Control in Micro-Grid Systems

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The demand for electricity is increased due to the development of the industry, the electrification of transport, the rise of household demand, and the increase in demand for digitally connected devices and air conditioning systems. For that, solutions and actions should be developed for greater consumers of electricity. For instance, MG (Micro-grid) buildings are one of the main consumers of electricity, and if they are correctly constructed, controlled, and operated, significant energy savings can be attained. As a solution, hybrid RES (renewable energy source) systems are proposed, offering the possibility for simple consumers to be producers of electricity. This hybrid system contains different renewable generators connected to energy storage systems, making it possible to locally produce a part of energy in order to minimize the consumption from the utility grid.

control approaches   Energy management   Micro-grid systems   predictive control

1. Introduction

Proper management of energy flow in MG (Micro-grid) systems must be carried out in order to improve the global performance of the system, to minimize the cost of the electrical bill, and to extend the lifetime of its components (e.g., converters, batteries, fuel cells). In general, energy management (EM) approaches involve an objective function, which could be used to maximize the efficiency of the hybrid RES system and to minimize energy consumption while improving the consumers' quality of services. For instance, an EM control strategy that considers only the availability of the electricity can be developed to switch, at each time, from RESs (renewable energy sources) to storage devices or to the utility grid without considering the electricity price or the profitability of the system. In other cases, control strategies can interact with the generators by limiting the power generation. The aim is to ensure the electrical quality of services and, consequently, minimize the profitability of the installation. However, despite the ability of these strategies to reach the defined objective, they might decrease the performance of other criteria, such as the batteries' lifetime, the system's installation cost, and profitability.

Actual commercial inverters provide high-performance energy balance by interconnecting RESs, energy storage systems, and the utility grid, taking into consideration only a single-objective function. This later is mainly implemented in order to increase the availability of the electricity for building's loads. With a limited configuration, the inverter can use batteries or the TEG at any moment without taking into account other constraints, such as the electricity cost and the C/D (charge/discharge) cycle of the batteries. For instance, high and frequent cycles of the C/D cycle of batteries could decrease their performance while reducing the system's profitability. EM strategies that are deployed in the actual inverters use "if-else" statements to perform real-time decisions. For instance, the defined setpoint values (i.e., control inputs) cannot be adjusted according to predictive variations of RESs

production, load demand, and battery SoC (state of charge). Such EM strategies are considered as "passive strategy" in their decisions and actions [1]. Control strategies incorporating multiple-objective functions are therefore required for efficient energy management (i.e., ensuring electricity availability) while taking into consideration operational constraints (e.g., costs, reliability, and flexibility). In fact, "active strategies" for EM should be developed in order to adapt the setpoint values accordingly. These strategies could use intelligent and predictive control techniques together with recent IoT/Big-data technologies (e.g., data monitoring, data analysis, data mining, machine learning) for efficient EM in hybrid RES systems. In this work, control structures and strategies from the literature are presented by highlighting their advantages and drawbacks in the context of MG for smart buildings.

2. Control Architectures

In hybrid energetic systems or MG systems, distributed and hybrid RES generators (e.g., PV (photovoltaic) panels and wind turbines) are used to produce clean energy (e.g., solar, wind), while energy storage systems are installed to compensate the fluctuation between RESs generation and load consumption. These hybrid systems can either operate on grid-connected or standalone modes depending on desired and fixed objectives. However, while the penetration of these distributed generators is continuously growing, new energy management approaches are required for their seamless integration within existing electricity network. Table 1 presents resent literature works concerning the deployment of hybrid systems. As highly stated in Table 1, batteries are the most commonly used devices for energy storage.

Table 1. Survey through collection of EM (energy management) for the hybrid MG (Micro-grid) system.

Ref.	Grid	DG	PV	WT	Biomass	FC	Hydrogen	Battery	Diesel	Super-Capacitor	EV	Performance Evaluation
[2]		✓	✓	✓		✓		✓				The Multi-Objective Particle Swarm Optimization algorithm is used to improve electric energy utilization in remote areas. Simulation results are presented.
[3]			✓	✓		✓		✓				The development of a methodology for modeling and optimally sizing a hybrid system of RESs and two energy storage devices (hydrogen and batteries). Simulation results are presented.

