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Cloud and machine learning experiments applied to the energy management in a microgrid cluster

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HIGHLIGHTS

- Cloud computing technologies applied to microgrid management.
- Supervised machine learning strategies associated with the energy management system.
- Used architecture by the energy management system to control a cluster of microgrids.
- Considered elements in developing a scalable and autonomous architecture.

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ABSTRACT

The way to organize the generation, storage, and management of renewable energy and energy consumption features has taken relevance in recent years due to demands that define the social welfare of this century. Like demand increases, other factors require grid infrastructure improvement, updates, and opening to other technologies that assuage the final customer needs. Precisely, the interest in renewable energy sources, the constant evolution of energy storage technologies, the continuous research involving microgrid management systems, and the evolution of cloud computing technologies and machine learning strategies motivate the development of this article. Tasks associated with a microgrid cluster like the integration of a considerable number of heterogeneous devices, real-time support, information processing, massive storage capabilities, security considerations, and advanced optimization techniques usage could take place in an autonomous and scalable energy management system architecture under a machine learning perspective running in real-time and using Cloud resources. This paper focuses on identifying the elements considered by different authors to define a cloud-based architecture and ensure the appropriately supervised learning functionality under a microgrids cluster environment. Namely, it was necessary to revise and run microgrid simulations, real-time simulation platforms usage, connection to a virtual server for microgrid control and set the energy management system using cloud computing and machine learning. Based on the review and considering the scenarios mentioned, this article presents a scalable and autonomous cloud-based architecture that allows power generation forecast, energy consumption prediction, a real-time energy management system using machine learning techniques.

1. Introduction

Microgrids (MG) are a relatively new technology that takes advantage of the rapid development of power electronics, communication, and control system technologies [1]. Most of the research work in this field has focused on regulating physical quantities within the system in a stable way [2]. Others have focused on control strategies research applied to a MG [3] and communication technologies implementation to optimize the performance of different metrics within a MG [4]. Another recognized that a microgrid cluster (MGC) gives the power system more flexibility to exchange power and energy among components [5], and energy demand can be satisfied with the integration of energy storage systems (ESS) and distributed generation (DG) systems through a MG. Consequently, the application of this concept will allow conceiving the future power grids as several interconnected MGs where each user is accountable for the generation and storage of the energy they consume, increasing the possibility of sharing their residual energy with neighbors [6]. The challenge is to integrate small distributed power generators and

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dispersed energy storage devices into the power grid. Under this perspective, the MG will be able to deliver the energy produced by the generators to consumers using digital technologies that allow them to control the consumption of the devices installed in the customers' homes, making it possible to save energy consumption, reducing spreading costs and increasing the reliability and transparency of the system [7].

Additionally, incorporating an interactive, intelligent, and distributed system to the MG management allows to include technological tools and virtual administration applications such as the Internet of Things (IoT), Big Data (BD), Blockchain, and Machine Learning (ML), among others [8]. Also, technological advances defined for wireless sensor networks (WSN), cloud computing (CC), and network technologies have contributed positively to the emergence of many intelligent applications. These new technologies offer an unprecedented opportunity to create a wide range of IoT applications that integrate various devices and objects integrated within the term Cloud of Things (CoT). In the CoT, applications expand over different domains, running software and self-management applications. Hence, it becomes a reality to supply processing services as public services where service providers take the responsibility of integrating the IT infrastructure, and final customers use the service through the internet as a service on demand [9]. Nevertheless, CC integration and ML development are demanding due to many reasons and has been analyzed under different perspectives as they improve [10]: The use of a considerable number of heterogeneous devices and objects, highly mobile elements and devices, the distribution of components and devices over large geographic areas, operation in un-attended or challenging places such as forests, deserts, mountains, or underwater locations, real-time support, extensive information storage, and processing capacity, as well as, scalability, consideration of critical applications that need to be protected and management of advanced optimization techniques that improve the operation of the systems.

Based on the mentioned and seeking to take advantage of the potentialities of cloud and ML technologies applied to the energy management systems (EMS) of a MGC, this paper summarizes various perspectives from different authors who have worked on this issue. According to the literature currently consulted, no author clearly defines an autonomous and scalable cloud-based architecture that can apply to real-time supervised-learning management of an interconnected MGC. For this reason, in this research, we propose an EMS architecture, which joins up maximum capacity generation, power consumption, and optimal economic operation under a ML perspective running in real-time and using CC resources [11]. The active algorithm will solve the economic dispatch problem (EDP) [12] giving adequate stability performance and optimal power reference tracking under unexpected load and generation changes. This paper has the following organization: Section II presents the methodology used for developing the article. In Section III, the paper briefly presents microgrid management, the cluster of microgrids and management architecture standardization concept, Emerging techniques and technologies used in the microgrid's EMS, Lab implementations for microgrid's EMS in the cloud, and cloud management applications for microgrid's hierarchical control structure. Section IV shows the Cloud-based real-time EMS architecture experiment for a cluster of microgrids using ML. In Section V, the authors discuss the results presented. Finally, Section VI concludes this paper.

2. Methodology

For the development of the article, the authors consulted the following databases: Science Direct, IEEE Xplore, Scopus, and Google Scholar. Table 1 summarized the search keywords used in the title, abstract, and keywords in each database.

Fig. 1 shows the consolidation of the Science Direct, IEEE Xplore, Scopus, and Google Scholar databases of the number of articles published using the search equations: Microgrids, Cluster of microgrids, Cloud Computing, Artificial Intelligence, and Machine learning, in the environment of engineering, smart grid, and renewable and sustainable energy. Notably, the number of publications on cloud computing applied to microgrids has been few throughout the years. After conducting an exhaustive review of the literature, this research identified a cloud computing architecture for the microgrid's EMS, a general vision was constructed and completed with the search for models including, specifically, Artificial Intelligence and Machine Learning.

Table 1
Search Keywords used as methodology.

Category	Keyword
Field of application	Microgrids, Cluster of microgrids, Cloud computing, Hierarchical Control Structure, EMS
Related words with cloud computing and microgrids	Cloud computing, Microgrids, EMS
Cloud computing applied to microgrids search equations	Cloud computing applied to Microgrids, Cloud computing applied to Microgrids EMS, Cloud computing and Hierarchical Control Structure in Microgrids
Machine learning and cloud computing applied to microgrids search equations	Cloud computing and Machine Learning to Microgrids, Cloud computing and Machine Learning applied to Microgrids EMS, Cloud computing and Machine Learning applied to Hierarchical Control Structure in Microgrids

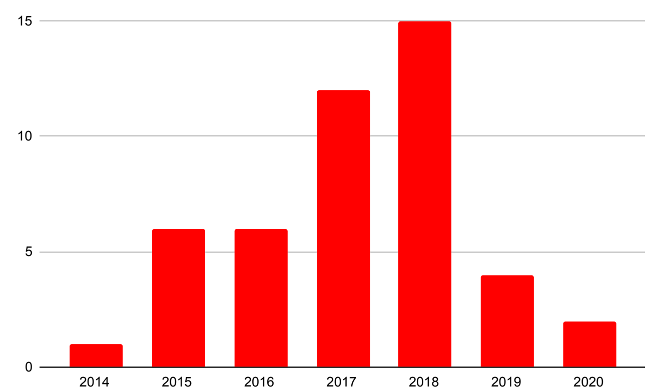

Fig. 1. Published articles. Source: Authors.

3. Theory and background

3.1. Microgrid management

A MG is a local network consisting of DGs, ESS, and dispersed loads, which can operate in two modes: connected to the power grid or in island mode [13]. The MGs install in the low voltage (LV) and medium voltage (MV) distribution networks. DGs frequently connect to the MG through a power electronic converter whose primary roles are to couple the primary energy resource to the power grid and control power injection. Therefore, power electronic converters allow the MGs to incorporate distributed energy sources that use renewable energy. Hybrid power systems, photovoltaic panels, micro-turbines, and wind turbines, as well as distributed storage devices, power supplies, and network management technologies, are a few [14]. MG's design uses DC or AC voltage in a local network and hybrid configurations using appropriate electronic power interfaces to control the power flow between the AC and DC sides [15]. The operational mode and EMS utilizes the capabilities of DGs through the application of grid management technologies. Fig. 2 exhibits a MG's general architecture [16].

