Chapter 7

Optimal Design and Operation Management of Battery-Based Energy Storage Systems (BESS) in Microgrids

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/intechopen.71640

Abstract

Energy storage systems (ESSs) can enhance the performance of energy networks in multiple ways; they can compensate the stochastic nature of renewable energies and support their large-scale integration into the grid environment. Energy storage options can also be used for economic operation of energy systems to cut down system's operating cost. By utilizing ESSs, it is very possible to store energy in off-peak hours with lower cost and energize the grid during peak load intervals avoiding high price spikes. Application of ESSs will also enable better utilization of distributed energy sources and provide higher controllability at supply/demand side which is helpful for load leveling or peak shaving purposes. Last but not least, ESSs can provide frequency regulation services in off-grid locations where there is a strong need to meet the power balance in different operating conditions. Each of the abovementioned applications of energy storage units requires certain performance measures and constraints, which has to be well considered in design phase and embedded in control and management strategies. This chapter mainly focuses on these aspects and provides a general framework for optimal design and operation management of battery-based ESSs in energy networks.

Keywords: energy storage system, microgrid, optimal design and control, renewable energy integration, optimization

1. Introduction

Nowadays, due to the increased operation and maintenance cost and issues related to transportation of fuels, conventional ways of power generation are no longer an optimal solution.

With more concerns about environmental footprints and global warming together with the steady progress in green technologies, renewable energy resources (RESs) are deemed to be key enablers for sustainable energy development, cost-effective operations, and pollutant emission prevention. The use of RESs in an integrated framework with different energy sources not only enhances the system efficiency at different levels (e.g., energy generation, transmission, and distribution) but also improves the energy supply reliability and allows empowering of consumers in the different locations (such as suburban districts, countrysides, and remote/islanded areas). Additionally, with the complementary characteristics of energy storage systems (ESSs) and hybridization of energy systems, it is possible to offer more affordable and reliable source of power and introduce more controllability to the generation mix. More importantly, with the application of ESSs, the issues related to unpredictable nature of RESs (mainly solar and wind energy sources) can be resolved, and a smooth-running power supply can be guaranteed. On the other hand, implementation of an integrated energy system supported with ESSs allows energy saving at different scales. By proper charging/discharging of the ESSs, we can economically benefit from dispatching cheaper energy sources during peak load hours and saving excess energy during low-demand periods. It is noteworthy that the term "ESS" could have different definitions; however, in this chapter we are talking about a "commercially available technology that is capable of absorbing energy, storing it for a period of time, and thereafter dispatching the energy" [1]. It should be also noted that the system operation can be further improved if demand response programs (DRPs) are considered in energy management portfolio. DRPs will incentivize the users to reduce their energy consumption over peak times or to shift part of their consumptions to other time intervals for matching energy supply [2]. However, a good DRP should have two primary features: the first feature is defined as the *adaptability* to different consumers with different dispositions toward the DRP, and the second one is defined as the *adjustability* to time preferences of consumers. This means that each consumer should be able to easily shift his/her demand from the high-price hours to the favorite hours according to his/her lifestyle [3]. With this introduction on advantages of renewable energy integration and reliable backup through energy storage options, this chapter discusses different battery-based ESS (BESS) technologies and presents potentials of BESS in distribution systems. Moreover, different design criteria and methodologies for ESS sizing and planning are proposed, and a general framework for optimal operation management and control of BESSs in energy networks is developed.

2. Criteria and methodologies for battery sizing and planning

This section provides an overview of criteria and methods that should be used to optimally size and use a battery energy storage system (BESS) for different applications.

2.1. Battery technologies

A battery is constituted of electrochemical cells connected in series, parallel, or both in order to obtain the desired capacity and voltage output. A cell consists of a set of two electrodes (oxidizer and reducer) in contact with an electrolyte and converts chemical energy into electric energy (and vice versa for rechargeable cells) [3–5]. Since the end of the eighteenth century with the development of the Volta pile, "voltaic pile," numerous designs of batteries have been invented (with different electrode materials, electrolytes, casings, separators, management systems, etc.). Hundreds of systems have been created, but almost 20 of them are currently commercialized (mainly derived from lead, zinc, nickel, or lithium materials) [6]. As presented in **Figure 1**, electrochemical cells can be classified into three main families:

- Flow batteries (also called redox flow batteries) are based on two electrolytes stored in external tanks. The electrolytes are pumped into an electrochemical cell in order to produce electricity. The energy density depends on the size of the tanks, and the power density depends on the rate of chemical reactions occurring in the electrochemical cell. These batteries can be fast to recharge by changing the electrolytes. In general, the chemical reactions are reversible.

- Primary batteries cannot be easily and efficiently recharged so they are usually only discharged once and discarded. They are often used in portable electric devices such as lighting, cameras, toys, and also in-home automation sensors (e.g., smoke and movement detectors). They offer a good energy density and a good shelf life.

- Secondary batteries are rechargeable and can perform a large number of cycle charge/discharge (100–1000). The market of rechargeable batteries comprises a very wide range of applications such as powering portable electronic devices, electric vehicles, storing surplus of energy from photovoltaic systems, etc. Since 1990, the average growth rate of rechargeable battery pack market is 5% per year [7]. For decades, lead-acid batteries (such as valve regulated and sealed) have been leading, by far, the global market of rechargeable batteries. Since the end of the 1990s, lithium-ion batteries have been gradually preferred to nickel-cadmium (Ni-Cd) and nickel-metal hydride (Ni-MH) batteries

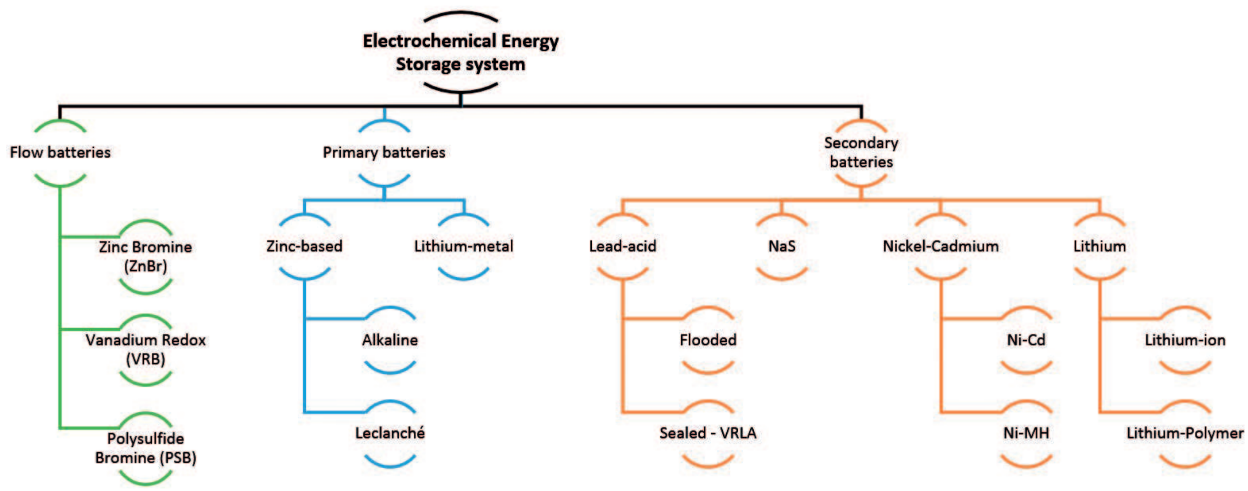

Figure 1. Main different electrochemical technologies.

in portable devices [7]. The historical development of the main battery chemistries and the key issues to create sustainable batteries with always higher performances are well presented in Ref. [8].