Ref.	Grid	DG	PV	WT	Biomass	FC	Hydrogen	Battery	Diesel	Super-Capacitor	EV	Performance Evaluation
[4]		✓	✓			✓	✓		✓			The Crow search algorithm is used to optimize and size a hybrid system. Two constraints are considered to minimize the total net cost: Loss of power supply probability and renewable energy portion. Simulation results are presented.
[5]	✓		✓	✓				✓				The operation of a grid-connected hybrid PV-wind system is performed using a standalone inverter capable of working in grid-connection mode and standalone mode. Experimental investigations are presented.
[6]								✓		✓	✓	The work proposed a real-time EM control strategy combining wavelet transform, neural network, and fuzzy logic methods. Experimental results exposed that the power variation and the peak power of the battery pack have been successfully suppressed.
[7]						✓		✓		✓	✓	An intelligent control strategy is developed for a hybrid energy storage system, composed of fuel cell, battery, and super capacitor. Multi-input/multi-output state-space model is used to perform the

Ref.	Grid	DG	PV	WT	Biomass	FC	Hydrogen	Battery	Diesel	Super-Capacitor	EV	Performance Evaluation

Ref.	Grid	DG	PV	WT	Biomass	FC	Hydrogen	Battery	Diesel	Super-Capacitor	EV	Performance Evaluation
												study. Simulation results are presented.
[8]	✓	✓	✓	✓				✓				A multi-objective optimization problem, over a receding control horizon, is used for energy storage dispatch and sharing of renewable energy resources in a network of grid-connected MG. The multi-objective optimization is formulated as a lexicographic program to allow preferential treatment of multiple MG. Simulation results are presented.
[9]	✓	✓	✓	✓	✓			✓				An economic linear programming model is developed with a sliding-time-window to assess design and scheduling of biomass, combined heat and power-based MG systems. Simulation results are presented.
[10]	✓	✓	✓	✓				✓				Distribution network including RESs is studied for optimal dispatch model of mixed-power generation by considering the charging/discharging scheduling of battery. Bee-colony-optimization method is proposed to solve the daily economic dispatch of MG systems. Simulation results are presented.
Ref.	Grid	DG	PV	WT	Biomass	FC	Hydrogen	Battery	Diesel	Super-Capacitor	EV	Performance Evaluation

Ref.	Grid	DG	PV	WT	Biomass	FC	Hydrogen	Battery	Diesel	Super-Capacitor	EV	Performance Evaluation
[11]			✓			✓	✓	✓				A combined sizing and EM methodology is proposed and formulated as a leader-follower problem. The leader problem focuses on sizing and aims at selecting the optimal size for the MG components. It is solved using a genetic algorithm. Simulation results are presented.
[12]			✓	✓	✓			✓				A strategy for the optimal management of a multi-good standalone MG integrated with RES is investigated. The proposed approach is defined through an EM model able to determine the schedule of each programmable unit to fulfil the community needs at the lowest operation cost. Simulation results are presented.
[13]	✓	✓	✓	✓		✓		✓			✓	Electrical vehicles are used for peak shaving and load curve correction in a MG system. The deployed methods deal with the simultaneous scheduling of electrical vehicles and reactive loads in order to minimize operation cost and emission in presence of RES in MG system. Simulation results are presented.

response ... ES power ... e system. ... ble 2, the ... ns. These control strategies can be classified into three main categories: Centralized, decentralized, and hierarchal control, as mentioned in Figure 1. These control strategies are presented in the rest of this section.

Ref.	Grid	DG	PV	WT	Biomass	FC	Hydrogen	Battery	Diesel	Super-Capacitor	EV	Performance Evaluation
[14]			✓	✓			✓		✓			A power management system is presented to manage the power output from RES, fuel cell, and batteries with delivery of hydrogen from an electrolyzer. The deployed strategy handles the source effectively by considering the limited lifecycle of storage devices. It eliminates the need for a dump load in the MG when the storage devices are charged to the maximum capacity. Simulation results are presented.

