for disconnecting loads. The optimization problem is solved by MILP technique. According to the results, the RO strategy shows a lower total cost than the deterministic approximation. However, it can be noted that a high degree of uncertainty will result in high conservatism with a long convergence time. Therefore, a distributional robust optimization (DRO) is proposed in [76] handling a chance-constrained problem for EMS of an IMG. Unimodality in the random variable is assumed for reducing the conservatism in the traditional RO scheme. In [89], the authors apply RO and propose to use a fuzzy predictive interval model together with the RHC strategy to forecast the upper and lower limits of the available energy of wind turbines (WTs). The UC problem is solved separately for the best and worst scenarios and the results are added up using constant weight factors (dynamic modification of these factors is recommended). This convex summation is used to avoid a high level of conservatism, which is caused by considering just the worst-case scenario in traditional RO. According to the results, the cost of the robust EMS was higher than an EMS using a simple fuzzy predictive model. However, the confidence level of energy supply is higher in the robust EMS.

3.6. Optimization Algorithms for EMS

This subsection is dedicated to introducing the widely-used optimization algorithms for EMS of IMGs. It should be noticed that many of the present optimizers have been used also in grid-connected MG studies since the main grid can be considered the reference DER. According to the survey conducted, these algorithms are classified as traditional (mathematical), meta-heuristic/heuristic, and hybrid methods. The traditional methods are mostly based on linear and non-linear mixed-integer programming techniques. Besides, the population-based heuristic methods are thoroughly discussed in this part and several hybrid methods corresponding to the algorithms which are a mixture of different methods are presented. Finally, rule-based (RB) decision-making techniques applicable to EMS of IMGs are introduced.

3.6.1. Traditional Optimization Strategies

Mixed Integer Programming

In [79], MILP method is applied for solving the optimization problem of a MG in grid-connected and islanded modes. Piecewise linearization technique is applied to the non-linear equations. According to the authors, real fore-

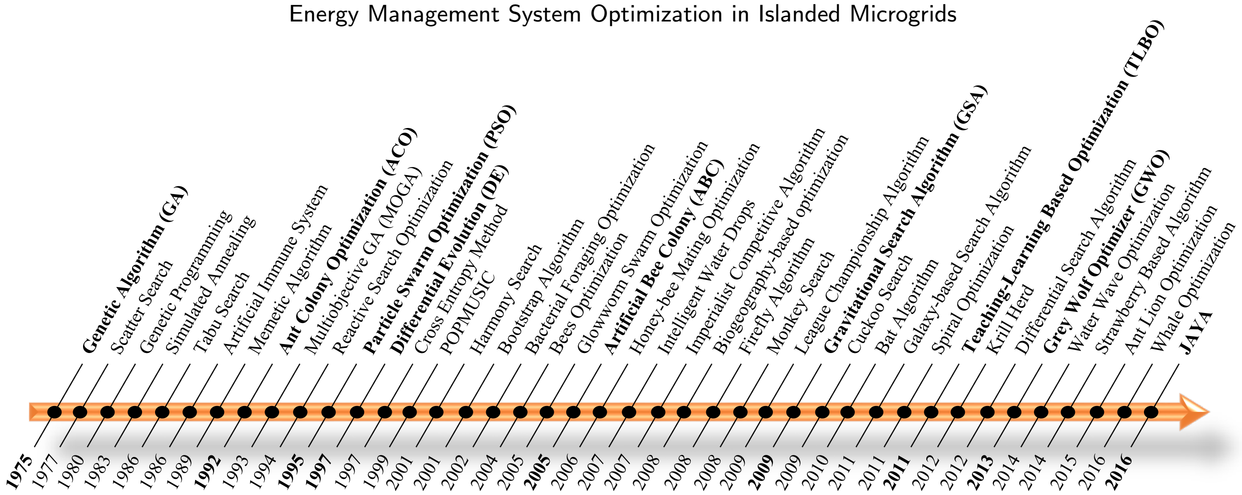

Fig. 6: Timeline of the commonly-used heuristic optimization algorithms, 1975-2016. (Bold) Trendy for EMS of IMGs [130, 131, 132, 133, 134].

casted data are used and a saving of 28.31% in energy costs is achieved. Piecewise linearization is also applied in [82] along with a power flow calculation stage while taking into account the network losses and using an algorithm for avoiding voltage and current violations. It is shown that the number of segments in the piece-wise approximation has a major impact on the processing time and a minor impact on the accuracy of calculations. The optimal UC is achieved using GA and compared with MILP. The MG cost is approximately the same in both cases, but GA spends almost double processing time compared with MILP in some cases. Nevertheless, GA shows better results in highly constrained cases. Additionally, it is shown by simulation that the higher SOC and the lower DOD, the higher the battery lifespan.

MILP is also used for reducing ramping power and minimization of operation cost in [65]. The equations are linearized using the Taylor method and it is shown that the inclusion of ESSs and controllable loads can reduce the operational cost. MILP is also applied to the EMS of an IMG with deferrable loads in [68]. In [47], a DSM is considered with the piecewise linear equations in an IMG. The optimization is solved by MILP while considering the water supply to the consumers. In [49], the authors apply MILP with special ordered type-1 sets for a constraint of mutual gensets exclusion; and type-2 to deal with the piecewise linear OF that is saving fuel in an islanded military MG. A linear equation of the output power vs fuel consumption flow in DGs is proposed while considering a mutual exclusion between the gensets. Besides, the Rainflow counter method is used to estimate the lifetime of the batteries according to the number of charging/discharging cycles (this method allows overlapping cycles) and determine the optimal battery sizing.

Considering imbalance conditions and modeling with phasors result in very expensive computations for commonly used software like GAMS, or even worse they cannot solve the problem [2, 53]. Therefore, in [2], the authors propose to split the problem into MILP+NLP, solving the problem in a processing time of roughly 30 seconds.