It consists of a group of radial feeders as part of a distribution system where each power unit has a switch that prevents severe disturbances

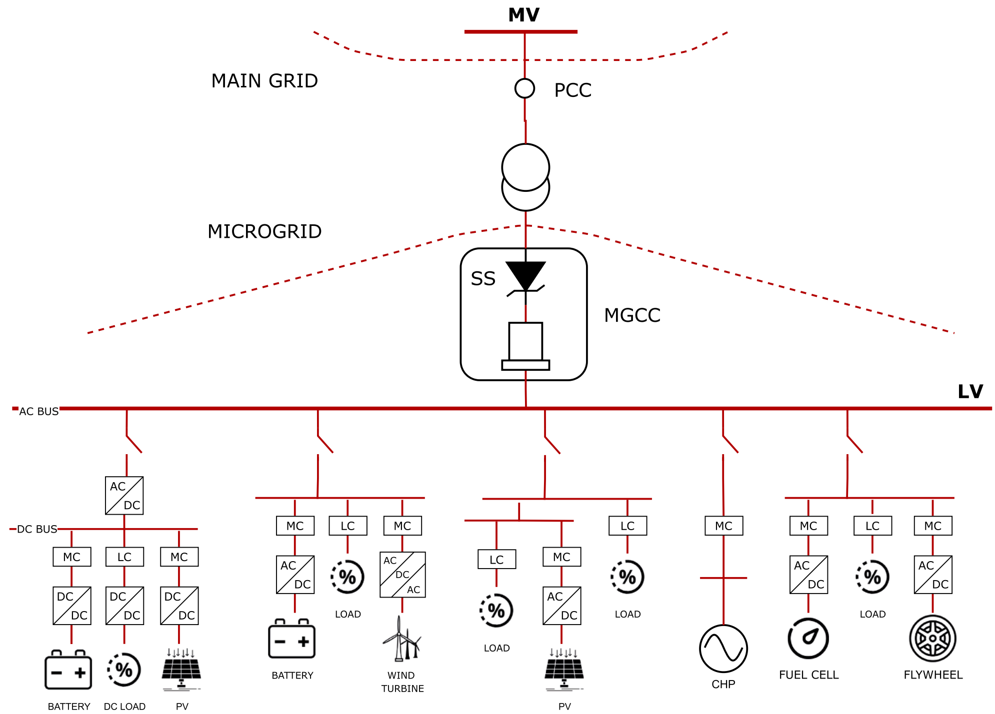

Fig. 2. The general architecture of a microgrid. Source: Authors.

through the MG and a power flow controller managed by a Microgrid Control Center (MGCC). The MG connects to the distribution system through a Point of Common Coupling (PCC) using a Static Switch (SS) responsible for isolating the microgrid to carry out preventive maintenance or when a fault or contingency arises [17]. The microgrid controllers (MC) control the MG and the ESS, and the load controllers (LC) manage the controllable loads. Depending on its relevance, load divides into two types, critical and non-critical. One or more MGs provisions the critical load, while the non-critical load could disconnect in contingency. Though the MG concept is not new, control strategies and EMS performing tasks like power exchange, system stability, frequency and voltage regulation, active and reactive power control, operation mode detection, network synchronization, and fault recovery system are still under development. The evolution of MG management, and the elements that constitute the hierarchical structure [18], are key factor considerations for developing this type of technology. The management of MGs requires the effective use of advanced control techniques at all the hierarchical control levels to guarantee the safe operation of the MGs under their different operation modes [19]. In addition, due to the diversity and variability in power generation and associated loads, the MGs present a non-linear operational behavior, changing dynamics, and functional uncertainty.

Close to conventional voltage systems, MGs can operate using various control loops that classify into four main groups: local, secondary, central / emergency, and global [20]. Local control focuses on primary management that includes voltage and current control loops. The secondary control forces voltage and frequency deviation of the microgrid setting to zero after each change in load or generation and supervises internal auxiliary services. The central / emergency control is in charge of managing emergency schemes and protection plans that guarantee the stability of the system and its availability in case of contingencies. It identifies the appropriate preventive and corrective measures to mitigate the effects of critical contingencies. Global control facilitates the operation of the MGs at optimal levels of profitability and organizes the relationship between the MG, the power grid, and other MGs. Fig. 3 illustrates the operational concept described for the control loops in the MGs.

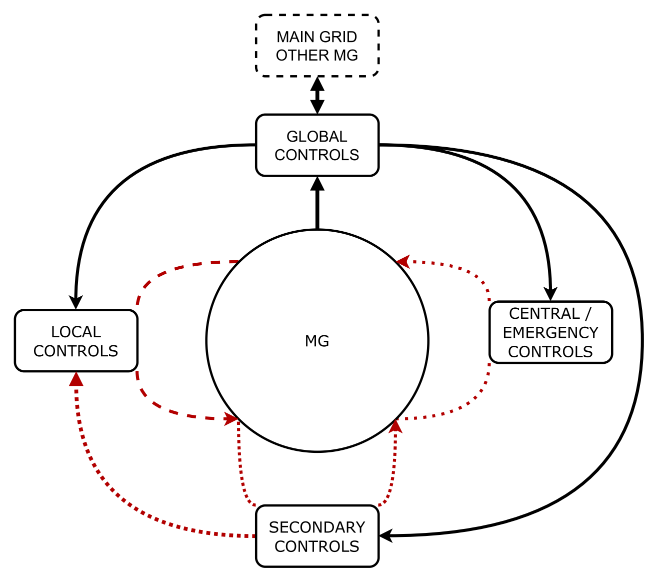

Fig. 3. Microgrid controls. Source: Authors.

Contrary to local control, the operation of secondary, global, and emergency controls requires the integration of communication channels. This feature associated with the operational perspective converts local management into a decentralized one. On the other hand, global, secondary, and emergency controls present themself as centralized controls. These characteristics require intelligent and robust control strategies that could improve the performance of these systems, and a ML perspective could be a solution. In the grid-connected operation mode, MGs integrate into an power grid that is constantly changing with the performance of the transmission lines, voltages, and frequencies. MG needs to use appropriate control loops to manage these variations and respond to network disturbances. Also, appropriate operating mode detection algorithms are required to ensure a smooth transition from grid mode to island mode and vice-versa. In island mode, control strategies must work appropriately to provide the requested active and reactive power and ensure frequency and voltage stability [21]. The management of MGs requires the effective use of advanced control techniques at all the hierarchical control levels to guarantee the safe operation of the MGs under their different operation modes. The functions necessary for the development and operation of MGs defines under hierarchical dependency [22]. In this perspective, the decision layers at the highest levels of the hierarchy define the tasks and coordinate the layers at the lower levels without ignoring their decisions. This architecture increases the solidity of the system and ensures its operation when one of the management units alters its functionality. Fig. 4 presents the hierarchical control structure of a MG.

The power management system (PMS) in centralized or decentralized structures acts on the instantaneous operational conditions of the MG and guides its operation towards desired parameters of voltage, current, power, and frequency. Strategies considered by this level are the voltage and frequency regulation of the MG and power dispatch in real-time between the different DGs available. PMS commits the four layers of control widely accepted as a standardized solution for the efficient operation of MGs. Firstly, the internal control loops are responsible for the current and voltage regulation of each module. Secondly, the primary control adjusts the frequency and voltage references supplied to the inner control loops. In third place, the secondary control deals with power quality control, in particular, voltage and frequency restoration, and voltage, unbalance, and harmonic compensation. Finally, tertiary control regulates the power flow between the network and the microgrid in the PCC or between the interior regions of the microgrid. The last layer is implemented in the MGCC and is typically associated with supervisory and control systems.

The objective of the EMS is to ensure power for longer time intervals than those considered in power management, analyzing prediction, power generation, and consumption costs. It focuses primarily on such features as fuel cost, capital cost, maintenance cost, operation profiles, life cycles. In general, this level divides into planning and operation sub-levels which work on different time scales. The operation sub-level defines the commands for the distributed generation units and loads of the MG holding days and hours in advance, and the planning sub-level schedules the maintenance or replacements of the components and defines the restrictions on which it should operate. In this way, a MG's EMS can gather measurement data, forecast information, and historical data received online, determine and transfer the optimized references to the microgrid network, and define control actions on the different components.

3.2. Cluster of microgrids and management architecture standardization

Fig. 5 exhibits a general outline of the operational controls in a MGC. Local controllers are installed on the controllable loads to provide load control capabilities. For each MG, there is an MGCC that manages the communication between the Distribution Network Operator (DNO) and the MG. The DNO has to manage the operation in medium and low voltages where more than one MG may exist [16]. All existing control loops in MGs have the following duties: Working for all MGs at predefined operating points, exchange of active and reactive power according to the programmed plans, keeping the voltage and frequency regulation, island mode transition and re-synchronization using appropriate techniques, optimization of energy market share, reduce circulating currents between inverters or parallel connected sources, ensure a safe power supply for sensitive loads, operate on restart in case of general failure, provide emergency control and protection schemes in situations such as load disconnection, remote operation of switches and use of ESS, among others.

A MG can perceive and control different parts of the power grid and enables two-way communication between utilities and customers to facilitate the users to be active participants in creating an advanced ecosystem of energy providers and consumers [23]. The cluster depends on estimations, networking, and data storage infrastructure coming from the devices connected to the different parts of the power grid. Fig. 6 exhibits the proposed idea of a MGC with CC management and includes a diverse and large-scale range of devices, services, consumers, and providers that interact intensely and in unique ways. The reason for establishing a CC standard architecture for the MGC's EMS, complementing [24], is to allow the interoperability of different controllers and components needed to operate it through cohesive and platform-independent interfaces and include supervised learning capabilities. This approach will grant the flexibility and customization of the microgrid and control algorithms deployed without limiting their potential functionality. The resultant EMS will join up the maximum capacity generation, the power consumption, and the optimal economical operation under a ML running in real-time and using CC resources. Therefore, the active algorithm will solve the EDP giving adequate stability performance and optimal power reference tracking under unexpected load and generation changes.