Ref.	Main Objective	EM Approach	MG Scale	Control Structure
[3]	A methodology for modeling and optimally sizing a hybrid system for renewable energy considering two energy storage devices: Hydrogen and batteries.	Wavelet transform, Neural network and Fuzzy logic (FL)	Large	Not specified
[4]	A method is developed to size an off-grid PV/diesel/FC hybrid energy system in order to optimize the number of system components with respect to the cost minimization of the installation.	Crow search algorithm	Large	Hierarchical
[8]	An EM method is deployed in a MG system containing energy storage devices and renewable energy based distributed generators in grid-connected MG. In the studied approach, the neighboring MG share the capacity of their distributed resources and energy storage devices aiming at reducing the operational costs.	Lexicographic programming, Linear programming, Receding horizon control	Large	Hierarchical
[9]	A deterministic constrained optimization and stochastic optimization approaches to estimate the uncertainties in biomass-integrated MG supplying both heat and electricity. The work developed an economic linear programming model with a sliding time window to assess design, scheduling of biomass-combined power and heat-based MG systems.	Linear programming model with a sliding time window	Small	Decentralized

Ref.	Main Objective	EM Approach	MG Scale	Control Structure
[10]	A MG energy management strategy by considering RES integration into the distribution network. The time-of-use, other technical constraints, and an enhanced bee colony optimization is proposed to solve the daily economic dispatch of MG systems.	Enhanced bee colony optimization	Small	Centralized
[11]	Authors proposed a combined EM and sizing methodology, formulated as a leader follower problem. The leader problem focuses on sizing and aims at selecting the optimal size for the MG components. The problem is solved using a genetic algorithm and the follower problem is formulated as a unit commitment problem and is solved with a mixed integer linear program.	Mixed integer linear program	Small	Centralized
[14]	Authors proposed an EM approach to divert excess energy of PV to the electrolyzer.	Linear Programming	Small	Centralized
[15]	An analysis of energy management system of a MG using a robust optimization taking the uncertainties of wind power and solar power generations and energy consumption into consideration.	Agent-based modelling	Large	Decentralized
[16]	An algorithm for EM system of a MG using multi-layer ant colony approach pointing on determining the optimum point of operation for local distributed energy generation with least electricity production cost. The studied algorithm has the capability of analyzing the constraints related to economic and technical aspects of the problem.	Multi-layer ant colony approach	Medium	Not specified
[17]	A method known as contingency-based energy management for a system of MGs. A stochastic optimization is proposed according to various scenarios of the contingencies.	Contingency-based energy management	Large	Hierarchical
[18]	A fuzzy EM approach is deployed to smooth the power flow of a MG containing heat and power unit. The aims is to use the surplus of electrical power of the MG for storing in electrical energy storage systems and ensuring the water temperature of the thermal storage system in the desired value in order to supply residential buildings.	Fuzzy energy management strategy	Medium	Not specified
[19]	A model predictive control technique to determine the optimal operation of the MG system using an extended horizon of evaluation and recourse. The EM problem is decomposed into Unit Commitment and Optimal Power Flow problems in order to avoid a mixed-integer non-linear formulation.	Model predictive control	Large	Centralized
[20]	Authors present an EM system to minimize the daily operating cost of a MG and maximize the self-	Convex Programming,	Medium	Hierarchical

Ref.	Main Objective	EM Approach	MG Scale	Control Structure
	consumption of the deployed RES by selecting the best setting for a central battery storage system based on a defined cost function.	Model Predictive, and Rolling Horizon		
[21]	The operating cost of MG is minimized, while considering droop controlled active and reactive power dispatch of AC side MG as a constraint.	Mixed integer nonlinear programming	Small	Centralized