If the system is not linearized, MINLP could be applied for optimization. However, the processing time could be very long [2, 53]. MINLP is also applied to the energy management of an IMG in [73], showing a saving of up to 15% in the generation cost compared with a modified conventional energy management system (MCEMS). The mixed-integer quadratically constrained programming (MIQCP) is another possible solution for non-linear optimization problems, which is applied in [99] and compared with a traditional non-optimal RB EMS. The comparison is done by simulation in both grid-connected and islanded configurations. The MIQCP-based EMS outperforms the RB method regarding the total generation cost.

3.6.2. Heuristic Optimization Strategies

In this section, widely-used heuristic optimization strategies for EMS of IMGs are introduced. These strategies include grey wolf optimization (GWO), ant colony optimization (ACO), particle swarm optimization (PSO), artificial bee colony (ABC), teaching-learning based optimization (TLBO), evolutionary algorithms (EAs), gravitational search algorithm (GSA), JAYA, and some of their improved versions. Figure 6 gives the chronological overview of the most popular heuristic techniques from 1975 to 2016. Besides, Fig. 7 provides the number of publications related to the application of heuristic algorithms to energy systems in MGs. According to this figure PSO and EAs are the most

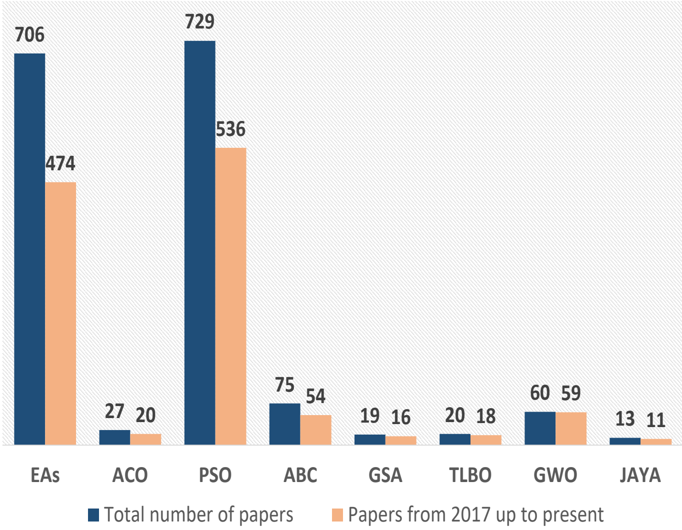

Fig. 7: Number of publications using a heuristic algorithm regarding energy systems in MGs. Source: Scopus. The search was carried out considering the articles title, abstract, and keywords, while conference reviews were excluded. The search keywords were: microgrid, EMS, energy management system, energy management, energy, and the name of the respective algorithm.

popular algorithms, whereas the ACO, GSA, TLBO, and JAYA are the least employed algorithms for this purpose. Moreover, it is observed that the research publications using these techniques from 2017 to the present hold the majority.

Evolutionary Algorithms

One of the most popular EA techniques is GA, which was proposed in 1975 by Holland. This population-based algorithm tries to mimic the natural selection process. The GA process includes initialization, OF evaluation, selection, crossover for giving birth to offspring, and mutation. Afterwards, the OF is evaluated in the offspring and the termination criterion is checked at the end. If the stopping criterion is met, the process is finished, otherwise, it should be repeated [100].

The effectiveness of this algorithm for the energy management of an IMG is evaluated in many studies. In [72], GA is used for single and MO optimization considering minimization of operational cost and emissions. Authors in [135] apply a covariance matrix adaptation - evolutionary strategy (CMA-ES) to an IMG and compare it with the numerical Nelder Mead algorithm for the MO optimization problem. The results show the CMA-ES superiority. Moreover, a non-dominated sorting genetic algorithm (NS-GA) is used in [136] for the economic operation of a real MG on Dong-Fushan Island in China, while considering the power generation cost and batteries life loss cost. The system is tested under abundant and poor availability of renewable energy, using real profiles, and the results are compared with a case without optimization process. According to the results, the proposed NS-GA strategy results in large savings in costs and the batteries lifespan. Furthermore, a niching evolutionary algorithm (NEA), called self-adaptive low-high evaluations–evolutionary algorithm, is proposed to optimize the operation of a medium voltage IMG aiming to minimize the operating cost, pollutants emission, and ESS use [137]. The optimization is performed in a generic IMG by studying nine different scenarios and nine different combinations of weighting factors for the MO problem formulation. Besides, the resolution time is set to 20 minutes. The results are compared to a non-optimal solution provided by the local controllers, showing more than 50% savings in operation cost and a saving of 40% in pollutants emission.

Several efforts to improve EAs are reported. For instance, in [100], it is proposed to enhance the traditional GA by adding a memory where the algorithm saves the best so far chromosome. The proposed method is applied to optimize the MG (IEEE 37-bus) ED. The results are compared with two variants of the traditional PSO (one with a weight damping factor and the other with a constraint factor) and the traditional GA. The memory-based genetic algorithm (MGA) and PSO (using weight damping factor) accuracies are very similar but much better than the others. Nevertheless, the processing time is almost twice in the PSO-based algorithms (around 2 seconds).

Ant Colony Optimization

This fast and simple heuristic optimizer was firstly presented by Dorigo in 1992. ACO is inspired by the ants behavior when they are searching for food. These tiny insects use to leave pheromones in their path, which can be detected by other peers. This path with pheromones, commonly named favorable path, is used by posterior ants increasing the pheromones intensity and eventually converging to the shortest path from nest to the food source [61, 138]. The process to find the optimal solution of a discrete optimization problem starts with the initialization of ACO parameters. Afterwards, a complete path should be found for a particular ant based on a probability distribution. Next, local updating of the pheromone amount is applied. When all ants have visited all nodes, the optimal path length is evaluated and its pheromone is updated using the global updating rule. If the optimal condition is reached, the process is finalized [139].