3.3. Emerging techniques and technologies used in the microgrid's EMS

The optimal programming presented in [25] considers one day in advance of the battery operation using an optimization technique with

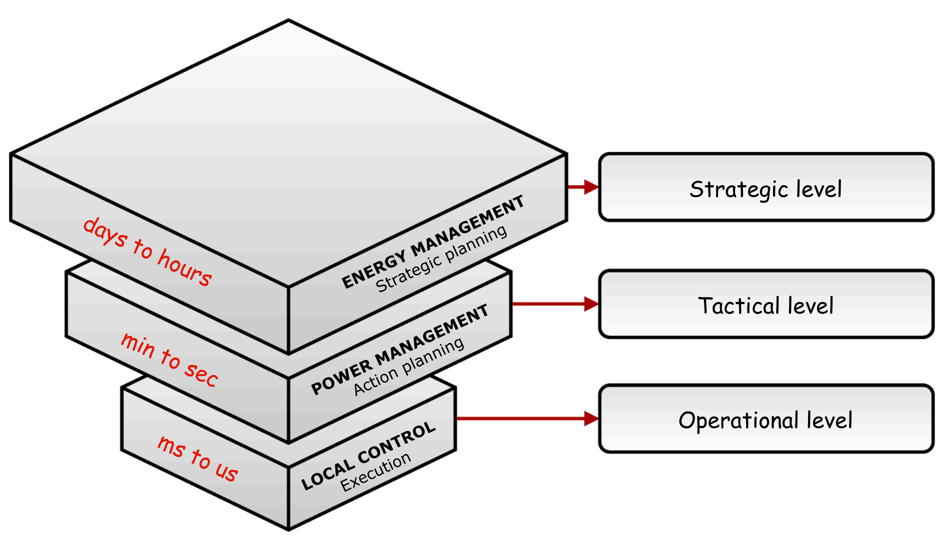

Fig. 4. Management and control layers of a MG. Source: Authors.

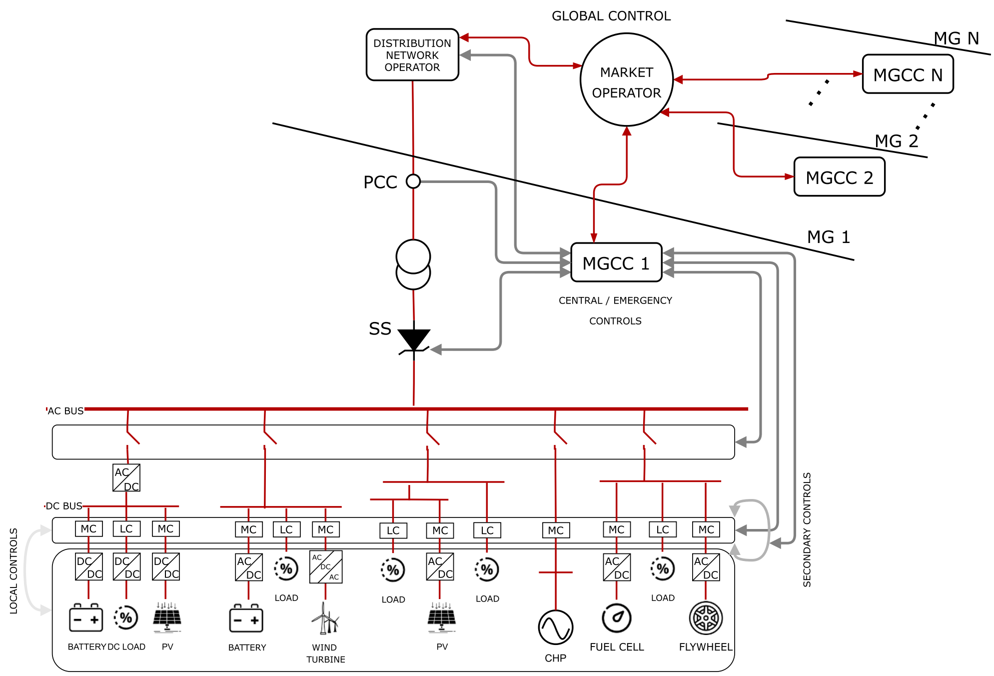

Fig. 5. General diagram of the microgrid controls. Source: Authors.

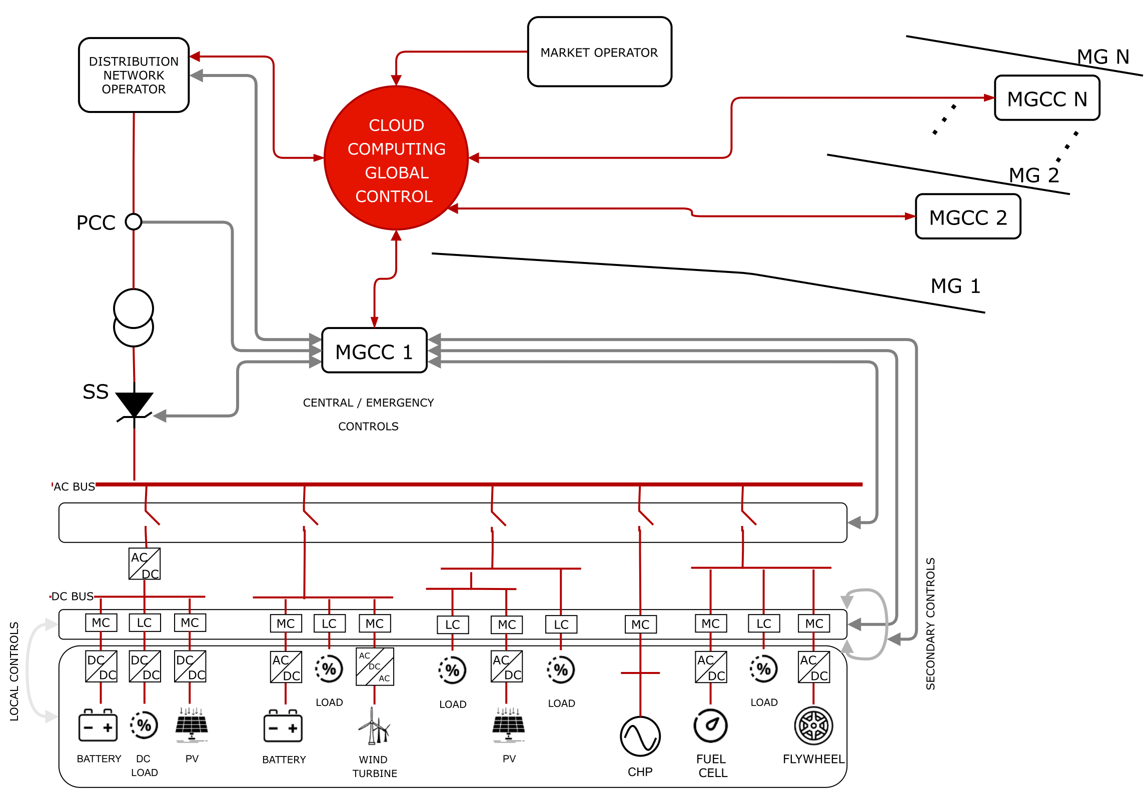

Fig. 6. Proposed diagram of the cluster controls using cloud computing. Source: Authors.

linear programming. Fig. 7 shows the optimization process workflow. The authors included information about forecast charging, PV generation, and electricity price information for optimal scheduling of battery operation. Based on the objective functions, the solution generates an optimal solution for the battery charge and the supported discharge rate in the forecast. The solution also considers that a day is divided into 12-time slots and determines an optimal loading and unloading rate for each one. The proposed scheme reduces the cost associated with exchanging power with the power grid with optimal battery scheduling. Also, when the generation exceeds the demand, renewable energy sources assume the load, and the power grid could acquire the energy surplus. Otherwise, when the energy available on the DC bus is not sufficient to satisfy the load consumption, the power grid would supply the energy deficit.

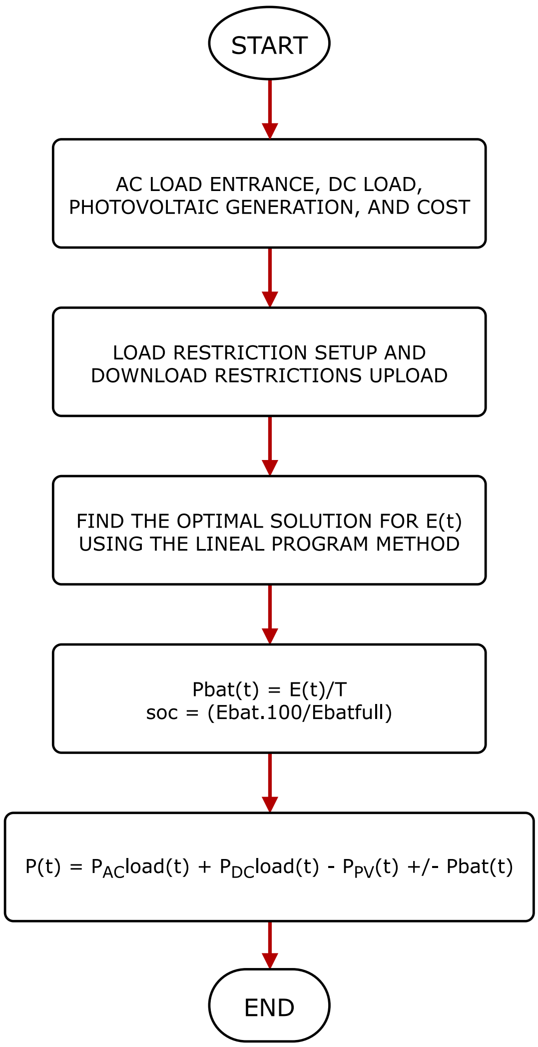

Fig. 7. Optimization process workflow. Source: Authors.