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controller while ensuring a flexible MG operation in both grid-connected and standalone mode (Figure 2). The CC collects data, such as RES energy production, energy consumption pattern, the energy price from market operators, and weather conditions, and then executes the optimal and efficient system's control.
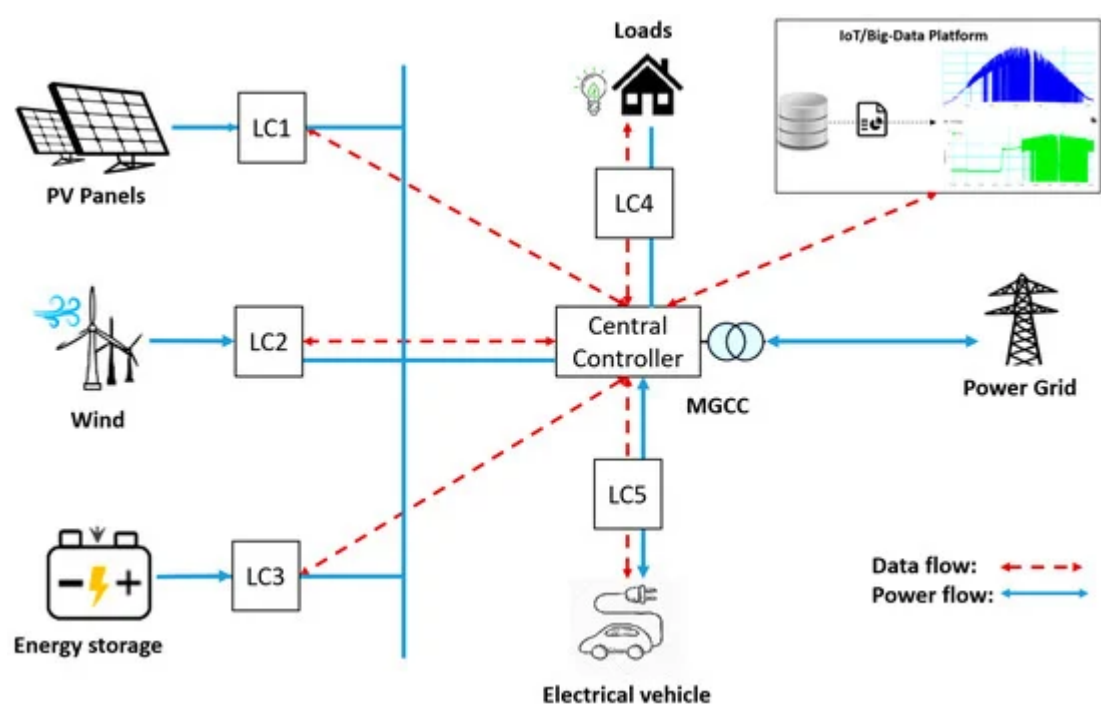

Figure 2. Centralized control structure.

Numerous research works have developed and deployed centralized EM strategies. For instance, the authors of [22] proposed a centralized controller in order to optimize the operation of MG by maximizing the production of distributed RESs generators while establishing back-and-forth energy transfer with the main utility grid. The efficiency of the proposed solution on the MG system was investigated by considering a typical case network operating under various market policies and spot market prices. Moreover, the authors of[19] developed a centralized EM system for a standalone MG system based on the model predictive control method in order to reduce the computational loads. In fact, the studied problem was solved iteratively by nonlinear programming (NLP) and mixed-integer linear programming (MILP) techniques. Other centralized control strategies are summarized in Table 2. However, despite the ease of implementing the centralized strategies, they have shown their limits, especially when dealing with large-scale hybrid systems[23].