In this chapter, the analysis will be focused on secondary batteries, especially on lead-acid and lithium-ion batteries, the most popular technologies (because of an attractive price for the first cited and because of high performances in terms of energy and power densities for the latter). The main useful characteristics of a BESS, when selecting a technology, are listed below:

- **Response time:** a BESS has to charge/discharge in a given period (e.g., fast response time from milliseconds to seconds is needed to remove power fluctuations inherited from renewable source production).
- **Capital cost:** depending on the application, different costs are useful to be considered such as the cost of rated power (€/kW), the cost of rated capacity (€/kWh), and the cost on the long run (€/(cycle kWh)).
- **Operation and maintenance (O&M) cost:** every BESS has its proper O&M requirements. It is difficult to find a clear trend in the literature because it is highly dependent on the location (labor costs) and on the age of the facility.
- **Specific energy (Wh/kg) and specific power (W/kg):** enables to know the BESS weight that achieves power and energy requirements of the application. Energy and power densities, respectively, in Wh/l and W/l, are other metric representative of the volume aspect.
- **Cycling lifetime (number of cycles):** maximum number of cycles that the BESS can perform.
- **Calendar lifetime (years):** maximum shelf life of the BESS.
- **Cycle efficiency (%):** also named round-trip efficiency, the energy discharged by the BESS is lower than the energy initially charged into it. This parameter can be measured by calculating the ratio between energies discharged to the energy charged E_{out}/E_{in}. This calculation should not take into account self-discharge.
- **Self-discharge:** due to parasitic chemical reactions, the charges stored in the BESS decrease. This process can be accelerated or slowed not only by external conditions (e.g., temperature, humidity) but also by operating conditions (e.g., state of charge (*SOC*) of the battery, previous rate of charge, etc.).
- **Operating temperature (°C):** some parameters such as the efficiency, the available capacity, and the lifetime depend on the operating temperature range of the BESS.
- **Environmental impact and safety:** the extraction of the main components and manufacturing processes of batteries have different impacts on the environment from a technology to another. These impacts can be expressed as an energy consumption or a mass of GHG emissions [9]. The toxicity of some materials and the stability of the battery (e.g., thermal runaway of lithium batteries with cobalt-based cathode) can be a crucial issue depending on the application.

http://dx.doi.org/10.5772/intechopen.71640

- **Maturity:** a strong scientific background is behind mature technologies which benefit from numerous user experiences. Only incremental improvements are expected. In comparison, a new technology is evolving fast thanks to breakthrough advances.

2.2. Potentials of BESS in distribution systems

Grid-scale storage facilities through the world have been gathered in a large database from the US DOE [10]. A full description is given for most of them such as the date of creation, the location, the technology, the rated capacity, the rated power, the use cases, a picture of the project, etc. It appears that the global storage resource is small (the operational maximum power storage is around 170–180 GW, corresponding to less than 1% of our energy production). The main storage technology (in terms of rated power) is by far pumped hydro (~96%), but electrochemical projects are the most numerous (nearly 1000) and represent nearly 2% of the total rated power. As listed in [10–12], a BESS can provide numerous benefits such as:

- **Environmental:** integration of renewable sources (the variability of these sources threatens the grid stability), replacement of diesel generators (in off-grid sites), pollution reduction (by reducing peak demand often met with harmful and costly plants), etc.
- **Societal:** electricity supply in remote areas, reliability improvement (possibility to maintain the grid stability or operate separately from the utility in a so-called islanded mode), duration of outages decreased (ESS can perform a black start), etc.
- **Economic:** energy cost decrease (due to electric energy time-shift that enables to buy cheap energy and then sell and/or use it when it is expensive), the use of expensive thermal power plant diminution (with advanced energy management strategies), electric peak demand flattening, power factor correction, transmission and distribution (T&D) investment deferral, etc.

Every actor of electricity from the end user to the utility operator may find one or more benefits to install a BESS facility [12]. Indeed, potential synergies might be achieved, for example, by charging batteries during off-peak demand and discharging during peak; energy cost may decrease (because energy is bought cheap and sold expensive); energy losses (I^2R) can be reduced (less power in transmission lines during on-peak demand); pollution may be reduced (because in general cleaner power plants are used for the supply of baseload demand), and T&D deferral or life extension of the utility can be fulfilled because it mainly depends on the level of the peak demand. Two typical use cases are illustrated in **Figure 2**, where (a) represents the use of energy storage in order to reduce the peak demand. In this case, the power plant responsible for the baseload generation will increase its production in order to charge the BESS (in general the cost and the pollution related to this plant are the lowest compared to the other plants that are used to meet the peak demand). During peak demand, the energy comes from the BESS which replaces costly and high-pollutant power plants. Case (b) represents a typical power production from a solar photovoltaic (PV) plant during a sunny day which is not correlated with the demand profile. The BESS is charging when there is a surplus of energy in order to ensure the stability of the grid (unintentional injection of renewable power is not allowed), and it is discharging when the cost of energy is high (i.e., flattening the energy peak demand in the morning and in late afternoon).