Compared to traditional solutions, the authors of [26] illustrate a data-driven architecture. The EMS implementation is flexible, reliable, and cheap. The solution also contemplates four aspects. First, the system approximates the objective cost function through an online Gaussian Process (GP), so there is no need to consider neither precise nor known objective functions. Second, the model associates all relevant uncertainties to the load and energy produced by the distributed generators. Third, the system proposes a data-driven model to find the final objective function. It does not have a defined expression obtained through observation at different points. Finally, the proposed EMS uses global information to optimize the cost each time. The objective function updates each time according to the observation samples obtained. In this way, the online EMS achieves long-term optimization and adapts itself to changes in the objective functions. Fig. 8 shows the EMS proposed. The energy produced by the microgrid distributed generation units depends on the environmental conditions characterized by high uncertainty and randomness. The EMS monitors the internal operating states of the microgrid and takes optimal decisions to keep the electricity charges at a minimum and achieve both energy balance and energy storage levels in the microgrid. The EMS strategy follows the Bayesian optimal algorithm that considers pre-prediction and post-update monitoring. The online solution can resolve and learn objective functions using GP and real-time observations. Similarly, it can solve the microgrid optimization problem in an open and information-controlled model, which is a promising approach to online optimization.

In [27], the authors propose an energy community structure consisting of smart-home users, non-smart-homes users, and a centralized power generation unit that seeks to facilitate power distribution among neighbors. Fig. 9 shows the schematic diagram for the energy-sharing community structures. The proposed community model allows neighbors to negotiate excess energy to maximize the use of renewable energy. Additionally, it includes a price determination mechanism based on the demand versus surplus relationship. The authors propose a Q fuzzy learning algorithm that obtains continuous variables from a discrete fuzzy set to facilitate trading decisions. The model evaluates the effectiveness of the proposed community structure and the algorithm used through a numerical analysis series under different scenarios that can be summarized as follows: First, the proposed pricing mechanism for the power generation maintains the price within determined generation levels and market price, reducing energy costs and increasing the profitability of generators-consumers. Second, the Q fuzzy learning algorithm applies to recurring tasks such as energy trading, making it possible to constantly train brokers to improve the EMS strategies and decisions without needing a complicated community model. Finally, this community model allows point-to-point energy negotiation. The users in the community can purchase energy from the local generation unit at reduced prices, and smart-home users can sell their energy surplus to the generation unit allowing users to participate in the energy market, influencing energy prices, and making profits with the assistance of intelligent storage and control equipment.

The IoT integration with a MG considers installing intelligent sensors and meters, controllable switches and valves, communication links, access points, among others. The smart-meter and other device's data stream is stored in the physical layer and sent to higher layers to ensure proper management. For this reason, a reasonable way to integrate IoT with a microgrid is to reorganize the original functions of the MGCC according to activated IoT capabilities [28]. Fig. 10 shows the improved hierarchical control theory proposed to facilitate this integration. The primary level associates the connection of the devices through different communication protocols. In the last decade, various standardization entities have made significant efforts to supply solutions to industrial, residential, and building production systems, which have helped to develop information structures and protocols. The secondary level of the MGCC integrates the IoT to improve the user experience, comfort level, and efficiency for temperature, humidity, ventilation, and lighting controllers. The tertiary level of the MGCC considers a complete list of scenarios in which the comfort and economic perspectives weights vary to achieve an optimal global operation in each specific setting according to the predicted information and real-time electricity price.

FOG computing moves the scope of CC toward the edge of the network and creates a decentralized intermediate control structure. It is a platform that provides IoT with the information pre-processing capabilities that satisfy the needs of low latency [29] and provides the devices with the execution, interoperability, and interactivity capabilities that facilitate the transfer and processing of the information generated at appropriate response times. The design of a FOG platform must adequately consider the integration of hardware, software, and communication architectures, as shown in Fig. 11. FOG computing platform implementation provides flexibility, interoperability, connectivity, information privacy, and real-time features needed by the EMS.

A complete application for the EMS in microgrids using cloud computing capabilities exhibits in [30] and proposes a multi-agent system (MAS). As illustrated in Fig. 12, the MAS incorporates microgrid agents (MA) and smart-home agents (SHA). SHA takes decisions using either a function from available options or the best operating time algorithms applied to electric vehicles and other controllable high-power loads. The algorithms avoid both peak demand times and high electricity prices. MAS will not only minimize the electricity costs of smart homes, but it will also prevent the overloading of the energy storage system. The results of the article show that the proposed MAS not only applies to load changes adjusting them appropriately when the

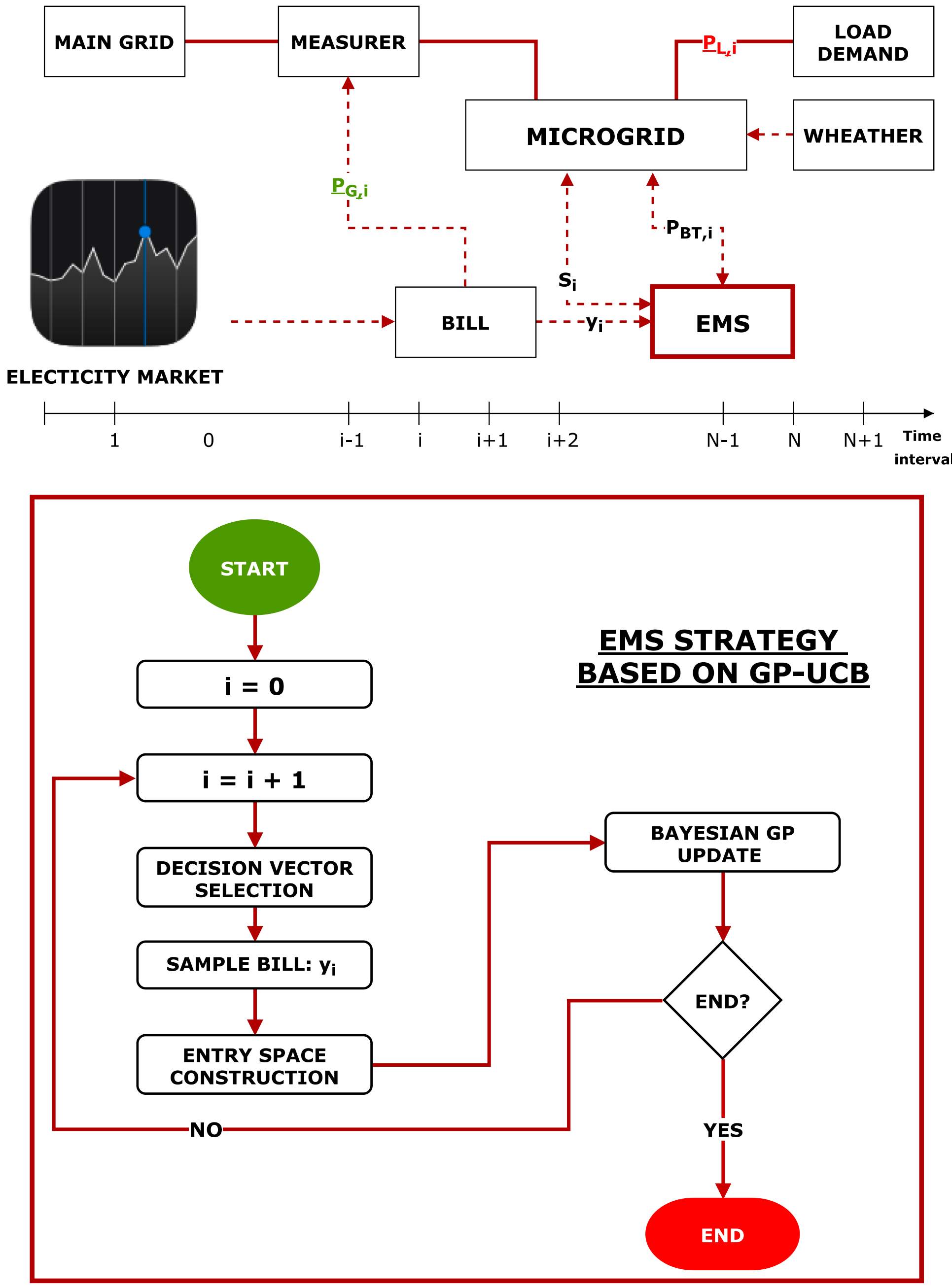

Fig. 8. Energy management system proposed. Source: Authors.

internal demand response is requested, but it also does so based on external demand requests. The proposed cloud-based MAS can improve the MG's performance minimizing peak loads, saving electricity costs, and increasing battery efficiency.