2.2. Decentralized Control

Unlike centralized strategies, in decentralized control, each entity is considered autonomous using an LC. This means that groups of entities are controlled separately by a leader. In literature, the terms 'decentralized' and 'distributed controls' are often used in place of each other[24][25]. The distributed control can be considered as a decentralized control in which LCs use local measurements, such as frequency and voltage values, to elect the leader entity. They are also allowed to share information with neighbors. For a distributed control, LCs do not only use local measurements but also are able to send and receive required information to other LCs[26]. In decentralized control approaches, limited local connections are required and the control decisions are made based only on local measurements (Figure 3). It does not require a high-performance computing unit and high-level connectivity[27].
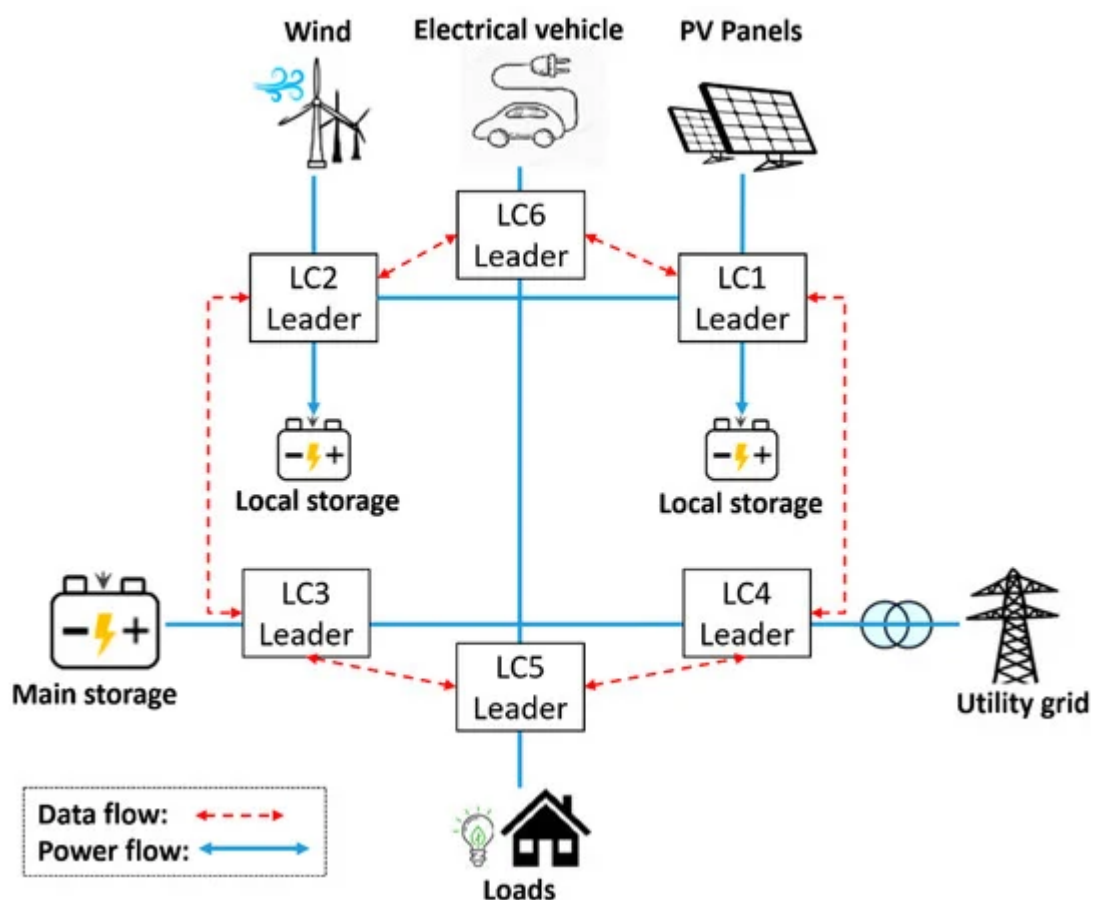

Figure 3. Decentralized control structure.

As depicted in Figure 3, each LC operates individually on managed energy sources, storage systems, and loads without central control. The control decisions are determined locally based on local measurements, which are shared among controllers using peer-to-peer communication.

However, monitoring, processing, and data visualization are considered critical in order to coordinate various distributed controllers and achieve a global operation goal. This process is standardized by the norm IEC-61968 for

a single-building energy management system and by IEC-61850 for interoperability between building MG systems[28][29][30]. Depending on the communication network availability, the decentralized control can be classified into three operation modes: (i) Fully dependent, in which the distributed controllers generate local control decision while communicating information with each other via a CC; (ii) partially independent, in which LCs communicate with each other and share information with the CC in order to generate central decisions; and (iii) fully independent, in which the distributed controllers communicate directly with each other and independently from the CC[31]. However, despite the flexibility of these operational modes, the decentralized control structure presents low performance compared to centralized control [32][33][34]. This is due to the low response time and incomplete information about the total MG system installation.