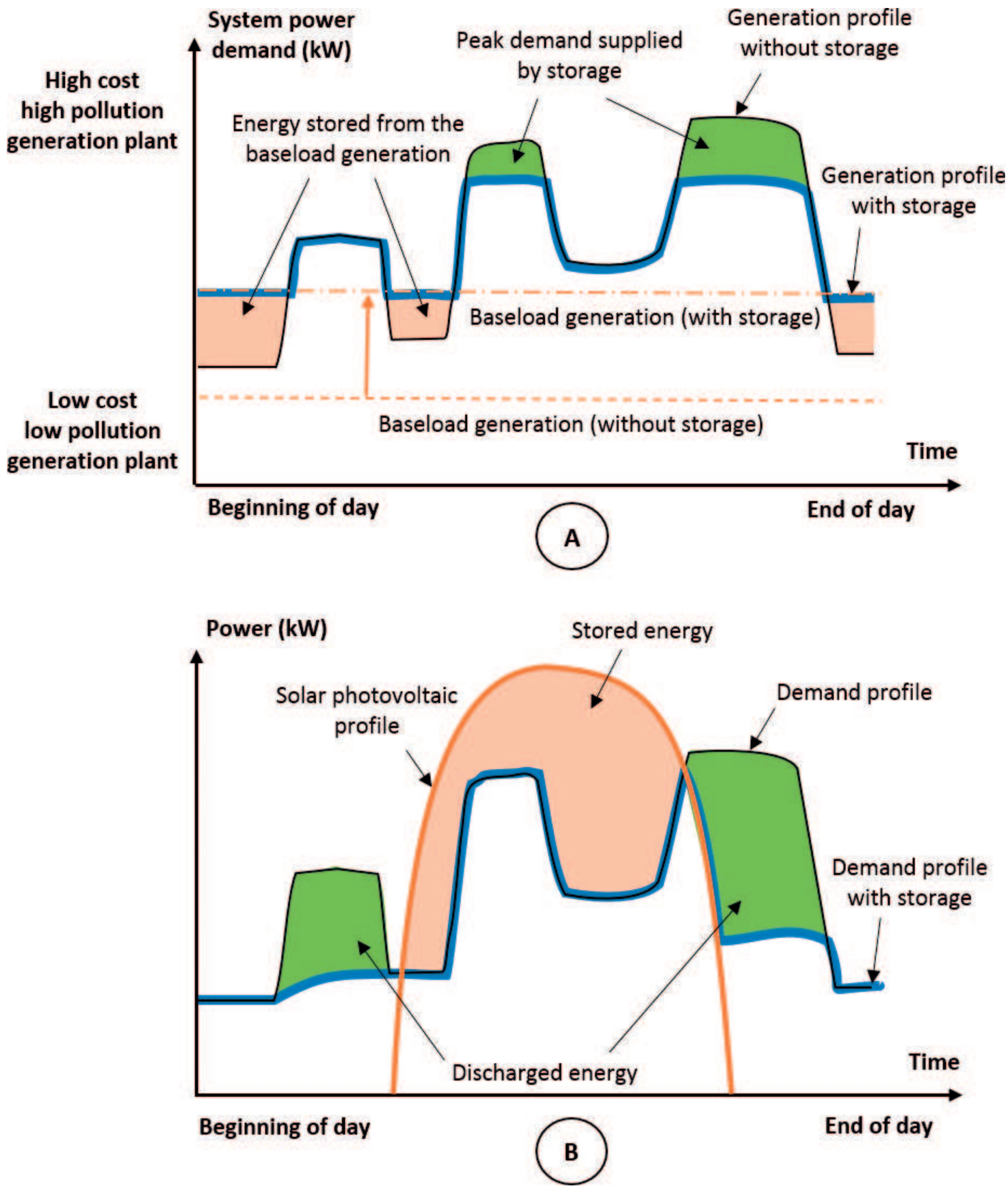

Figure 2. Typical use cases of a BESS, (A) peak shaving and load leveling and (B) integration of renewable sources.

2.3. Criteria

The following criteria help to quantify the benefits brought by a BESS associated to renewable sources such as solar PV panels and wind turbines (WT).

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First of all, the reliability of the distribution system can be assessed by Eqs. (1) and (2):

- Loss of power supply probability (LPSP) is defined as the ratio of energy deficit to the load demand for a given period [13]:

$$\mathrm{LPSP}(t) = \frac{\int_{t_0}^{t} E_{deficit}(t)\,dt}{\int_{t_0}^{t} E_{load}(t)\,dt} \tag{1}$$

- Level of autonomy (LA) is derived from the ratio of the hours that exhibit a loss of load ($\mathrm{H_{LOL}}$) to the total hours of operation ($\mathrm{H_{TOT}}$) [13]:

$$\mathrm{LA} = 1 - \frac{\mathrm{H_{LOL}}}{\mathrm{H_{TOT}}} \tag{2}$$

Concerning the economic issue, the BESS can be analyzed by calculating the annualized cost of system (ACS). The formulation (3) is derived from [14, 15] in which the annual cost of a renewable plant (PV or WT) with batteries is calculated. In these studies a replacement cost is added in the calculation of ACS because the duration of the project is often based on the lifetime expectancy of renewable sources which is longer than battery lifetime:

$$\mathrm{ACS} = C_{cap} \times CRF + C_{O\&M} \tag{3}$$

where C_{cap} is the initial capital cost of the BESS (€), CRF is the capital recovery factor defined in Eq. (4) to calculate annual equal payments over the lifetime of the BESS based on the initial capital cost, and $C_{O\,\&\,M}$ is the annual cost of operation and maintenance (€):

$$\mathrm{CRF} = \frac{i_r\,(1+i_r)^n}{(1+i_r)^n - 1} \tag{4}$$

where i_r is the interest rate (between 5% and 10% for such projects [16]) and n is the BESS lifetime (years).

Another popular metric used in renewable plants is the levelized cost of energy (LCOE) which indicates the total cost of energy (generally per kilowatt-hour) by taking into account the cost of all equipment involved in energy production over their entire lifetime. It can be adapted to BESS by using the annualized discharged energy E_{dis}, as proposed in Eq. (5):

$$\mathrm{LCOE} = \frac{ACS}{E_{dis}} \tag{5}$$

A good criterion to take into account the environmental aspect is the PV self-consumption Eq. (6) that can be highly improved by the integration of a BESS. A high PV self-consumption implies a good use of the PV source and a local use of produced energy (transmission losses are reduced). In case of grid-connected system, some energy is exchanged with the grid, E_{DU} is the energy directly used from the PV installation to the load, E_{BC} is the PV energy used to charge the BESS, and E_{PV} is the total energy produced by the PV installation:

$$s = \frac{E_{DU} + E_{BC}}{E_{PV}} \tag{6}$$

Other criteria can be taken into account such as the life cycle analysis (LCA) which aims at assessing the environmental impact of a device by taking into account four life stages that are manufacturing, transportation, use, and end of life. A life cycle inventory (LCI) analysis, only focused on the manufacturing of different batteries, is presented in Ref. [9]. In such studies, some data are difficult to obtain and are often estimated (especially those concerning the manufacturing processes which are fast evolving due to improvements of technologies).

2.4. Optimization techniques

Several optimization techniques are available for the sizing and the planning of renewable energy-based systems [17]. Some popular software tools such as Hybrid Optimization Model for Electric Renewables (HOMER) and Hybrid Power System Simulation Model (HYBRID2) both developed by the National Renewable Energy Laboratory (NREL), United States, and Hybrid Optimization using Genetic Algorithm (HOGA) developed in the University of Zaragoza, Spain, are presented in Ref. [17] to simulate and optimize any microgrid configuration. Nevertheless, in order to have the highest flexibility in terms of modeling and optimization, other classical tools are commonly used such as MATLAB and General Algebraic Modeling System (GAMS).

In optimization problem, the objective function can be mono-objective (e.g., cost of the entire installation during 20 years) or multi-objective (e.g., a combination of reliability, cost, and environmental impact). Very often, the cost function of a multi-objective problem is defined as a weighted sum of multiple criteria that can be expressed in different quantities. In this case, some arbitrary weighting coefficients are necessarily introduced, and the difficulty is to determine their right value. For example, if the cost function, expressed in euros per year, evaluates the yearly cost of a BESS in a microgrid, what equivalent cost (in euros per kilogram) should be associated to the greenhouse gas (GHG) emissions induced by the production, use, and end of life of batteries? This cost depends on environmental and social impacts that are not globally standardized and are fluctuating from a year to another, whereas the mass of GHG emissions is a fixed value. In this sense, the Pareto representation is very practical because each objective is expressed in the most appropriate quantity and defines its own axis.

In Ref. [18], a robust mixed-integer linear programming (RMILP) is proposed to minimize the cost of the system. In order to take into account uncertainties such as renewable production, load demand, or costs, a stochastic simulation can be achieved through the generation of multiple Monte Carlo scenarios. Heuristic and meta-heuristic optimization techniques are very popular to find the optimal solution among a large number of solutions while using the least computational resources. Two multi-objective problems combining genetic algorithms and Pareto representation are presented in [19, 20]. This method is very promising because a large number of feasible solutions are analyzed and a set of optimal solutions, best trade-off between all criteria, are obtained.

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3. Modeling of a BESS

In order to simulate the system, a model of BESS has to be defined. In the literature, BESS models developed for the sizing and the scheduling are simple with a few parameters (e.g., nominal capacity, cycle efficiency, maximum number of cycles, etc.) in order to limit the complexity of the problem.

3.1. Instantaneous characteristics

The state of charge (*SOC*) of the BESS is the parameter related to the number of charges stored in the battery (a *SOC* of 100% means that the BESS is fully charged, whereas it is considered to be empty at 0%). In [21–23], the online estimation of *SOC* named "coulomb counting" is proposed. This method is based on the measurement of current and takes into account the coulombic efficiency (ampere-hour efficiency):

$$SOC(t) = SOC(t-1) + \eta_{Ch} \frac{I_{Ch}(t) \cdot \mathrm{D}t}{C_n(t)} - \frac{I_{Dis}(t) \cdot \mathrm{D}t}{\eta_{Dis} \cdot C_n(t)} \tag{7}$$

where η_{Ch} and η_{Dis} are, respectively, the charge and discharge coulombic efficiencies of the BESS (in Ref. [21], the coulombic efficiency is considered equal to 1 during the discharge and smaller than 1 during the charge, due to unwanted side reactions). $I_{Ch}(t)$ and $I_{Dis}(t)$ are the current level at the charge and discharge, respectively. $C_n(t)$ is the nominal capacity of the BESS. It is to notice that the nominal capacity of the BESS is decreasing all along the lifetime of the BESS; this point will be explained in the next section.