3.4. Experimental implementation for microgrid's EMS in the cloud

In [31], the researchers propose a novel approach based on a CC environment to solve the optimal power routing problem in a cluster of DC MGs. For this purpose, they define a network routing design that uses a small amount of memory and assumes that the MGs belonging to a specific group do not know the current state of the group. They also consider that each MG doesn't have access to the current flow through the multi-terminal DC system nor the generation capacity or load demand of other MGs. The optimal routing strategy considers two main objectives: first, manage congestion across lines, and second, minimize power loss across the network. A MATLAB simulation [32] permits verify the proper operation of the proposed algorithm. A cloud-based OMNeT ++ environment emulates the network connection between the MGs [33]. In this article, the authors converted the EMS performance into a power routing problem for a MGC under the optimization perspective. They also present a complete simulation for the microgrid and the communication protocols avoiding the EMS implementation.

The objective of [34] is to outline a new architecture for the evolution of MG's information infrastructure. The article identifies the main principles for the infrastructure and describes how the new architecture considers them. One of the most relevant principles is ensuring the security and adaptation of the system rather than its scalability in an autonomous distribution architecture. As an advantage, a local and dedicated computing infrastructure manages each microgrid independently. A distributed and highly scalable architecture results by connecting these infrastructures through WAN connections. Also,

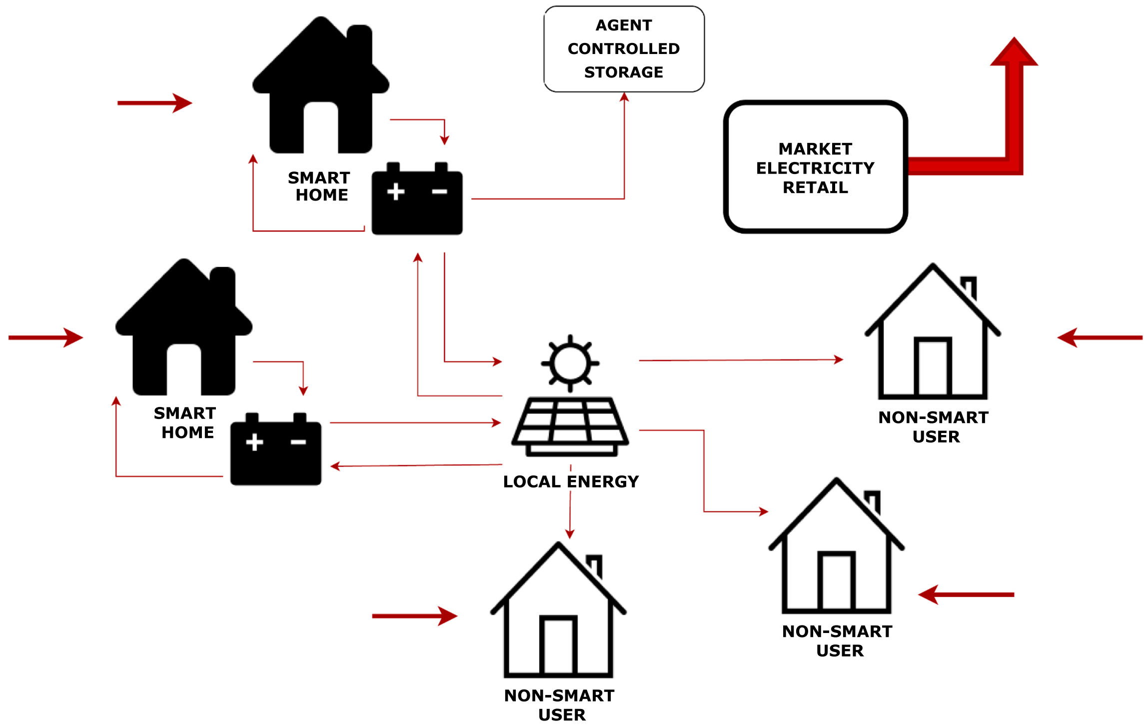

Fig. 9. Community structure sharing energy. Source: Authors.

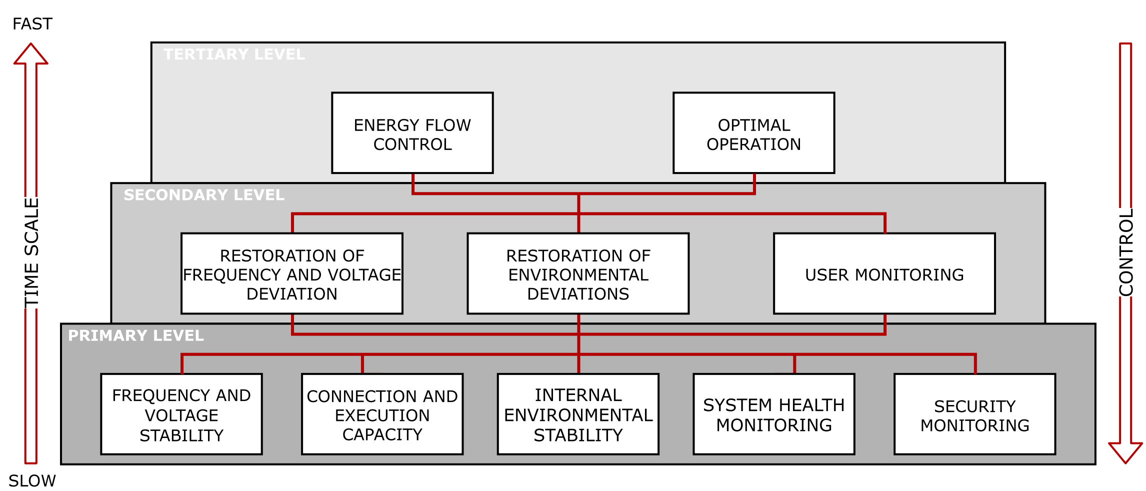

Fig. 10. Microgrid hierarchical control structure. Source: Authors.

independent control policies protect each MG. The CC simulation of the research ran in the data center of the DELL research laboratory integrating the MG simulator available at Clemson University. Although the authors present an attractive protocol for resources management, the simulations include only one MG limiting the application of CC to run an instance within the infrastructure software.

In [35], the authors proposed an IEEE 802.11 mesh network using a hybrid wireless protocol for optimization at a local level and a cloud communication protocol for higher-level optimization that considers interconnected MGs. The authors developed a nested optimization algorithm using a diffusion strategy to solve the two-level optimization problem, local and global. At the local level, they implemented an adaptive information exchange to find the power setting. Optimization mismatches in this level are entries for the global optimization problem. They solved the distributed optimization of interconnected MGs at a high level. The last concept is an IoT idea applied to MGs that the authors implemented in a laboratory-based environment. Regrettably, the local and global perspective developed in simulation orients only to improve the efficiency of the communications system and the advances in the delay, limiting the CC usage.

Parallel to the mentioned above, in [36] the authors propose a decentralized CC architecture that assumes a dynamic real-time pricing model to control download and upload services of different applications. The authors complement their work using software-defined network technology (SDN) available in the cloud. They reduce the network administration cost by including a flexible software network controller. They also virtualize functions in the cloud - distributed aspect, memory capacity, and scalable processing. Based on this research, it is necessary to adopt CC-SDN technology in future MGs but considering a centralized environment that allows a single EMS for the components that integrate a MGCs.

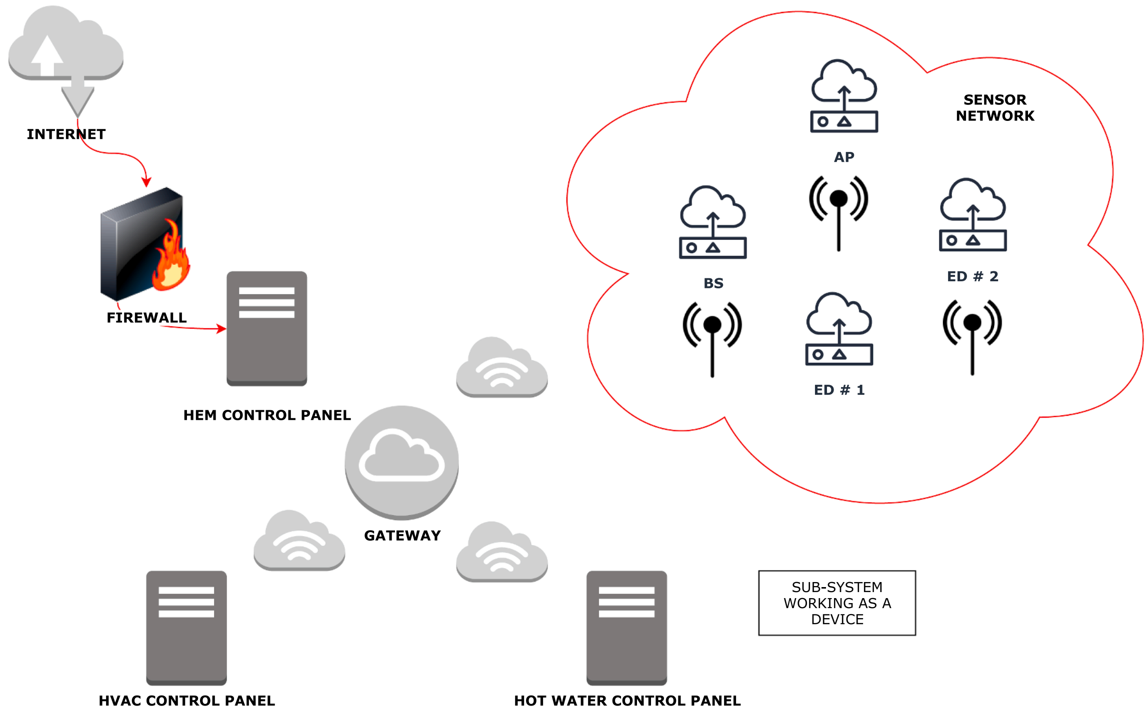

Fig. 11. FOG architecture for a microgrid. Source: Authors.