In [61], the authors compare the performances of ACO, a traditional gradient-based method, and a Lagrange-based method for energy management of an IMG, showing that ACO outperforms the other methods. ACO is also compared with MCEMS and PSO in [58] for an IMG through simulation studies and hardware-in-the-loop (HiL) tests. The results show the superiority of ACO in terms of accuracy and speed to find the optimal ED. Besides, ACO is applied to an IMG in [102] for ED along with emission minimization. The ACO results are compared with a gradient-based method while the MG is tested in two scenarios with and without NCDERs. ACO algorithm shows better performance compared to the gradient-based method in both scenarios. Furthermore, simulation studies for ED of the IEEE 34-bus radial system with CDERs and NCDERs are presented in [140] using ACO and GA. The results show better accuracy and speed of ACO. In [141], it is shown by simulation that using more than 20 colonies (50 ants each) for optimal ED of an IMG will increase dramatically the CPU time while the performance is not improved considerably.

Particle Swarm Optimization

This algorithm was proposed in 1995 by Kennedy and Eberhart. PSO is inspired by the behavior of social individuals, such as birds, ants, or fishes. The algorithm imitates the way in which members share information between them. The mathematical formulation contains two terms for representing the cognitive and social influence upon each member of the group to find the optimal solution [142].

PSO algorithm is applied successfully for ED to grid-connected and IMGs with high penetration of CDERs in [71, 143]. In [91], PSO is applied for DERs ED with a deep recurrent artificial neural network (ANN) to forecast PV energy availability and load demand. The results show that a lower cost can be achieved when the ESSs are used and the charging/discharging process in EVs is controlled. The EV behavior is modeled by normal distributions regarding running distance and charging start time. Another study show the feasibility of the PSO algorithm to be used in real-time EMS applications for IMGs [144]. The algorithm's results show the same results as those of the analytical sequential quadratic programming (SQP) while 90 times faster to converge for a 24-hour horizon and a resolution of 3 minutes.

Furthermore, some improvements to the PSO have been proposed. For instance, the authors in [98] use a regularized PSO algorithm for limiting the velocity of the particles. Focusing on the grid-connected configuration, they propose a dynamic cost function for battery charging/discharging by including a penalty term when the battery is not fully charged while there is a surplus of energy production or the price is low. In [77], it is proposed to modify the inertia term in traditional PSO by multiplying it with a linear damping factor as another attempt to keep the velocities of the particles bounded. It is shown by simulation that PSO outperforms the random search optimization (RSO). Another attempt to keep particles velocity restricted is used in [54] by proposing a modified PSO, which increases linearly the inertia term between certain limits during the time. In such a work, ED using modified PSO is compared with GA and the simulation results show higher economic benefits and faster convergence of the modified PSO. Besides, in [46], it is shown by simulation that multi-objective particle swarm optimization (MOPSO) is faster than MOGA for energy management of an IMG. In [96], MOPSO is applied to EMS in MGs and compared with evolutionary programming (EP), GA, MOGA, PSO, and an enhanced bee colony optimization (EBCO) algorithm. The results show that EBCO is the fastest while MOPSO has the lowest cost and the second lowest processing time. In [80], to speed up the convergence, it is proposed to split the serial process of the PSO into parallel tasks by using a message passing interface (MPI) technique. Comparing with the traditional PSO, a shorter processing time and a comparable cost are achieved. Another improvement to the accuracy of PSO applied to IMGs is presented in [92]. The improved particle swarm optimization (IPSO) introduces a neighborhood chaotic search to avoid getting trapped in a local minimum. This chaotic search is implemented when the global optimal solution is not changing for a certain number of iterations. This algorithm tries to search for a better global minimum, but if after the implementation of chaotic search the global minimum no longer changes, the last global minimum will be the solution. The results show the IPSO superiority.

In [145], a PSO algorithm with adaptive compression factor (ACF) is developed for an IMG considering price-based DR for reducing the total operation cost. Simulation results show an economic saving compared to the case without DR.

Artificial Bee Colony

This algorithm was proposed by Karaboga in 2005. ABC tries to mimic the foraging process of a bee colony. The bees are classified into three categories: 1) Employed bees corresponding to 50% of the total population, which search for food and send this information to the onlooker bees. 2) Onlooker bees, which are the other 50% of the population, are responsible for selecting the best food found by the employed bees. 3) The third sort of bees are the scouts, which come from a few employed bees. These bees leave the common food source and search for new resources [146].

This algorithm is applied for the energy management of an IMG in [147]. The study considers four scenarios with/without ESS and with different initial SOC levels, showing also the important role of ESS in remote MGs reliability. ABC shows better accuracy than PSO and GA. Unfortunately, this algorithm easily gets trapped in a local minimum and has poor stability in high dimensional optimization problems like energy management of MGs [148]. Therefore, based on the traditional ABC optimization method, two modifications are proposed for enhancing its performance including using a different probability function for exploitation mechanism and a new search process. This algorithm is compared with PSO and MCEMS in simulation and HiL implementation for an IMG. It is shown that ABC outperforms PSO and MCEMS in terms of accuracy (considering MINLP solution as a benchmark), economic saving, and processing time [64]. The same modified-ABC algorithm was compared with the MCEMS in [90], showing superior performance of the modified-ABC in terms of economic saving. Furthermore, the same algorithm was applied to the UC and ED optimization of a home-MG (grid-connected) in [101]. The study is done by simulation and HiL. The results are compared with MINLP, showing that ABC is faster and slightly more accurate than MINLP. Another attempt to improve the ABC performance is performed in [148], where self-adaption and repulsion factors improve the search efficiency and accuracy of each bee. Simulation studies are conducted to evaluate the performance of the proposed enhanced ABC (EABC) for ED of a MG and the performance is compared with EA, GA, PSO, and traditional ABC. According to the results, EABC is faster and more accurate.