2.3. Hierarchical Control

Hierarchical control is mainly proposed for SG (smart grid) systems. In fact, the extended geographic areas of these systems and the extensive communication and computation requirements make the implementation of fully centralized approaches a difficult task. At the same time, the higher coupling between the different LCs requires a maximum level of coordination, which cannot be achieved by decentralized control structures. However, a compromise between the fully centralized and decentralized control structures is realized by providing hierarchical control structures[35][36] according to three control levels: Primary, secondary, and tertiary, as depicted in Figure 4.
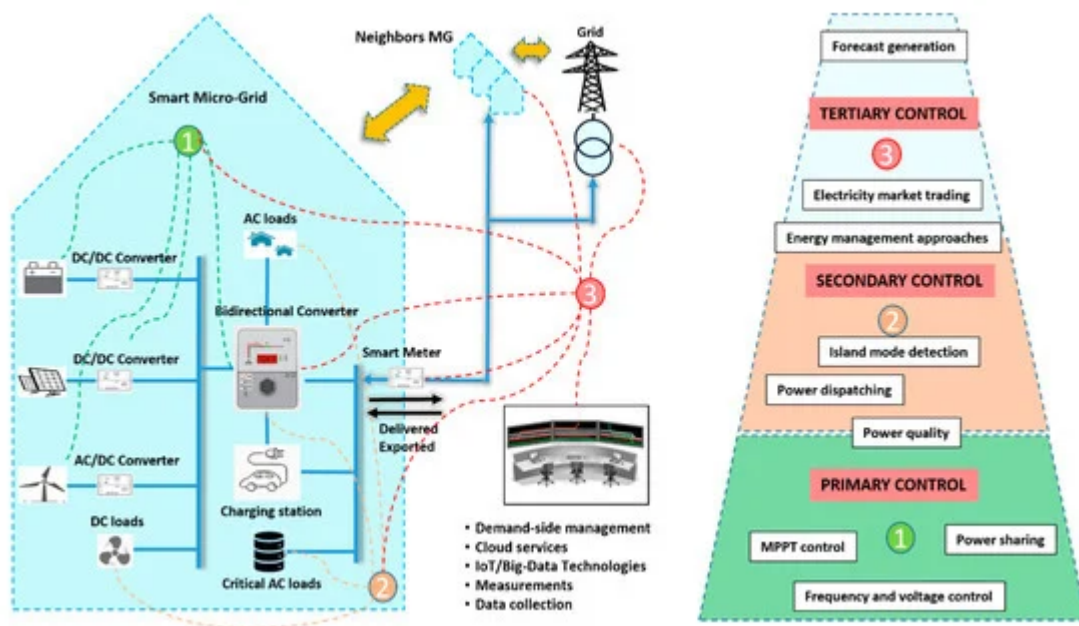

Figure 4. Hierarchical control structure.

The primary control level stabilizes the voltage and frequency generated from each source in order to respect the limits required by the standards[37][38][39]. In addition, the primary control level detects the operating mode of MG systems, offering the ability to operate in grid-connected and standalone modes [40]. For the secondary control level, the MG voltage and frequency are restored after the system's load variation. The aim is to ensure and

enhance the power quality within the required standards values, allowing the synchronization between the MG systems and the main electrical network [41].

The main objectives of tertiary control are the power flow control in the grid-connected mode, ensuring then the optimal operation in both modes like capacitance and inductance[42]. Figure 5 includes the structures of each level of the hierarchical control. The control levels differ in the response time frame speed in which they operate as well as the infrastructure requirements, especially for the communication, which is normalized by the standards IEC 61850-7-420 and EN13757-4 [36]. The hierarchical control can be implemented in parallel in both centralized and distributed structure. The advantages and disadvantages of each control structure are presented in Table 3.
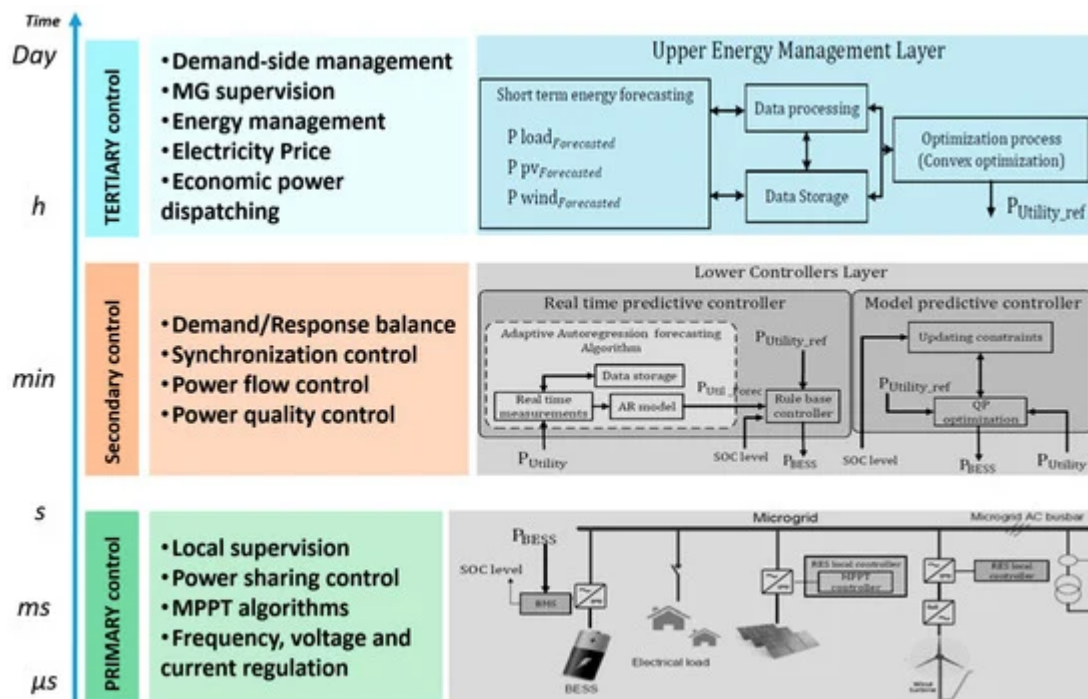

Figure 5. Hierarchical control levels.