Another variable widely used in the literature is the depth of discharge (*DOD*) which describes the emptiness of battery (complement of the *SOC*). Battery manufacturers often provide the maximum number of cycles that a battery can perform for different *DODs*, as depicted in **Figure 3**:

$$DOD(t) = 1 - SOC(t) \tag{8}$$

In order to model the effect of other operating conditions (e.g., C-rate and temperature) on the BESS behavior, the *SOC* can be formulated by introducing the concept of equivalent current. Three technologies of batteries have been tested in Ref. [24], exhibiting both the effect of the C-rate and the temperature on the available discharged capacity. Indeed, it has been empirically formulated by Peukert for lead-acid batteries at the end of the nineteenth century that the discharged capacity is related to the C-rate. The main issue is that this relation is given for a constant level of current during all the discharge conditions (not representative of real conditions). In [25], an improved method is proposed for management of lithium-ion batteries, but the model is difficult to parameterize because it needs a lot of experimental tests to be adapted to the BESS. Usually, a BESS operates at low C-rate in renewable power plants, and the temperature can be assumed to be constant. This is why the state of health (SOH) is the main parameter taken into account in sizing and planning studies.

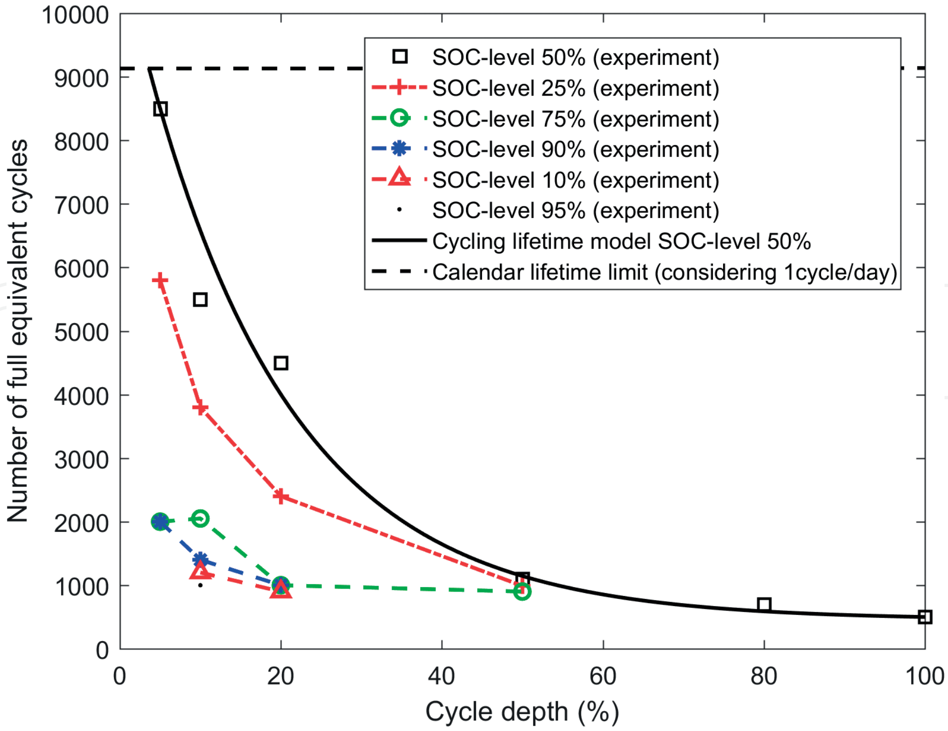

Figure 3. Calendar and cycling lifetime model of the BESS derived from [27].

3.2. Lifetime analysis

Due to irreversible reactions, the active material is decreasing, and the electrode interfaces are deteriorated. Thus, the capacity decreases, and the internal resistance increases (power capability fade). In order to know when to replace a BESS, a common criterion is to consider the end of life (EOL) of a battery when its capacity drops to less than 20% of the initial nominal capacity [26]. This limit of 20% has been initially set because of the behavior of lead-acid batteries: the capacity fade is quite linear until 20%, and then there was a sudden drop of capacity. Of course all the batteries do not exhibit this large decrease of capacity; this is why some projects such as the second life of batteries have been created (old batteries that do not fulfill the automotive requirements are reused in stationary projects).

Usually, the aging of batteries is monitored by measuring the nominal capacity and comparing it to the initial nominal capacity $C_n(t_0)$. In this case, the battery reaches its EOL when the state of health (SOH) goes below 80%:

$$SOH(t) = \frac{C_n(t)}{C_n(t_0)} \tag{9}$$

The lifetime of batteries is related to calendar aging (shelf life) and cycle aging. In renewable microgrids, a BESS is subjected to variable cycling conditions. The lifetime of a BESS depends on the cycle depth and the *SOC* level (mean of *SOC* during the cycle). As shown in Ref. [27], the degradation of the nominal capacity can be considered linear for both calendar and cycling lifetime. As presented in **Figure 3**, experimental studies performed on lithium-ion batteries [27] revealed that the maximum number of cycles performed by the BESS is higher for low cycle depths and medium *SOC* levels (close to 50%). Assuming that the BESS will perform at least 1 cycle per day, a limit can be set on the maximum number of cycles that is defined by the calendar aging.

Two main methods are used to estimate the aging of a BESS. In Ref. [28], a simple method called "ampere hour throughput" is based on the assumption that the exchangeable energy of a battery is fixed (because nearly constant) whatever the cycle depth performed by the BESS. In this case, the maximum energy that can be exchanged is calculated as follows:

$$\mathrm{E}_{\max} = 2\,\mathrm{N}_{\max}(\mathrm{DOD}) \times \mathrm{DOD} \times C_n(t_0) \tag{10}$$

in which the initial nominal capacity is expressed in Wh. Another method is called the rainflow counting. A very popular algorithm of rainflow counting has been presented by Downing and Socie [29]. Initially developed to estimate the effect of mechanical stress in automotive and building industries, the rainflow counting is often employed to describe the aging of batteries, as in Ref. [30]. Given a battery *SOC* time series, it is possible to extract the number of cycles with their associated cycle depth and *SOC* level and then update the value of nominal capacity.

4. BESS power/energy management schemes

For optimal operation of an energy system equipped with BESSs in different working modes (i.e., grid-connected or islanded), it is crucial to properly design and implement energy management systems (EMSs). These system optimizers normally determine the best possible operating scheme at supply and demand sides in terms of optimized set points for controllable units such as energy storage devices and send them as the control signals into the dedicated control system of interfacing converters. Generally, there are two types of energy/power management strategies used in energy system applications. These are named as interactive schemes based on information sharing mechanisms and passive schemes based on self-autonomy [31].

4.1. Interactive power/energy management strategies

In a given interactive power/energy management system (IP/EMS), local and global system information (such as line currents, nodal voltages, frequency, and powers) is communicated in the system and exchanged between corresponding nodes in order to determine operation point of each controllable ESS or distributed generation (DG) unit. These strategies also benefit from a sort of intelligence in the integration of the computing and communications technologies which help them to define and develop the communication structure based on the computation burden of each node and other related system's objectives and constraints [32]. In this regard, three different communication schemes can be realized for an IP/EMS: centralized, decentralized, and hybrid. In each of the mentioned schemes, different communication technologies such as microwave (μW), power line carrier (PLC), fiber optics, infrared, and/or wireless radio networks (such as global system for mobile (GSM) communications and code division multiple access (CDMA)) can be effectively used and integrated into the existing infrastructures [33, 34].