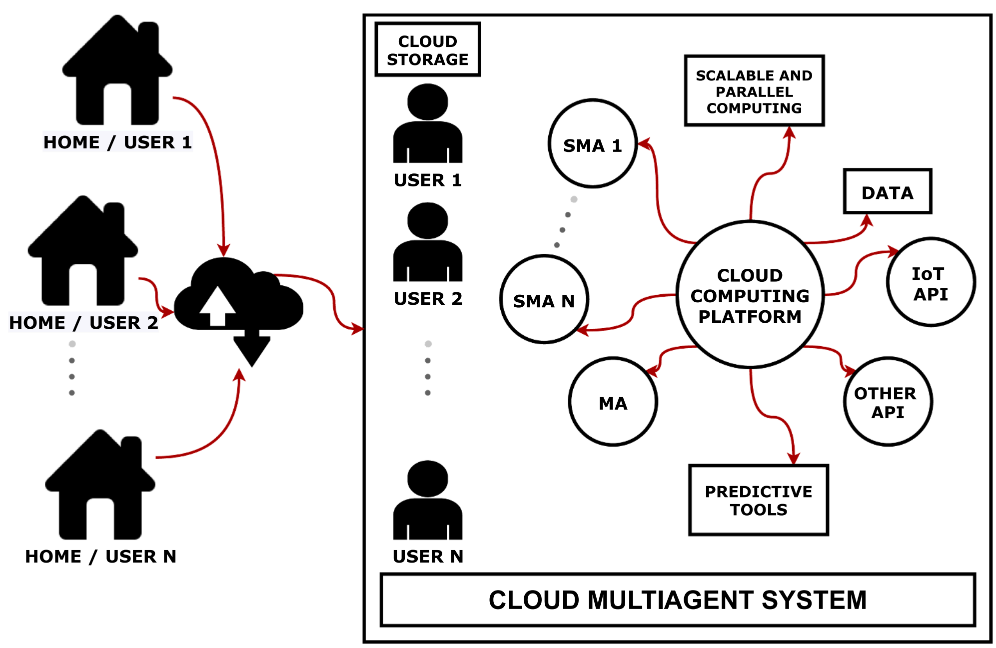

Fig. 12. MAS cloud platform. Source: Authors.

3.5. Cloud management applications for microgrid's hierarchical control structure

Table 2 includes publications identified, associated, and classified according to relevant categories within the usage of CC to optimally manage one MG or a MGC. Even though the proposals presented in the table address different aspects of MGs management such as regulation, optimization, prediction, load management, and communication architecture, among others, none clearly defines an autonomous and scalable cloud-based architecture that can be applicable and expandable to the energy management of a cluster of interconnected MGs based on real-time ML learning perspective.

4. Cloud-based real-time EMS architecture experiment for a cluster of microgrids using machine learning

Proposals outlined in chapter 3 show a favorable application of CC to the MG's EMS. However, the results do not focus on defining a cloud-based EMS architecture that could apply to a cluster of integrated MGs. To our knowledge, this issue has been less studied, so that their results guided not only to integrate CC in the management of the MGC but also taking advantage of other capabilities like ML in a production

Table 2
Publications associated with the hierarchical control structure. Source: Authors.

Category	Potential advantages	Potential disadvantages	References
Voltage regulation using IoT	Online optimization for the operating voltage	Decentralized architecture	[37]
Optimization algorithms	Real-time simulation of a MGC	Misuse of cloud computing capabilities	[38]
	Multi-objective optimization algorithm	Validation algorithm for one microgrid	[39]
	Load balancing algorithm	Architecture not defined	[40]
	Load balancing algorithm	Decentralized architecture	[41]
Energy forecasting	Energy forecast algorithm	Architecture not defined	[42]
Home energy management	Web services under a service-oriented architecture	Misuse of cloud computing capabilities	[43]
Secondary control	Solution for low latency, storage, and processingcapabilities	No verification of the results	[44]
	Decentralized FOG computing scheme	Architecture not defined	[45]
	IoT gateway development	Decentralized EMS that limits the integration of a MGC	[46]
Global control	Performance comparison for cloud and fog computing architecture	Decentralized EMS that limits the cloud computing capabilities	[47]
	Definition of an intermediate layer between IoT and cloud computing	Architecture not defined	[48]
	Operation analysis of load balancing algorithms	Decentralized EMS that limits the cloud computing capabilities	[49]
	Fuzzy adaptive method and a fog-cloud-device architecture	Decentralized EMS that limits the cloud computing capabilities	[50]
MGC architecture	Hybrid communication platform for the EMS	Cost function for the EMS that does not consider either scalability or autonomy features	[51]
	Multiple microgrid cluster modeling	Focused on frequency control under simulation	[52]

environment. However, several obstacles and challenges need to be overcome, including the development of complex control strategies and the definition of user trends with the participation of consumers. Trends cited in this paper involve ML application into the real-time EMS, including new computing infrastructures and high-volume dataset analysis to develop and train models for managing MGs. Based on the above, this article presents a complete architecture that applies solutions available in the cloud and ML tools in the MGC management.

Fig. 13 shows the scheme of the proposed architecture, which supports its performance on solutions available in the cloud, in particular Amazon Elastic Compute Cloud (EC2) [53] and MATLAB Production Server (MPS) [54]. The architecture divides into four sections deployed in the cloud: data access, application development, integration with ML tools, and integration with a scalable server. The precise integration of the mentioned sections permits defining and implementing a supported architecture in the cloud that allows the scalable management of the EMS for a MGC which joins up maximum capacity generation, power consumption, and optimal economic operation under an ML perspective running in real-time and using CC resources. The active algorithm solves the EDP giving adequate stability performance and optimal power reference tracking under unexpected load and generation changes. In the first section, development, the EMS algorithm that manages the MGC is created, compiled, and then deployed to the MPS. The access section allows calling EMS functions, and input and output parameters deployed in the production server from enterprise applications and web and mobile applications. The third section, integration, permits access to the analytics tools that the EMS requires to include BD and ML processes to improve both its performance and the management of the cluster of interconnected MGs. Lastly, the scalability section provides CC capabilities that implement low latency processing of concurrent work requests, scale capacity, and redundancy needed by the EMS demands to expand its management to the number of interconnected MG in real-time.

4.1. Real-time EMS description

As stated in [55], the cloud-based EMS involves three units (see Fig. 14): supervisory system interface, data storage, and scheduling and optimization.

The supervisory system interface deploys in the MPS, where the agent associates each MGC with a process. In this mode, the communication between each MG and the EMS takes a supervisory perspective. All the data collected by the supervisory system upload into the integration section using BD tools offered by Amazon Simple Storage Service (S3) by Amazon Web Services (AWS). Data storage is a collection of measurement files accessible either by the supervisory system or the scheduling and optimization method to provide the models and forecasting algorithms the needed information to perform specific tasks. Lastly, the scheduling and optimization unit performs the models and algorithms conceived in the development section to get optimal references for the distributed energy resources.