Gravitational Search Algorithm

This algorithm was introduced by Rashedi *et al.*, in 2009. GSA is based on the physical laws of gravity and motion, where each agent is considered an object and its performance is measured by the object's mass. This process causes a movement of the total objects with a tendency to go in direction of the agents with heavier masses (better results). Given that the heavier the mass, the slower the displacement, the algorithm conducts a wide search [103, 149, 150, 151].

This algorithm is applied for energy management of an IMG in [74] by simulation and HiL tests. The GSA-based EMS is compared with the PSO-based EMS and a MCEMS. The results show that GSA is faster and gets lower costs.

Several improvements are proposed for the traditional GSA. In [103], it is proposed to compare the starting guesses with their opposite ones. According to the probability theory, a guess will fit better the optimal solution in 50% of the times compared with its corresponding opposite guess. Thus, it is better to choose the best guesses for starting or even applying this process in each iteration. This process will speed up the convergence process according to the authors. The proposed algorithm is tested in the IEEE 30-bus system (with a different number of units and with/without considering losses) for fuel and emission cost minimization. The algorithm results are compared with the results of linear programming (LP), multi-objective stochastic search technique (MOSST), NS-GA, strength pareto evolutionary algorithm (SPEA), niched pareto genetic algorithm (NPGA), modified bacterial foraging optimization (MBFO), fuzzy clustering PSO (FCPSO), and differential evolution (DE). The proposed algorithm outperforms the other methods in terms of accuracy. In [152], to improve convergence characteristics and deal with uncertainties, not only in energy availability, but also in market prices and load demand, authors propose to use probability functions (normal and weibull) for uncertainty modeling and a self-adaptive mutation technique for GSA to decrease the total operation cost of a typical grid-connected MG. Regarding the third scenario, when the battery starts at zero SOC, self-adaptive GSA outperforms GA, PSO, FSA-PSO, and trad. GSA using a deterministic scheme.

Teaching-Learning Based Optimization

The success of the most heuristic optimization techniques mainly depends on their parameters tuning. To resolve this issue, the TLBO algorithm was proposed by Rao *et al.*, in 2011, which does not require a specific parameter tuning. TLBO is based on the flow process of interaction between a teacher and students for teaching and learning information about a subject. The algorithm process includes [78, 153, 154]: *Initialization*, where each control variable (DER output power) is initialized with a vector of different values within the allowable limits. *Teacher phase*, where the mean value of each variable is calculated and the best population member (with the lowest cost) is selected as the teacher of the corresponding iteration. Afterwards, each control variable is shifted between its mean value and the corresponding value of the teacher. *Learning phase*, which could be considered as the team working, given that in this stage the control variables (learners) interact with each other to reinforce their knowledge. The algorithm ends when a stopping criterion is met.

In [78], the TLBO algorithm is applied for ED of CDERs in a MG (islanded and grid-connected) and is compared with three gradient-based optimizers: bisection method, regula falsi method, and golden section method. The results show that TLBO reaches the optimal operating points similar to the gradient-based algorithms without the need for complex formulations. A shortcoming is the higher processing time. In [153], it is proposed to use the TLBO algorithm for optimal sizing of MG elements. It is observed that the TLBO algorithm outperforms PSO and GA in terms of cost and processing time.

Several modifications to improve the TLBO algorithm have been proposed. In [97], the authors propose to modify the learning phase in TLBO for avoiding to get trapped in a local minimum and to search wider in the global search space. The ED-UC optimization is carried out in a grid-connected MG for operation cost minimization. The results are compared with the traditional TLBO, GA, PSO, and a fuzzy self-adaptive PSO. The modified TLBO shows superiority over the others not only in terms of accuracy, but also in processing time. Another attempt for improving the TLBO performance is given by [23], where the authors aim to avoid premature convergence. To do so, two steps are added: mutation and crossover. The proposed enhanced differential teaching-learning algorithm (EDTLA) is compared with GA, traditional TLBO, and enhanced DE (EDE) algorithm for the optimization of a DSM in a grid-connected MG. The economic and environmental aspects are considered the main goals. The results show the EDTLA superiority over the others in terms of accuracy. However, regarding the processing time, EDE is the fastest.

Grey Wolf Optimization

This algorithm was firstly presented by Mirjalili *et al.*, in 2013. GWO is inspired by the hunting rules of grey wolves and their roles in the herd, which commonly has between 5 to 12 members. The leader of the group is called *alpha*, the second in charge is named *beta*, which helps to reinforce the leader orders and gives feedback to the leader. The wolf at the lowest level of the hierarchy is called *omega* that always has to be submissive to others. Other wolves that are not in these categories are named *delta* and are commonly the hunters. In terms of optimization problems, the best solution is usually called α, while the second and third best solutions are named β and δ, respectively. The rest of the solutions are known as ω [5, 155].

In [155], GWO is applied to an IMG under the MAS framework for ED optimization while considering the action of primary and secondary controllers. The results are compared with other traditional heuristic methods, such as PSO, and it is possible to see the superiority of GWO regarding the number of iterations required to converge. The convergence is approved under different test conditions with changes in communication structure and system topology. In [88], GWO is applied for operation cost minimization of a grid-connected MG. The analysis is developed in three different cases regarding the ESS. The performance of GWO is compared with GA, PSO, bat algorithm (BA), improved bat algorithm (IBA), tabu search (TS), DE, biogeography-based optimization (BBO), and TLBO. The results show the superiority of GWO with a very narrow standard deviation. Besides, the multi-objective grey wolf optimization (MOGWO), which is carried out in a similar way to the MOPSO with an external archive to save dominant solutions, is applied in [83] for the optimization of a 70-bus grid-connected MG. Furthermore, the GWO algorithm is tested in a generic IEEE 33-bus system while considering uncertainty [156].