4.1.1. Centralized P/EMS

In a centralized P/EMS, also known as a supervisory scheme, there is a centralized entity or a control center that monitors the system's behavior, collects information from different parts of the network, makes decisions based on the observations, and accordingly updates set points for the controllable units in supply/demand sides [35–37]. In other words, a centralized P/EMS acts as a master unit, while other local controllers within the system are treated as slaves to follow the reference signals coming from the master unit as shown in **Figure 4**. To improve the effectiveness of a P/EMS, it is also very important to clearly define system's objectives and constraints. These objectives (such as operating cost minimization, emission mitigation, power loss reduction, *SOC* equalization, etc.) together with the constraints might be conflicting in some cases which in turn make the optimal decision-making process a difficult or even an impossible task. Different examples of centralized P/EMS for microgrids can be found in the literature [38–40]. The advantages of a centralized scheme mainly lie within the simplicity of implementation and globality of optimal solution; however, it brings two disadvantages: single point of failure which implies that a centralized P/EMS has to be securely designed

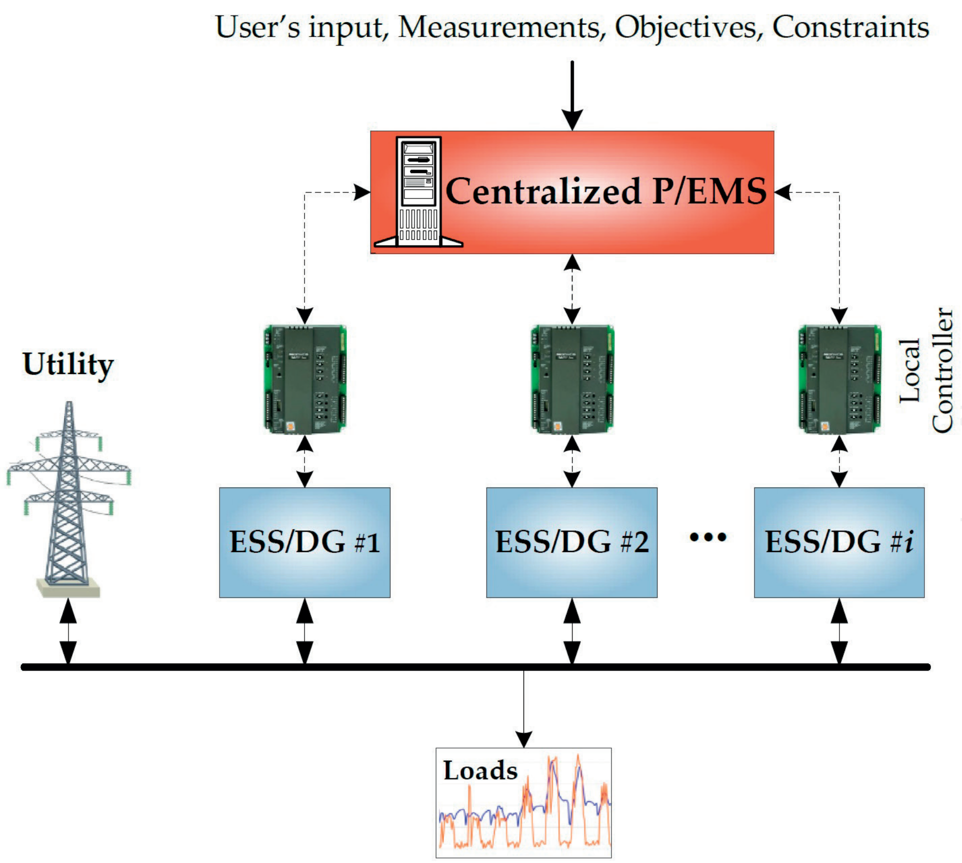

Figure 4. Block diagram of a centralized P/EMS.

with appropriate built-in redundancy and massive communication expenditure. The latter is not a challenging problem in small-scale networks, but it could be problematic for larger systems as the complexity of the centralized optimization grows exponentially with the number of units (control variables) in the system.

4.1.2. Distributed P/EMS

Distributed P/EMS is the second interactive scheme for management of a given system in which there is no central supervisory unit, but all the local controllers are connected and communicate with each other through a communication bus [41]. In this sense, each controller not only captures local measurements but also receives information from neighboring nodes which helps in decision-making process according to different optimization objectives [42–43]. In this scheme, intelligent algorithms are often used for better exploration/exploitation of the environment in order to find optimal operation point. **Figure 5** shows the block diagram of a decentralized P/EMS. A distributed scheme has some advantages over a centralized one. First, it supports a scalable structure with Plug-and-Play (PnP) feature for newly added/removed energy sources or load blocks. Second, computation burden of each local controller is mitigated which in turn reduces the required communication bandwidth. Finally, a distributed P/EMS could improve the redundancy and modularity of the system where it is needed. However, there is still a problem if a communication link fails in the system. This failure would not end to a total system collapse, but the performance of the system would not be optimal any longer. Also, a distributed P/EMS suffers from degradation of performance on small/medium networks, increased use of database space, and complex use and administration. Multi-agent system (MAS) is one of the best illustrations for a distributed scheme [44].

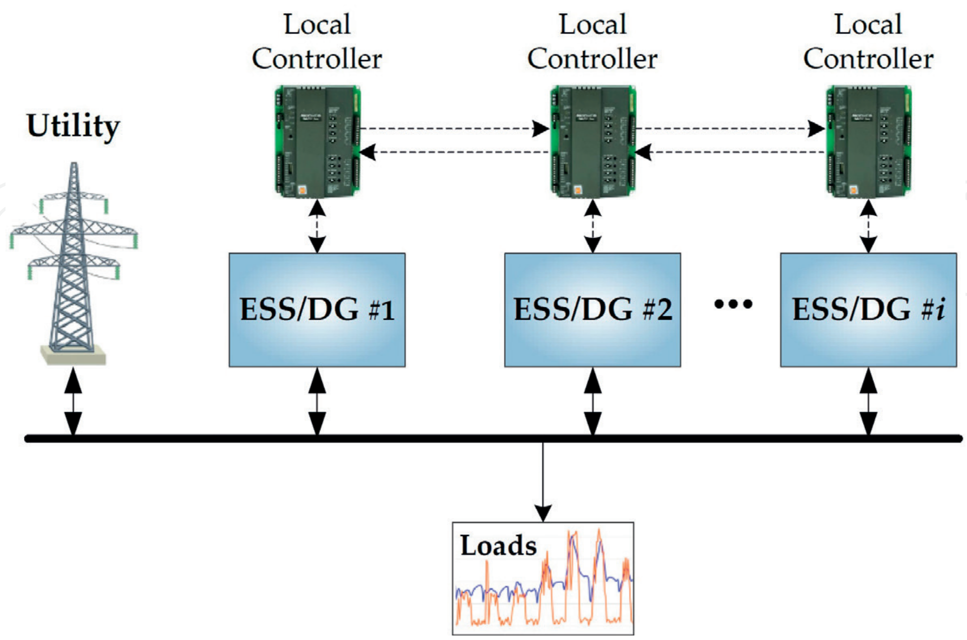

Figure 5. Block diagram of a decentralized P/EMS.

4.1.3. Hybrid P/EMS

Hybrid scheme for power/energy management can be realized as another interactive structure that is mainly based on a combination of centralized and distributed schemes. In a hybrid structure, local controllers which are used for operation management of different energy sources are divided into groups [45]. Within each group, a centralized scheme is used to control and optimize the performance of local controllers. On a higher level, a distributed scheme is utilized to coordinate the operation of centralized controllers in different clusters for global optimization. Such a hybrid strategy can be seen in **Figure 6**.