4.2. Setting up the test environment for the architecture proposal

The experiment uses five tools for testing the proposal application: MATLAB, Simulink, 4-Quadrant Power Amplifier of Opal-RT [56], dSPACE-Scalexio [57] and AWS. MATLAB and Simulink's code incorporates the model for the MG's EMS and expands it to integrate the EMS for a MGC under the MPS. The model definition includes a workflow that allows data analysis to forecast energy generation and consumption. The proposed plan defines an application that allows selecting any microgrid within the cluster and displays the current load and generated energy condition. It also forecasts the load and energy generation. So the information would allow the user to understand the effect of factors such as irradiance, wind speed, location, and weather on energy consumption, and facilitate its administration, namely, determine how much energy should be generated or purchased in real-time. The Opal-RT and dSPACE-Scalexio simulation platforms emulate the performance of the MGC in terms of data generation and EMS monitoring in real-time. The data incorporation in the energy generation and consumption characterization lets us obtain a more accurate forecast allowing the EMS to get better decisions keeping in mind both energy excesses and shortages. S3 guarantees the access and storage of the files used by the models and forecasting algorithms under suitable conditions of scalability, data availability, security, and performance. When considering the energy generation intermittency of renewable resources and the users' consumption behavior for a MG or a MGC, it is necessary to precisely forecast these aspects to obtain efficient energy management but focusing on three items: power generation forecast, energy consumption prediction, and EDP automation using solutions available in the cloud. A large amount of information is available and enables the development of accurate forecast models, and the challenge consists of defining the data analysis workflows that make it possible to convert the low-quality information into actionable information. The documents presented in [58] and [59] display an interesting ML workflow and

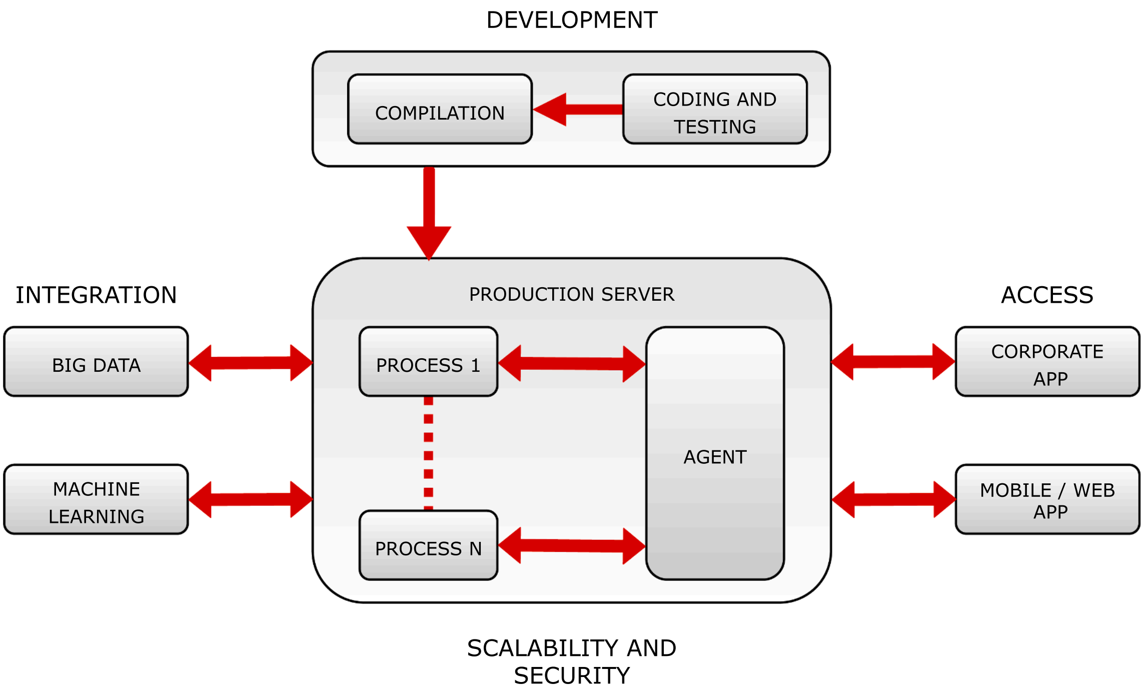

Fig. 13. Applied architecture. Source: Authors.

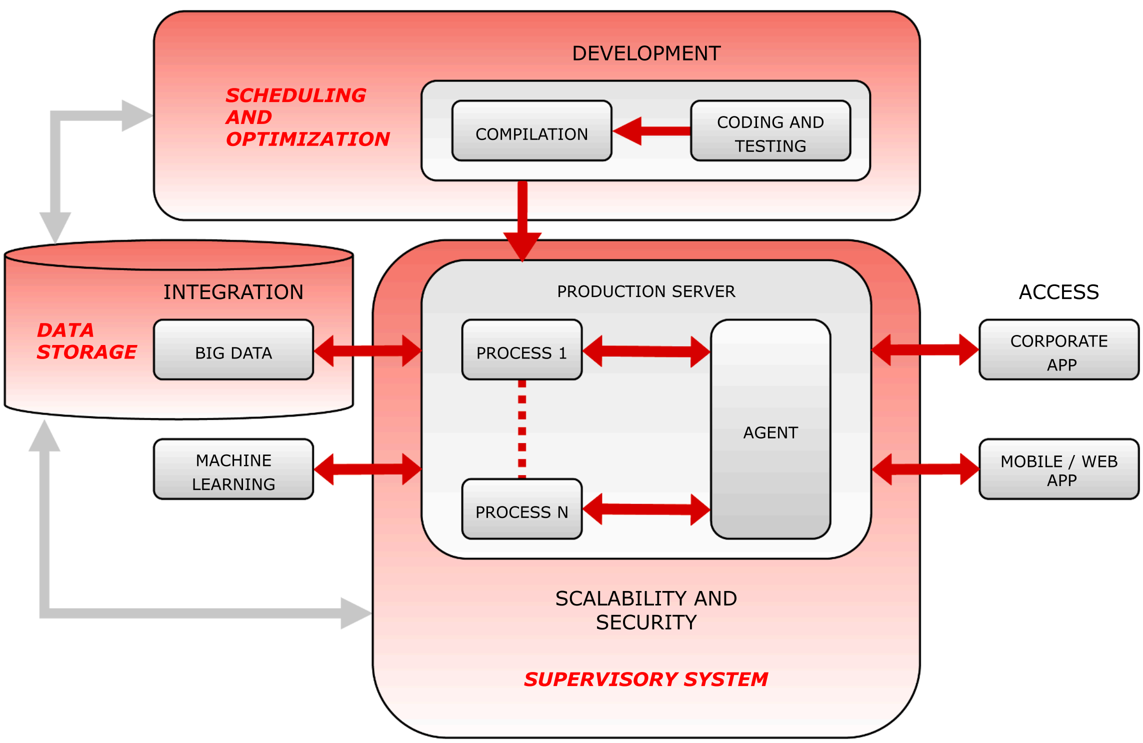

Fig. 14. EMS description. Source: Authors.

considers seven steps applied in this solution:

1. Collection of data. Directly from structured source data, web scraping, API, chat interaction.
2. Data preparation and missing/outlier treatment. Data acquires the format as per the chosen ML algorithm. Additionally, missing value treatment replaces missing and outlier values with the mean/median technique.
3. Data analysis and characterization. Data needs to be analyzed to find any hidden patterns and relations between variables.
4. Train algorithm on training and validation data. Data divides into three chunks - train, validation, and test data. ML algorithms execute on training data, and the model hyperparameters are tuned based on validation data to avoid overfitting.
5. Test the algorithm on test data. The model runs on unseen test data once the model has shown good performance on train and validation

data. If the performance is still good enough, the algorithm is ready for deployment.
6. Deploy the algorithm. Trained ML algorithms deploy on live streaming data to classify the outcomes.
7. Deploy the model as an application in a production environment.

4.3. Machine learning energy generation and consumption forecasting used by the EMS in this proposal

The EMS of the residential or commercial sector plays a role of importance in improving the scalability and reliability of the grid. Soon, it would be necessary to predict energy generation precisely to carry out efficient energy management as these sectors trend to integrate energy generation devices such as wind turbines and solar panels. Generally, the energy generation from these sources is projected by having defined timelines: days and hours. Getting close to real-time measurement is necessary and will reduce the impact of different weather conditions, such as cloudiness, irradiance, wind speed, humidity, and others, and will facilitate the energy generation forecast in a MG or a MGC.

The generation forecast based on the conditions of a season could be a starting point. Fig. 15 shows the target and forecast generation within an area of interest. The solution considers both the environmental and load profile conditions. It is only possible to verify the power consumption status compared to the installed generation capacity, whether it is available in the microgrid's power generation forecast.

In the same way, it's possible to know in advance that the energy demand will not be satisfied even with 100% of the generator's capacity regardless of how the generation sources operate, forcing the economic dispatch algorithm to negotiate the acquisition of electricity either from another microgrid or the power grid. A target generation slightly higher than the forecast generation is intentionally selected to generate protection against the variability in the system and the model inaccuracies. Also, the ML techniques included in the model push the forecast generation to follow the target generation in most spots [60]. However, there are some points where the target generation is higher than the forecast generation producing an energy surplus. This energy excess can be negotiated within the cluster (see Fig. 16).

5. Discussion

Conventional electric power systems are experiencing a radical transformation due to the increasing worldwide demand and the urgency to reduce carbon emissions. Including more renewable generation into the power grid and innovative communication technologies will allow accomplishing these objectives. MG's implementation within the smart-city processes through renewable resources, efficient generation, smart-measurement, optimal load acquisition, and incorporation of ML tools increases the platform capabilities with minimal additional cost [61]. The maturity and availability of renewable energy are moving energy generation closer to where it is needed, enabling the development of MGs. MGs facilitate numerous operations, such as resilience, distributed generation, efficient use of resources, and dependency. Considered as small-scale energy grids that operate independently or in conjunction with the power grid, MGs could take advantage of the advanced technological developments to improve their features including, CC, IoT, intelligent devices, and embedded ML. Eventually, all of them define the use and price negotiation of electricity.