JAYA Algorithm

This population-based algorithm was proposed by Venkata in 2016. The word JAYA means *Victory* in Sanskrit [131]. Similar to TLBO, this algorithm has been recently proposed for optimization without needing parameters tuning (only the population size, number of generations, and the stop criterion are required). But unlike TLBO, which needs two stages in each iteration, JAYA requires only one. This heuristic technique searches for the best solution while trying to avoid the worst one. Each variable is updated by adding up a term, which carries the variable to a better solution and subtracting another term to avoid the worst solution [157].

This algorithm is applied to energy management of grid-connected and IMGs in [75]. Besides, it is compared with the EDE technique and strawberry-based algorithm (SBA). Using the critical peak price scheme in the demand profile, a lower production cost is achieved using JAYA with the lowest computational time. In the time of use (ToU) price scheme for load demand profile, the lowest cost was reached by SBA, while the shortest processing time was achieved by JAYA. Furthermore, JAYA, SBA, and EDE algorithms were compared with the Earliglow algorithm in a Home-MG in [158] under ToU and critical peak price schemes. The results show the JAYA superiority in terms of the total energy cost and processing time when the MG uses ESSs. Another application of JAYA for DSM in a Home-EMS using ToU scheme is presented in [159]. The results show the JAYA superiority over EDE and SBA in the reduction of energy cost. However, lower customer satisfaction in terms of waiting time of loads is observed. In [104], simulation results show the outperforming of JAYA over a gradient-based algorithm for EMS optimization in an IMG. The MO economic-environmental dispatch optimization is carried out using JAYA, ACO, PSO, and a gradient-based algorithm in [105]. The results spot JAYA in the best position.

Several modifications of the JAYA algorithm have been proposed to improve its accuracy and processing time. In [160], three modifications are proposed to the traditional JAYA; variable population size, three mutations, and a modification to enhance the search ability. The algorithm is tested in a modified IEEE 33-bus system. The study shows that a population larger than 40 elements does not show an important improvement. Furthermore, the enhanced JAYA behavior is compared with PSO, TLBO, and JAYA, under a deterministic scheme; showing better performance for JAYA.

So far, different heuristic algorithms and their improved versions have been introduced and their application in operation optimization of IMGs has been addressed. Besides, comparison studies of different heuristic algorithms for energy management of IMGs have been discussed. Based on the review performed, no answer can be given to this question that which algorithm is the best to find the global optimum solution for the EMS optimization. In fact, theorems like the no-free-lunch have been proposed, indicating that the best heuristic algorithm does not exist since on average, all the algorithms have a good performance considering all the objectives [161]. However, regarding the heuristic algorithms in general, a qualitative assessment can be provided, see Table 6. Moreover, a brief summary of the algorithms introduced in this section is presented in Table 7 including the accuracy and processing velocity of each algorithm mostly for the specific application in EMS of IMGs. It should be noted that this information is based on the results provided in the references given in the last column. The qualitative assessment is selected to prevent numerical values, which are quite dependent on many conditions, such as the computational resource, implementation of the algorithm, problem formulation, *etc.*Thereby, to see the specific conditions of each study, the interested readers are referred to the associated references. The main stages of each algorithm along with some remarks identified throughout the review process can be also found in Table 7.

Table 6: Advantages and disadvantages of some heuristic algorithms

Algorithm	**Advantages**	**Disadvantages**
GA [162]	Easy to understand. No need for derivatives. Possible to be applied with both discrete and continuous decision variables. Suitable for complex and not well-defined problems. Bad solutions do not affect the final optimal result.	Likely to be slow. It can get trapped in a local minimum.
ACO [162, 163]	Conducting parallel search. Fast. Adaptable to changes (dynamic problems). No need for a central control in the colony.	The probability distribution functions can change every iteration. Concept is not very simple to understand. Dependency on random decisions. It has received more attention in practical researches rather than theoretical studies. The convergence is guaranteed whereas the time to converge is uncertain.
PSO [162]	Easy to understand and implement. Few tuning parameters. Suitable for parallel computing. Robust. Fast convergence. No need for crossover and mutation.	Difficulty to define initial tuning parameters. Scattering problems cannot be solved. Easy to get trapped in a local minimum.

Table 6: Advantages and disadvantages of some heuristic algorithms (continuation)

Algorithm	Advantages	Disadvantages
GSA [151]	Easy to implement. Suitable to solve highly non-linear problems. Need for few CPU resources. Stable convergence. Accurate. Adaptive learning. No memory is required. Easy to escape from a local minimum.	Complex terms. Difficulty to define initial tuning parameters. The longer the time, the slower the searching speed.
GWO [164, 165]	Simple and easy to implement. Flexible. Robust. Easy to avoid local minimum. Few tuning parameters. Fast.	Single-objective nature. Difficulty to address multi-modal problems. Considerable performance degradation when the number of variables increases. Changing the number of groups reduces the accuracy. Easy to get trapped in a local minimum for large-scale problems.
ABC [166, 167]	Easy to implement. Highly flexible. Robust against initial values. Need for few control parameters. Easy to hybridize with other algorithms. Stochastic nature. Possible to be applied with both discrete and continuous decision variables. Suitable for complex and not well-defined problems. Suitable for parallel computing. Low likelihood to get trapped in a local minimum. Local and global search.	It can loose relevant information in the optimization process. Need for a large number of function evaluations. Slow. Need for large memory and capacity. Lower accuracy than traditional methods when they do not get trapped in local minima.
TLBO [78]	No need for tuning parameters. High precision. Easy to avoid local minimum.	Slow.
JAYA [168]	No need for tuning parameters. Simple. Fast.	Premature convergence. Possibility of having low-accuracy results due to the lack of an strategy to improve the best solution.