It is notable that a hybrid P/EMS scheme is normally implemented for large-scale networks such as interconnected energy systems or microgrids, where the optimal operation of the entire system depends on cooperation and coordination of different control layers over time. By doing this hybridization, it is very possible to improve the system reliability and resiliency for long-run operations due to the unique features that inherently exist in centralized/decentralized schemes [46].

4.2. Passive power/energy management strategies

Self-autonomy of operation for a local controller without having information from neighboring nodes is the main idea of a passive power/energy management scheme (PP/EMS). In this structure, it is assumed that making an information sharing mechanism is too costly or not viable; thus, independent operation of energy sources is required. Moreover, it is needed to clearly define the control objective of each energy source to assure reliable operation of the system. Block diagram for such a power/energy management scheme is shown in **Figure 7**.

Among the existing methods for PP/EMS, droop-based control strategy is regarded as a dominant method [47–49]. This control methodology adopts the behavior of synchronous machines

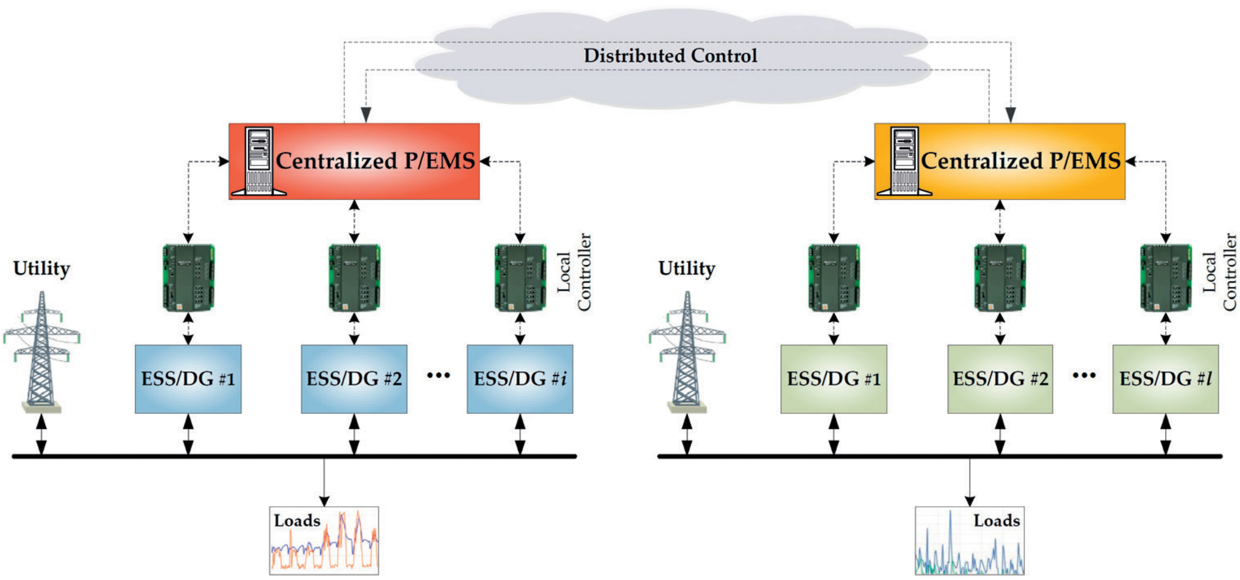

Figure 6. Block diagram of a hybrid P/EMS.

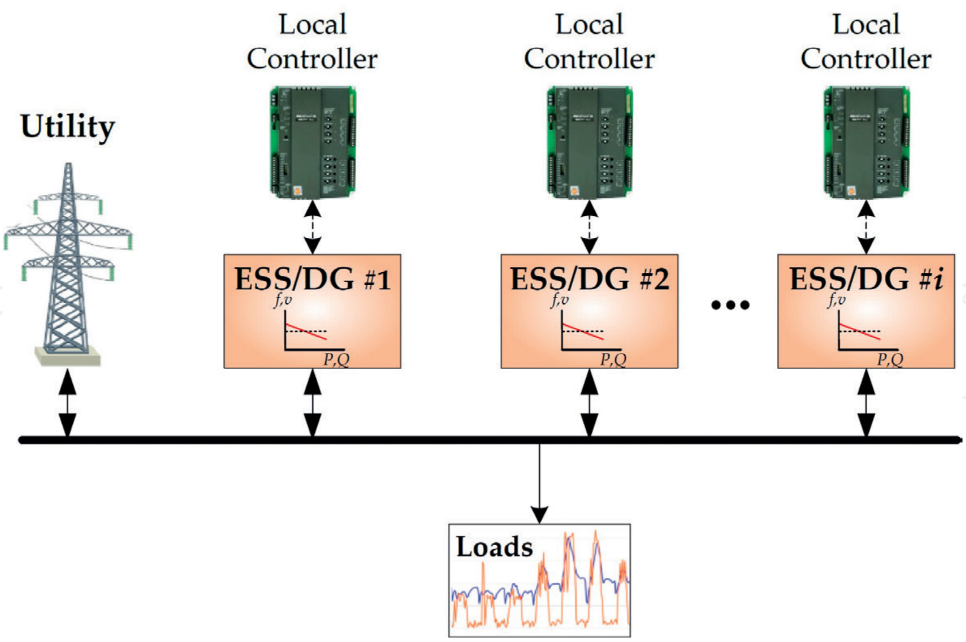

Figure 7. Block diagram of a PP/EMS.

in responding to the changes in voltage and frequency and applies similar rules in operation management of converters in ac/dc sides. The droop-based control strategy works based on the assumption that the output impedance of a controllable unit (such as a micro-source) is mainly inductive, and it utilizes droop characteristics of voltage amplitude and frequency of each controllable unit to control its output. In case of a dc microgrid, bus voltages and in case of an ac microgrid the system voltage and frequency are the information sensed by each local droop controller and used subsequently to adjust output active (and/or reactive) power of a BESS or a generation unit. **Figure 8** shows such control strategy for a given dc microgrid. As can be seen in the same figure, either output power or output current can be selected as the feedback signal in droop control. For dc microgrids with power-type load, output power can be used as droop feedback, as shown in Eq. (11).

On the other hand, when current signal is used, as shown in Eq. (12), droop coefficient m_c can be regarded as a virtual internal resistance. In that case, the implementation and design of the parallel converter system in a dc microgrid can be simplified to some extent as the control law is linear:

$$v_{DCi}^{*} = v_{DC}^{*} - m_p \, . \, P_{oi} \tag{11}$$

$$v_{DCi}^{*} = v_{DC}^{*} - m_c \, . \, i_{oi} \tag{12}$$

where v^{*}_{DCi} is the output of the droop controller, i.e., the reference value of dc output voltage of converter #i; v^{*}_{DC} is the rated value of dc voltage; and m_p and m_c are the droop coefficients in power-based and current-based droop controllers, while P_{oi} and i_{oi} are the output power and current of converter #i, respectively. Since there is no communication requirement to fulfill the