In this research, CC showed benefits that could impact the flexibility and competitiveness of MGs or MGC. The first one is the scalability of the application because it favors capital investment. This solution considered only pay the proportional usage of the cloud, reducing the economic impact of possible disaster recovery, and eliminating the need to update the servers as the contracted service includes it. Additionally, cloud services are a relatively environmentally friendly solution because the server capacity adapts to the fluctuation of the cloud and its usage. The second benefit was the increasing application autonomy resulting from collaborative work under adequate security conditions and the constant inclusion of ML tools that facilitate remote working conditions in the pandemia. In addition, the application of cloud capabilities and ML to real-time EMS was relevant because the implementation of different strategies extends over a region and performs more economically and efficiently. In other words, this approach integrated the management of MG with virtual computing devices, allowing to improve data processing, process interaction, obtain savings in operating costs, and quick access mechanisms to support the computational needs of the MG and the MGC [62]. In addition to being simplified, the impact on the EDP can easily extend to the development of distributed and controlled MGCs connected to the cloud. Adequate management was particularly critical when the cluster components worked in island mode since issues such as stability, reliability, and voltage and frequency regulation problems had to be solved by the MG through the efficient architecture that facilitates data storage, resource location, and power management.

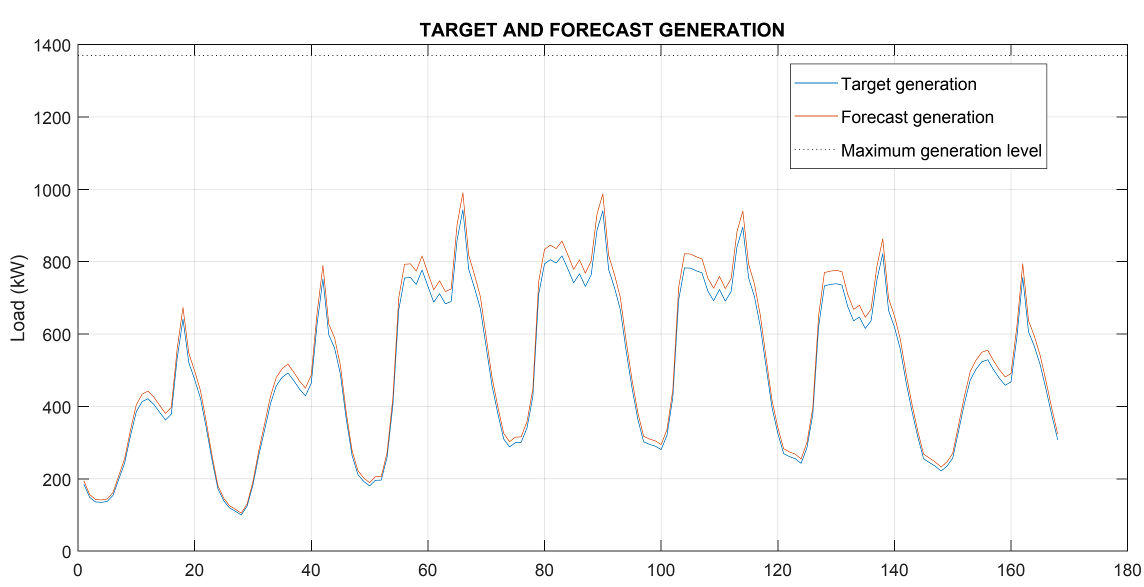

Fig. 15. Example of generation forecast considering the data available in www.datos.gov.co. Source: Authors.

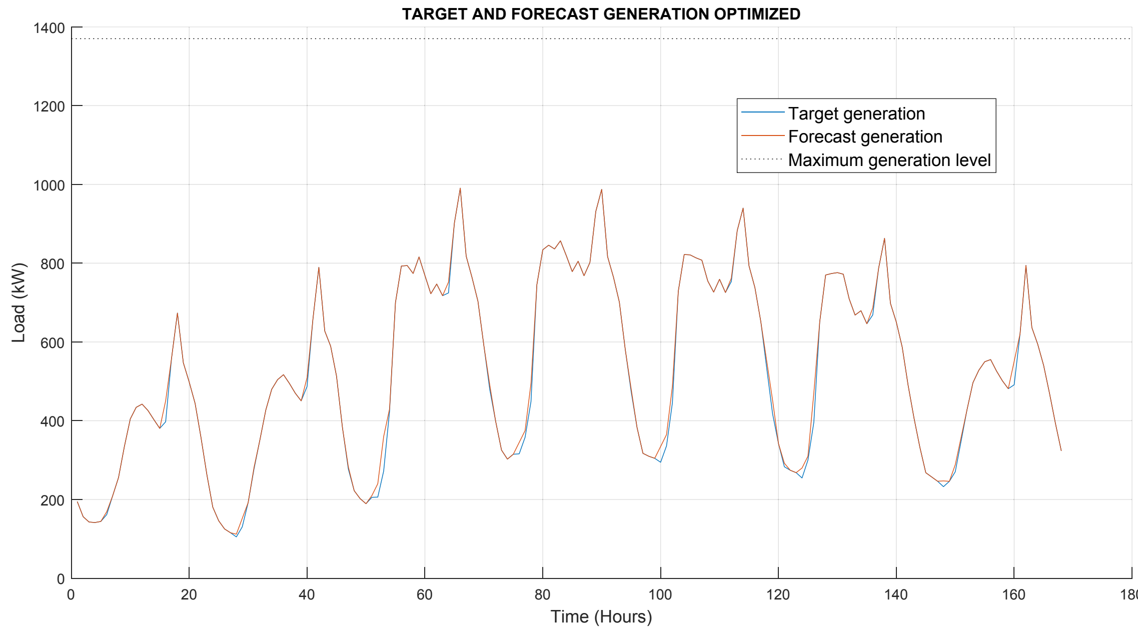

Fig. 16. Example of generation adjustment based on consumption forecast. Source: Authors.

Under the mentioned context, cloud and ML tools applied to cluster management arouses interest as a reliable and stable alternative to ensure optimal operation of energy systems that take into account a large integration scale of different generation and storage elements.

There are several advantages of the cloud-based real-time operation EMS for MGCs. Its optimal component interaction, the secure communication between the MGs, the optimal energy flow, and the active algorithm optimal managing [31], are a few. CC capabilities and ML are seen as a possible solution to meet the highly flexible and distributed computing needs of MGs: the cloud provides the necessary economy, flexibility, and recursion that the systematic growth of the management of a MGC requires [63] and, at the same time, new applications, actors, and needs of the system will demand granular controls and information management that allow them to actively participate in the development of MG under a ML perspective. In short, the exponential growth in the need for computational infrastructure in a MGC is associated with the permanent maintenance of resources while achieving adequate scalability, which presents a complex challenge [35]. As stated in [64], from a scientific point of view, it is interesting to know the context and significance of the cloud and ML utilization, its value in the research, theories, and approaches, and its applicability in the real-time management for MGC. Since there could be gaps in the sparse theoretical results and the empirical verification, or if you want to consider, its degree of applicability and potential outcome. Based on the literature currently consulted and notwithstanding the mentioned, no author clearly defines an autonomous cloud-based architecture that can be applicable and expandable to the real-time supervised learning management of a cluster of interconnected MGs.

6. Conclusion

Renewables were the only energy source for which demand increased in 2020 despite the pandemic, while consumption of all other fuels declined. Integrating higher shares of renewable energy systems technologies in power systems is essential for decarbonizing the power sector, while it is necessary to satisfy the growing energy demand. As a result of the sharply falling costs and supportive policies, renewable energy systems deployment has expanded dramatically in recent years. However, the inherent variability of wind and solar photovoltaic power generation raises challenges for power systems operators and regulators. For this reason, in this research, we proposed an energy management system that joins up maximum capacity generation, power consumption, and optimal economic operation under a machine learning perspective running in real-time and using cloud resources. The active algorithm solves the economic dispatch problem giving adequate stability performance and optimal power reference tracking under unexpected load and generation changes - a relevant business issue for the renewable energy market growth.

Machine Learning capabilities deployment inside the energy management system allows data sampling at much faster intervals improving the “generalized” one-day ahead range and decreasing it to less than one minute, overcoming the limitations given by network congestion, storage, and offline computing. The inclusion of state-of-the-art technologies in the cluster’s management turns the system capable of reacting adequately and performing analyzes to generate models based on the information collected in real-time. In this way, the entire system becomes autonomous, scalable, and cost-effective - less than USD100 for grid consumption in a week - while other requirements such as bandwidth and connectivity become measurable – 2.56 Mbit/s for a wired connection in one cluster. Also, the experiments showed that power generation decentralization requires local computing capabilities to filter and understand local signals and pass the necessary information to the microgrid central controller by executing information processing near information sources, within, or near the Microgrid Cluster. Despite this, cloud resources insertion, machine learning techniques, and new information and communications technologies to facilitate decentralized information and management systems bring additional challenges for the Energy as a Service future approach. The rapid expansion of cloud computing turns local servers obsolete, the usage of live tracking smart meters becomes a requirement, and system security becomes an essential element, to mention a few.

CRediT authorship contribution statement

D.G. Rosero: Conceptualization, Investigation, Methodology, Data curation, Software, Writing – original draft. **N.L. Díaz:** Conceptualization, Resources, Supervision, Writing – review & editing, Funding acquisition. **C.L. Trujillo:** Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.117770.

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