3.6.3. Hybrid Optimization Techniques

Hybridization of different optimization strategies has been proposed for improving the performance of the EMS optimization problem. Such a mixture depends on the specific problem conditions. The combination of fuzzy logic (FL) and GWO (FL-GWO) is developed in [5]. FL is used to determine the optimal size of the battery and the GWO algorithm to find the optimal ED. According to the results, FL-GWO outperforms a RB strategy and traditional GWO with higher economic savings. However, the renewable power share is low, especially in winter. In [169], using the mutation method of GA in ABC, a mutation-based artificial bee colony (MABC) algorithm is proposed, which is used to solve a day-ahead ED problem in an IMG in RHC framework. The algorithm is compared with PSO, GA, ABC, and MINLP. The results show the superiority of MABC in terms of accuracy, but with the longest processing time.

3.6.4. Non-Optimal Rule-Based Algorithms

Another common approach in the energy management of MGs is applying the RB techniques. RB methodologies are based on the accumulated knowledge and experience of the experts, which have been organized in the form of a number of rules that simplify the system operation but the outcome might not be optimal. In [170], two RB algorithms are proposed for controlling the active and reactive power of an IMG. The former tries to keep the real power constant or minimizing the DGs output power, while the latter aims to keep reactive power or power factor constant. The simulation results show a reduction in fuel consumption when minimization of the DGs' output power is considered. In [69], a RB EMS is used for keeping the SOC of the battery within the allowable limits and the frequency deviation is compared in two different cases using current SOC and near future SOC. It is shown that the frequency deviation is lower when the near future SOC is considered. The algorithm schedules the output power of DGs, which are assumed to be always on unlike in [67, 171] where the DGs are switched on only when the energy in the NCDERs+ESS is not enough to meet the demand or the SOC of the ESS is below the lower limit. When SOC reaches the upper limit or when NCDERs generation is higher than the demanded power, DG is shut down. Another similar RB algorithm is

Table 7
Heuristic optimization methods (EMS of IMGs).

Method	Accuracy	Velocity	Main Stages	Remarks	Reference
EA	I	I	Sort, crossover, mutation.	Simple and flexible. CMA-ES beats Numerical Nelder Mead Algorithm. MGA beats traditional GA, mod. PSO with damping factor in inertia term and PSO with a constriction factor. GA beats sequential quadratic programming. Increasing the population size (25-200) could help to improve the best results with a narrower standard deviation (SD). Saving the best so far chromosome might improve the performance.	[87, 100, 130, 135]
ACO	I	F	Process solutions, compute transition probability, update pheromones.	ACO beats trad. gradient-based method, Lagrange-based method, MCEMS, PSO, GA. More than 20 colonies (50 ants each) will increase dramatically the processing time without significant improvement.	[58, 61, 102, 140, 141]
PSO	I	F	Identify individual and global optimal values, update positions and velocities.	Reg. PSO limits velocity. Mod. PSO applies linear damping factor to inertia term and beats RSO and GA. MOPSO beats MOGA, EP, GA, PSO, EBCO (in cost). IPSO introduces a chaotic search and beats PSO. PSO-ACF improves the population diversity to prevent premature convergence and beats PSO. MPI technique is used to parallelize the tasks and shorten the processing time. More than 50 members in population might lead to worse results in accuracy or SD.	[46, 54, 77, 80, 92, 96, 98, 130, 145]
GSA	I-H	F	Update gravity, compute mass and acceleration, update velocity and position.	GSA beats PSO, MCEMS, LP, MOSST, NS-GA, NPGA, SPEA, MBFO, FCPSO, and DE. Self-adaptive GSA avoids local minimum and beats GA, PSO, fuzzy self-adaptive PSO, and trad. GSA. Opposite numbers in the initial guess can speed up convergence. GSA is improved by adding up memory and mutation process.	[74, 103, 152]
GWO	H	S	Set alpha/beta/gamma, update variables/position.	GWO beats PSO, GA, BA, IBA, TS, DE, BBO, TLBO. Increase population size (50-100) does not improve the accuracy largely. Using 200 wolves could get worse results.	[88, 130, 155]
ABC	I	F	Send employee bees to the food, place the onlooker bees, and send scout bees to search for more food.	ABC beats PSO and GA. Mult. ABC uses different probability functions (exploitation and search) to beats PSO, MCEMS, and MINLP. EABC is self-adaptive and uses repulsion factors to beats EP, GA, PSO, and trad. ABC. Mutation-based ABC beats (accuracy) PSO, GA, ABC, and MINLP. No need for parameters tuning. Improvements in accuracy and processing time by modifying the search mechanism properly.	[64, 90, 101, 147, 148, 169]
TLBO	H	S	Process the mean of each subject, identify the teacher, teaching stage, learning stage.	TLBO beats (accuracy) Grad.-based methods (Bisection, Regula falsi, Golden section), GA, PSO, BA, IBA. TLBO beats PSO and GA for sizing. Mod. TLBO improves learning stage to beats trad. TLBO, GA, PSO, fuzzy self-adaptive PSO. EDTLA (for DSM) adds steps for mutation and crossover to beat GA, EDE, trad. TLBO. No need for parameters tuning. Improved versions focus mostly to upgrade the learning stage.	[23, 78, 97, 153, 172]
JAYA	H	F	Identify best and worst solutions, modify solutions based on the best and worst, update solutions.	JAYA beats EDE, SBA (using ToU scheme), Grad.-based algorithm, ACO, PSO, Earliglow. Enhanced JAYA applies three modifications to beats PSO, TLBO, and trad. JAYA. A population larger than 40 members does not improve the results largely. No need for parameters tuning.	[75, 104, 105, 158, 160]

I: Intermediate, H: High, S: Slow, F: Fast.

presented in [70] for the SOC regulation of a package of three battery banks. The SOC in each package is measured and the highest and the lowest SOC is determined. If there is a difference of 10% (or higher) between these two SOCs, the algorithm disconnects one of the two batteries for avoiding deep charging/discharging.