Table 3. Control architectures for hybrid system, advantages and inconveniences.

EM	Advantages	Inconveniences
Centralized	• Strong controllability and real-time observability of the whole MG system; • Provides strong supervision and wide control of the whole system; • Mature and established approaches for control of many systems;	• The failure of the CC affects the whole system operation; • Heavy computation burden is a technical barrier for the deployment; • Not well designed to support plug-and-play functionalities of a large number of entities;

EM	Advantages	Inconveniences
	• Suitable for small size MG systems where the collected information is performed by low bandwidths communication[43] ; • Suitable for the internal control in MG system; • Global optimization of all entities of the same MG; • Offers high-performance computing unit and a secure communication infrastructure; • Holds the control strategy that considers the MG entirely and depends on the simple architecture of the system to build a global knowledge making the EM control easier to be deployed; • Straightforward implementation, the CC allows economic implementation and it is easy to maintain; • Optimal decision is guaranteed.	• Need a high level of connectivity due to the direct interaction of each entities with the central; • Requiring high processing unit for the CC; • More prone to failures since only one unit regulates the voltage and leads to reduce life spam of Battery bank stack [44]; • Poor scalability and responsible for shorter battery life [45] ; • Since all information is collected and handled at one CC, the computational burden increases making the control less effective for real-time communication requirements; • Reliability is degraded for the whole system.
Decentralized	• Distributed processing system with autonomous control capability; • Peer-to-peer nodes communication, allowing greater flexibility of operation, and avoiding single-point failure; • Higher reliability due to the redundancy of controllers and communication; • Distributed generators are controlled by independent controllers through their local variables offering redundancy communication link;	• Incomplete information about the overall MG status; • Voltages and currents average regulation requires more data transmission through the MG; • Local optimization in EMS is not able to provide a global solution for operating cost minimization of the total MG; • The distributed processing does not guarantee global optimal results for the whole MG system;

EM	Advantages	Inconveniences
	• Insufficient information about other entities of the MG systems; • Droop control strategy is usually used to avoid circulating currents between the converters without the use of digital communication link; • Avoiding single-point failure, enhancing the expandability, and allowing greater flexibility of operation; • High privacy for the entities and less amount of information; • Reduction of the computational need and releasing the traffic on the communication network; • Reduces computational burden and increases reliability and robustness; • Easy realization of plug-and-play functionality.	• A high complexity of implementation compared to centralized and hierarchical control; • Load dependency problem, responsible for the circulating currents in distributed generators, accuracy of load sharing can be achieved with the compromise of deviation in the voltages compared to their rated values; • Unsuitability for non-linear loads due to harmonics and inability to achieve coordinated performance of multiple components with different characteristics, and poor transient performance; • Requires effective synchronization and strong communication to achieve synchronicity; • Requires fast periodical reconfiguration.
Hierarchical	• More suitable for DC MG systems; • The voltage and the current are regulated locally by the source converters; • Flexible regulation of the system voltage within acceptable intervals; • Economic power dispatch among the converters, between the MG, the utility grid as well as the neighboring-MG; • Synchronous generators with the same frequency for all over the grid;	• The distributed generators should participate in voltage regulation and frequency control; • Some generators operate in limited power mode while supplying only the power planned by the electricity market; • The distributed generators are responsible for adjusting the differences between the planned demand and the actual load. Therefore, the demand should be forecasted to plan correctly the output of the generators;

EM	Advantages	Inconveniences
	• The operation constraints are dispatched to different levels reducing the processing time; • Improving the current mismatches among the controllers; • Combining the previous control structures; • Optimal decision is possible.	• Adjacent layers coordination is required; • There is no transfer of information and energy if there is a communication fault in the upper layer; • Fewer computation burdens.

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