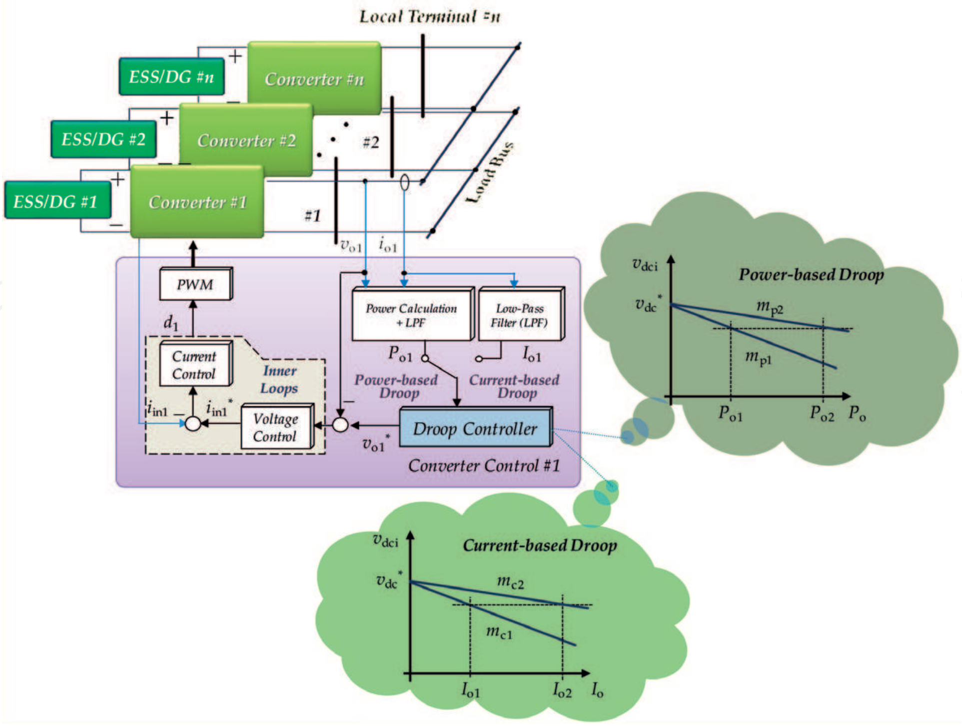

Figure 8. Droop control for dc microgrids.

control objectives, this control strategy is highly reliable. Moreover, this control structure could be easily extended to different energy sources while enabling true PnP features. Apart from the benefits, there are several issues in such power/energy management strategy. First, low-voltage regulation and proportional current sharing cannot be addressed directly by this method. Instead, nonlinear and adaptive droop techniques are proposed as key solutions for achieving acceptable voltage regulation at full load and ensuring proportional current sharing. Second, low X/R line impedance ratio may result in active and reactive power coupling and instability issues in low-voltage microgrid systems and cause power sharing errors for generation units [50]. Recently, several works have been done to improve the performance of a conventional droop-based control method by implementing the droop in virtual frames [51], adding virtual impedance in control loops [52], or adjusting the output voltage bandwidth [50]. However, without a coordinating unit such as a central controller or a system optimizer, it would be a challenging task to optimally manage the operation of a microgrid system with PP/EMS.

As another type of PP/EMS, maximum power point tracking (MPPT) control methodology is also applied in microgrids to maximize power extraction from RESs (mainly WTs and PVs) under all conditions [53]. In such power management technique, unit's voltage and current are sampled frequently, and the duty ratio of the interfaced converter is adjusted accordingly. However, it should be noted that in islanded renewable-based microgrids which are controlled based on MPPT principles, ESSs must also be dispatched to provide voltage and frequency regulation services [54]. Considering the drawbacks of IP/EMS and PP/EMS, it seems that a combined P/EMS structure (e.g., a consensus-based droop framework [55] or a droop-based distributed cooperative control [56]) could not only address reliability issues but also enhance control performance of the system both in grid-connected and stand-alone modes.

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References

[1] Malashenk E, Lee R, Villarreal C, Howard T, Gupta A. Energy storage framework staff proposal. California Public Utility Commission Energy Storage Proceeding, April 3; 2012

[2] Anvari Moghaddam A, Mokhtari G, Guerrero JM. Coordinated demand response and distributed generation management in residential smart microgrids. In: L Mihet editor, Energy Management of Distributed Generation Systems; InTech; 2016. ISBN: 978-953-51-4708-4

[3] Sharifi R, Anvari-Moghaddam A, Fathi SH, Guerrero JM, Vahidinasab V. An economic demand response model in liberalized electricity markets with respect to flexibility of consumers. IET Gener. Trans. Dist., to appear; 2017

[4] Linden D, Reddy TB, editors. Handbook of Batteries. 3rd ed. New York: McGraw-Hill; 2002 ISBN: 978-0-07-135978-8

[5] Broussely M, Pistoia G. Industrial Applications of Batteries - from Cars to Aerospace and Energy Storage. Elsevier; 2007. ISBN: 978-0-444-52160-6

[6] Bagotsky VS, Skundin AM, Volfkovich YM. Electrochemical Power Sources - Batteries, Fuel Cells, and Supercapacitors. Wiley, Hoboken, New Jersey; 2015. ISBN: 978-1-118-46023-8

[7] Pillot C. The rechargeable battery market and main trends 2014-2025. In 32th Annual International Battery Seminar & Exhibit; 2015

[8] Armand M, Tarascon J-M. Building better batteries. Nature. 2008;**451**(7179):652-657

[9] Sullivan JL, Gaines L. Status of life cycle inventories for batteries. Energy Conversion and Management. 2012;**58**:134-148

[10] Sandia Corporation. DOE Global Energy Storage Database. 2017, energystorageexchange.org, [Accessed: 06 Jun 2017]

[11] Electric Power Research Institute (EPRI). Electricity Energy Storage Technology Options - White Paper Primer on Applications, Costs, and Benefits. Electric Power Research Institute. Palo Alto, CA, 1020676; 2010

[12] Eyer J, Corey G. Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide - a Study for the DOE Energy Storage Systems Program, Sandia Report, SAND2010-0815. 2010

[13] Luna-Rubio R, Trejo-Perea M, Vargas-Vázquez D, Ríos-Moreno GJ. Optimal sizing of renewable hybrids energy systems: A review of methodologies. Solar Energy. Apr. 2012;**86**(4):1077-1088

[14] Poonpun P, Jewell WT. Analysis of the cost per kilowatt hour to store electricity. IEEE Transactions on Energy Conversion. Jun. 2008;**23**(2):529-534

[15] Yang H, Wei Z, Chengzhi L. Optimal design and techno-economic analysis of a hybrid solar–wind power generation system. Applied Energy. Feb. 2009;**86**(2):163-169

[16] Rathgeber C, Lävemann E, Hauer A. Economic top–down evaluation of the costs of energy storages—A simple economic truth in two equations. Journal of Energy Storage. Aug. 2015;**2**:43-46

[17] Sinha S, Chandel SS. Review of recent trends in optimization techniques for solar photovoltaic–wind based hybrid energy systems. Renewable and Sustainable Energy Reviews. Oct. 2015;**50**:755-769

[18] Dragicevic T, Pandzic H, Skrlec D, Kuzle I, Guerrero JM, Kirschen DS. Capacity optimization of renewable energy sources and battery storage in an autonomous telecommunication facility. IEEE Transactions on Sustainable Energy. Oct. 2014;**5**(4):1367-1378

[19] Dufo-López R, et al. Multi-objective optimization minimizing cost and life cycle emissions of stand-alone PV–wind–diesel systems with batteries storage. Applied Energy. Nov. 2011;**88**(11):4033-4041

[20] Katsigiannis YA, Georgilakis PS, Karapidakis ES. Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables. IET Renewable Power Generation. 2010;**4**(5):404

[21] Lu L, Han X, Li J, Hua J, Ouyang M. A review on the key issues for lithium-ion battery management in electric vehicles. Journal of Power Sources. Mar. 2013;**226**:272-288

[22] Chang WY. The state of charge estimating methods for battery: A review. ISRN Applied Mathematics. 2013;**2013**:1-7

[23] Gholami A, Shekari T, Aminifar F, Shahidehpour M. Microgrid scheduling with uncertainty: The quest for resilience. IEEE Transactions on Smart Grid. Nov. 2016;**7**(6):2849-2858