In [95], it is proposed to consider dynamic cost functions for the battery and FC to increase their utilization price while the device age increases. It is shown that as a result, the battery lifespan considerably increases with a lower cost, but with a reduction in FC lifespan as well as battery utilization. The battery lifespan increase is possible by using a RB algorithm proposed by the authors. In another study, the implementation of a RB MCEMS along with a local energy market (LEM) algorithm is proposed for an IMG [173]. The proposal is based on day-ahead and real-time scheduling and aims at maximizing the DERs utilization, the battery lifetime, and the average energy stored in the battery. The results show a reduction of the energy cost up to 8.5% for a day when the LEM is used and the MT is always on. In [174], the authors propose a RB algorithm for saving fuel in an IMG, which is tested in three cases: surplus of generation, deficit of generation, and perfect balance of generation and demand.

4. Future Trends in Energy Management Systems

Nowadays, the IMGs are becoming more popular given their versatile applications where an electric system has to work independently in a self-sufficient manner. For instance, apart from the ground systems, recently the IMGs have found interesting applications in marine, aviation, and automotive industries, space bases, satellites, spacecrafts, and so on. However, the new applications of IMGs are challenging even more the EMS. In this respect, after doing an in-depth analysis of the state-of-the-art, several challenges of EMSs of IMGs have been identified that are discussed in the following.

MG Modelling: The reliability of supply, the stability of the MG, and the robustness against unexpected events, among others in an IMG, depend to some extent on the effectiveness of the EMS. And the EMS performance relies heavily on the modelling accuracy and computational burden. However, in the existing literature, mathematical models of MGs equipment are rarely used or the accuracy of the mathematical representations is not accurate enough. For instance, the dependency of equipment efficiency on the operating point, the relation between charging/discharging rate of ESSs and their operating condition, SOC, device degradation, unbalance conditions, and so on. Besides, regarding the available power of RESs and power demand of consumers, commonly production and consumption profiles are only considered, but efficient (with enough accuracy and speed) forecasting systems suitable for real-time EMS of IMGs are still lacking. The reason mainly lies in the fact that the problem complexity and the required computational time increase considerably by using accurate models. On the other hand, accurate models commonly rely on experimental data, which is usually not available or limited. In this regard, several strategies have been proposed for modelling the MG equipment based on empirical and/or physical expressions. Nevertheless, the use of empirical expressions usually restricts the model's applicability to specific conditions to have accurate results. Besides, empirical models are not suitable for physical interpretation of any variable, which limits even more the applicability of such models in other conditions. On the other hand, the physical models are not restricted (or the operation ranges are much wider than empirical models) and usually are fast, but these models are more complex and sometimes the accuracy is also limited. Therefore, the need for models with a trade-off between accuracy, complexity, physical interpretability, and computational time still exists.

Advanced forecasting and learning techniques: The application of accurate forecasting techniques along with improved models might reduce considerably the power and energy estimation error of the RESs, as well as the error in load demand prediction. However, the study of forecasting techniques along with the EMS of IMGs is still limited to techniques which are inaccurate for long time horizons. In fact, many studies neglect the effect of uncertainties in weather conditions and power demanded of customers in spite that the high impact of such assumptions over the EMS performance and lifetime of the ESSs has been proven. Therefore, the need for accurate forecasting techniques not only for the short term, but also for the long term, is still present. Besides, the study of such forecasting systems in EMSs of IMGs will be required. In this regard, some studies are taking advantage of advanced monitoring systems and IoT technologies in an attempt to cover the gap. A great benefit of these smart systems is the continuous generation of data with valuable information that can be used to extract knowledge about the behavioral patterns of MGs consumers, available power of RESs, electricity price, degradation pattern of MGs components, and so on deploying artificial intelligence and advanced machine learning techniques. However, the challenge still exist, specially for the new applications of IMGs.

Integration with lower level controllers: An efficient MG should be able to cover its consumers demand and guarantee the stable and efficient operation of the system in any operating condition while being resilient to unexpected events that could threat the MG stability. Such requirements are quite difficult to fulfil simultaneously, specially for IMGs without the support of the main grid. In this respect, many studies have proposed the use of coordinated control architectures, *e.g.*, the hierarchical scheme, while the EMS works along with it. There exist several studies that are dedicated either to the control of IMGs while mainly focused on the primary and secondary control levels or to the EMS. However, there are few studies that consider all control levels together. One reason is possibly due to the assumption of different time scales that prevents to have overlaps between the control actions. Nevertheless, a growing trend is for the real-time EMSs to reduce the error of power and demand predictions. Hence, the performance of the whole control hierarchy needs to be further evaluated in real-time schemes to ensure an efficient synergy between all levels of control in real MG implementations and specially for islanded configurations.

Fully effective decentralized EMSs: Commonly, there exist three main configurations for the EMS architecture of MGs, namely centralized, distributed, and decentralized. Depending on the application, the most suitable architecture is selected. However, it is well-known that the distributed configuration can be more robust and faster than the centralized one, but more complicated to be implemented. On the other hand, it has been suggested that an effective decentralized EMS might be potentially the most robust and the fastest while it would keep moderate economic and computational costs. In this regard, many attempts have been done to achieve a decentralized configuration. For instance, frameworks based on the GT and MAS, which have shown to be effective but having some important issues, *e.g.*, problems to fully meet the constraints, a high dependency on the CDERs, high complexity, and always requiring a communication link. Therefore, a reliable and fully effective decentralized EMS for IMGs with a high ratio of RESs is still required.

Communication system and cyber security: With the widely implementation of distributed and hierarchical EMSs, the interaction of controllers through communication system has been considerably increased. Thus, system performance is heavily dependent on the communication system quality and data security. In this sense, considering the effect of communication delay and loss of data on system performance and developing intelligent cyber security techniques for IMGs are of vital importance.

Proof of concept and validation: During the last years, the interest for the EMS of IMGs has increased substantially, especially in applications different from the traditional ground-based systems, *e.g.*, marine, avionic, and automotive systems, space bases, satellites, and spacecrafts. However, most of the studies are based on traditional simulation platforms, which might not represent properly the reality due to many reasons, *e.g.*, inaccurate models, deterministic approximations, assumptions like balance conditions or absence of harmonics, *etc.* On the other hand, some studies consider real data obtained by means of HiL techniques. Nevertheless, even when the signals are real, they are coming from predefined models, which might not properly represent the real behavior. Therefore, further validation of the new EMSs under real operating conditions is essential for future implementations to increase confidence in expected outcomes. Besides, a deep study of these systems and identifying their main operating requirements and restrictions will help designing advanced EMSs and control strategies to enhance the performance of IMGs in their real-life applications.

5. Conclusion

The emerging diverse applications of IMGs such as marine, avionic, and automotive systems, space bases, satellites, and spacecrafts are challenging even more the EMSs. In this respect, several studies have been reported aiming to improve the effective deployment and operation of EMSs toward more efficient, robust, reliable, and resilient MGs. Nevertheless, many challenges still remain that need to be addressed in future studies. Thereby, a deep exploration of the recent advances in EMSs of IMGs, as well as the identification of remaining challenges was provided in this paper. The present overview gave a detailed introduction to the EMS optimization problem of IMGs, and presented the significant aspects of EMSs optimization, including the optimization framework, time-frame, optimization algorithm, uncertainty handling approach, objective function, and constraints.

The first general aspect usually considered for the EMS optimization problem is the optimization framework, which can have three architectures, namely centralized, decentralized, and distributed. Among the most popular optimization frameworks are the DP, GT, MAS, RHC, and several hybrid frameworks. The RHC is maybe the most widely-used technique due to its high resiliency against failure in electric and communication systems.

The second general aspect that was discussed is related to the uncertainty treatment, which can be classified as deterministic, stochastic, or robust. The uncertainty is not explicitly considered in the deterministic approximations, thereby the energy management performance is highly dependent on the accuracy of the forecasting techniques. The stochastic approach takes advantage of probabilistic distribution functions to model the uncertainty, however this could lead to big inaccuracies if the distribution is not well known. Finally, the robust approximation does not make any assumption regarding the uncertainty of random variables, but requires assumptions about the uncertainty limits. The RO has demonstrated to be able to increase the reliability of the EMS in IMGs, however an important conservatism is usually presented, which is still an issue under study.

The third identified aspect was the EMS optimizer. Popular strategies implemented for the optimizer involve the use of traditional mathematical techniques based on linear and non-linear mixed-integer programming. Piecewise linearization techniques are commonly used for the former, while no assumptions should be necessarily made for the latter one at the expense of a long processing time. Reduction of processing time for NLP-based techniques is still under study. Another kind of optimizers belongs to the heuristic algorithms family, which have attracted a lot of attention in the last years due to their high flexibility to be applied in practically any optimization problem. One important reason of their popularity relies on the ability to overcome the limitation of traditional mathematical techniques regarding discontinuous and non-differentiable functions while keeping a short processing time. The most popular heuristic algorithms utilized for energy systems in MGs are the PSO and the EAs, whereas the GSA, TLBO, and JAYA have a limited use for this purpose. Some of the most popular heuristic optimization algorithms along with their main advantages and disadvantages, recent improvements, and applications in EMS of IMGs were presented in this study. Specifically, GWO, ACO, PSO, ABC, TLBO, EAs, GSA, and JAYA were thoroughly discussed. Moreover, researchers have proposed different hybrid techniques to improve the performance of the original algorithms in terms of accuracy and processing time.

Energy management constraints were the fourth EMS aspect that were classified as technical, economical, and logical constraints. The technical constraints are used to bound physical parameters of the MG to ensure a safe and stable operation. The power balance, power limits, unbalance limits, SOC and DOD limits, voltage limits and unbalance conditions, power ramping limits, on/off minimum time and maximum number, operating reserve constraint, limits in the tank diesel volume, controllable load limits and actual load demand, peak demand constraint, and allocation of excess of generation are between the most widely-used technical constraints. The most popular environmental constraint regards the limit in the amount of pollutants released to the atmosphere by traditional CDERs. Finally, the logical constraints are committed to avoid any conflict between the decision variables.

The fifth general aspect identified was the objective function, which can be classified as single-OF and MO function while usually regards economic and environmental aspects. Between the most widely-used cost functions are the minimization of operation costs, generation cost, fuel consumption, emissions, dump energy, charging cost, power ramping, among others.

The sixth general aspect identified was the time-frame, which refers to the optimization horizon and resolution. The horizon usually ranges from a few hours to several days (for operation management), to several months or even several years (for maintenance planning, feasibility studies, or planning and sizing of the MGs). The time resolution commonly ranges from several seconds, to one hour, depending on the computational capacity mostly.

Moreover, during the review process, six main challenges of existing EMSs were identified, which should be addressed to enhance efficiency and reliability of IMGs. The identified challenges include: the need for more accurate models with a satisfactory balance between model accuracy, complexity, computational burden, and physical interpretability; the need for more advanced forecasting techniques with accurate predictions for both short and long horizons; the need for assessing the EMS performance in the full control hierarchy of IMG for real-time conditions; the need for more studies considering the effects of communication delays and loss of data on the EMS performance and taking into account cyber security of IMGs; And finally, the need for more validations and proof of concept of the EMS in real IMGs to identify possible phenomena not observed in simulations or even laboratory-level setups.

This review study introduced a scheme for the EMS optimization problem in IMGs. It should be noticed that the scheme is not universal and essential elements might be missed. However, it is the hope that this study can be used as a reference for future EMS implementations. Moreover, the identification of future trends can help experts and junior researchers in the topic to guide their efforts to overcome such challenges for more reliable, robust, resilient, optimal, and stable IMGs. This paper aimed to provide a complete overview of the state-of-the-art of EMSs of IMGs and the open problems that need to be addressed in future studies to fully realize benefits of IMGs.

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