[24] Stan AI, Swierczynski M, Stroe DI, Teodorescu R, Juhl Andreasen S, Moth K. A comparative study of lithium ion to lead acid batteries for use in UPS applications. In: Telecommunications Energy Conference (INTELEC), 2014 IEEE 36th International. 2014. p. 1-8

[25] Omar N, Bossche P, Coosemans T, Mierlo J. Peukert revisited-critical appraisal and need for modification for lithium-ion batteries. Energies. Oct. 2013;**6**(11):5625-5641

[26] IEEE Power & Energy Society and Stationary Batteries Committee. IEEE Recommended Practice for Sizing Lead-Acid Batteries for Stationary Applications - IEEE Std 485TM-2010. New York: Institute of Electrical and Electronics Engineers; 2011

[27] Ecker M, et al. Calendar and cycle life study of li(NiMnCo)O2-based 18650 lithium-ion batteries. Journal of Power Sources. Feb. 2014;**248**:839-851

[28] Bindner H, Cronin T, Lundsager P, Risø National Lab, Roskilde (DK). Wind Energy Department, Lifetime Modelling of Lead Acid Batteries. Risø National Laboratory, Roskilde, Denmark; 2005. ISBN: 978-87-550-3441-9

[29] Downing SD, Socie DF. Simple rainflow counting algorithms. International Journal of Fatigue. 1982;**4**(1):31-40

[30] Beltran H, Swierczynski M, Aparicio N, Belenguer E, Teodorescu R, Rodriguez P. Lithium ion batteries ageing analysis when used in a PV power plant. In: Industrial Electronics (ISIE), 2012 IEEE International Symposium on. 2012. p. 1604-1609

[31] Li Y, Nejabatkhah F. Overview of control, integration and energy management of microgrids. Journal of Modern Power Systems and Clean Energy. Aug. 2014;**2**(3):212-222

[32] Ghasemkhani A, Anvari-Moghaddam A, Guerrero JM, Bak-Jensen B. An efficient multi-objective approach for designing of communication interfaces in smart grids. In: IEEE PES Innovative Smart Grid Technologies (ISGT 2016). 2016. p. 1-6

[33] Islam SZ, Mariun N, Hizam H, Othman ML, Radzi MAM, Hanif M, Abidin IZ. Communication for distributed renewable generations (DRGs): A review on the penetration to smart grids (SGs). In: PECon 2012 - 2012 IEEE Int. Conf. Power Energy, no. December. 2012. p. 870-875

[34] Liyanage KM, Manaz MAM, Yokoyama A, Ota Y, Taniguchi H, Nakajima T. Impact of communication over a TCP/IP network on the performance of a coordinated control scheme to reduce power fluctuation due to distributed renewable energy generation. In: 2011 6th Int. Conf. Ind. Inf. Syst. ICIIS 2011 - Conf. Proc. 2011. p. 198-203

[35] Anvari-Moghaddam A, Mokhtari G, Guerrero JM. Coordinated demand response and distributed generation Management in Residential Smart Microgrids. In: Mihet L, editor. Energy Management of Distributed Generation Systems. 1st ed. InTech; 2016. p. 27-57

[36] Nejabatkhah F, Li YW. Overview of power management strategies of hybrid AC/DC microgrid. IEEE Transactions on Power Electronics. 2015;**30**(12):7072-7089

[37] Olivares DE, Member S, Cañizares CA. A centralized energy management system for isolated microgrids. IEEE Transactions on Smart Grid. 2014;**5**(4):1864-1875

[38] Anvari-Moghaddam A, Monsef H, Rahimi-Kian A. Cost-effective and comfort-aware residential energy management under different pricing schemes and weather conditions. Energy and Buildings. 2015;**86**:782-793

[39] Modes S, Jiang Q, Xue M, Geng G, Member S. "Energy Management of Microgrid", 2013;**28**(3):3389-2013

[40] Becker DJ, Sonnenberg BJ. DC microgrids in buildings and data centers. In: Telecommunications Energy Conference (INTELEC), 2011 IEEE 33rd International. 2011. p. 1-7

[41] Wang Z, Chen B, Wang J, Kim J. Decentralized energy management system for networked microgrids in grid-connected and islanded modes. IEEE Transactions on Smart Grid. 2016;**7**(2):1097-1105

[42] Anvari-Moghaddam A, Guerrero JJM, Rahimi-Kian A, Mirian MS. Optimal real-time dispatch for integrated energy systems: An ontology-based multi-agent approach. In: 7th International Symposium on Power Electronics for Distributed Generation Systems (PEDG'16). 2016. p. 1-7

[43] Mokhtari G, Anvari-Moghaddam A, Nourbakhsh G. Distributed control and management of renewable electric energy resources for future grid requirements. In: Mihet L, editor. Energy Management of Distributed Generation Systems. 1st, July; InTech ed. Janeza Trdine, Rijeka, Croatia. 2016. p. 1-24

[44] Anvari-Moghaddam A, Rahimi-Kian A, Mirian MS, Guerrero JM. A multi-agent based energy management solution for integrated buildings and microgrid system. Applied Energy. 2017;**203**:41-56

[45] Dou CX, Duan ZS, Liu B. Two-level hierarchical hybrid control for smart power system. IEEE Transactions on Automation Science and Engineering. 2013;**10**(4):1037-1049

[46] Lu T, Wang Z, Ai Q, Lee W-J. Interactive model for energy Management of Clustered Microgrids. IEEE Transactions on Industry Applications. 2017;**9994**(c):1-1

[47] Rodriguez E, Vasquez JC, Josep M, Rodriguez-diaz E, Anvari-moghaddam A, Vasquez JC, Guerrero JM. Multi - Level Energy Management and Optimal Control of a Residential DC Microgrid. IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, 2017, pp. 312-313. DOI: 10.1109/ICCE.2017.7889333

[48] Anvari-moghadam A, Shafiee Q, Vasquez JC, Guerrero JM. Optimal adaptive droop control for effective load sharing in AC microgrids. IECON-42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 2016, pp. 3872-3877. DOI: 10.1109/IECON.2016.7793515

[49] Tah A, Das D. An enhanced droop control method for accurate load sharing and voltage improvement of isolated and interconnected DC microgrids. IEEE Transactions on Sustainable Energy. 2016;**7**(3):1194-1204

[50] Li Y, Li YW. Power management of inverter interfaced autonomous microgrid based on virtual frequency-voltage frame. IEEE Transactions on Smart Grid. 2011;**2**(1):18-28

[51] Guan Y, Guerrero JM, Zhao X, Vasquez JC, Guo X. A new way of controlling parallel-connected inverters by using synchronous-reference-frame virtual impedance loop - part I: Control principle. IEEE Transactions on Power Electronics. 2016;**31**(6):4576-4593

[52] Zhang Y, Wei Li Y. Energy management strategy for Supercapacitor virtual impedance. IEEE Transactions on Power Electronics. 2017;**32**(4):2704-2716

[53] Tank I. Renewable Based DC Microgrid with Energy Management System, IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES), Kozhikode, 2015, pp. 1-5. DOI: 10.1109/SPICES.2015.7091542

[54] Anvari-Moghaddam A, Dragicevic T, Vasquez JC, Guerrero JM. Optimal utilization of microgrids supplemented with battery energy storage systems in grid support applications. IEEE First International Conference on DC Microgrids (ICDCM). 2015;**2015**:57-61

[55] Lu L, Chu C. Consensus-based distributed droop control of Synchronverters for isolated micro-grids. IEEE Transactions on Power Apparatus and Systems. 2015;**30**(5):914-917

[56] Lai J, Zhou H, Lu X, Yu X, Hu W. Droop-based distributed cooperative control for microgrids with time-varying delays. IEEE Transactions on Smart Grid. 2016;**7**(4): 1775-1789