CHAPTER 15
ENERGY STORAGE MANAGEMENT SYSTEMS

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Abstract

Over the last decade, the number of large-scale energy storage deployments has been increasing dramatically. This growth has been driven by improvements in the cost and performance of energy storage technologies, the need to accommodate renewable energy generation, as well as incentives and government mandates. Energy management systems (EMSs) are required to utilize energy storage effectively and safely as a flexible grid asset that can provide multiple grid services. An EMS needs to be able to accommodate a variety of use cases and regulatory environments.

Key Terms

Arbitrage, battery management system (BMS), customer demand charge reduction, device management system (DMS), distribution deferral, energy management system (EMS), energy storage, energy time shift, frequency regulation, optimal operation, power conversion system (PCS), renewable, renewable smoothing, safety, small signal stability, state-of-charge (SOC), state-of-health (SOH), transmission deferral, voltage support

1. Introduction

Energy storage applications can typically be divided into short- and long-duration. In short-duration (or power) applications, large amounts of power are often charged or discharged from an energy storage system on a very fast time scale to support the real-time control of the grid. In long-duration (or energy) applications, large amounts of energy are supplied to and pulled from the grid on much slower time scale. Some examples of power applications include frequency regulation, voltage support, small signal stability, and renewable smoothing. Energy applications include energy arbitrage, renewable energy time shift, customer demand charge reduction and transmission and distribution deferral. More details on energy storage applications are discussed in Chapter 23: Applications and Grid Services.

There are two main requirements for the efficient operation of grid storage systems providing the above applications and services:

1. Optimal control of grid energy storage to guarantee safe operation while delivering the maximum benefit
2. Coordination of multiple grid energy storage systems that vary in size and technology while interfacing with markets, utilities, and customers (see Figure 1)

Therefore, energy management systems (EMSs) are often used to monitor and optimally control each energy storage system, as well as to interoperate multiple energy storage systems. This chapter provides an overview of EMS architecture and EMS functionalities. While it is a high-level review of EMS, it can be the starting point for any further reading on this topic.

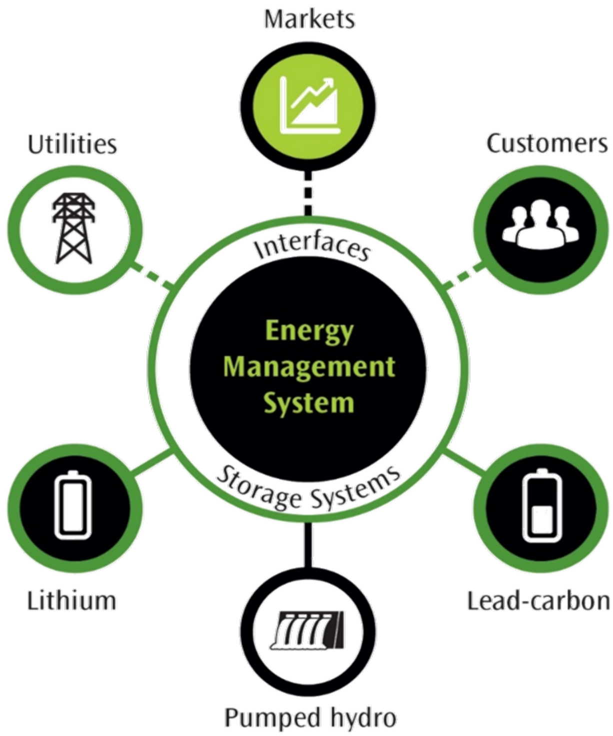

Figure 1. Energy Management System Overview

1.1. Energy Management System Architecture Overview

Figure 1 shows a typical energy management architecture where the global/central EMS manages multiple energy storage systems (ESSs), while interfacing with the markets, utilities, and customers [1]. Under the global EMS, there are local EMSs that are responsible for maintaining safe and high-performance operation of each ESS. Just as an ESS includes many subsystems such as a storage device and a power conversion system (PCS), so too a local EMS has multiple components: a device management system (DMS), PCS control, and a communication system (see Figure 2). In this hierarchical architecture, operating data go from the bottom to the top while commands go top to bottom. For example, in the case of a battery energy storage system, the battery storage modules are managed by a battery management system (BMS) that provides operating data such as the state of charge, state of health, battery cell temperature [2]. These data, together with the operating data of the PCS, are given to the local EMS for calculating the charge or discharge power that are sent to the PCS as power commands. While delivering these required powers, the PCS also interfaces with the BMS to ensure that none of the battery limits are violated.

In a highly centralized architecture, the optimal dispatches (i.e., power commands) are calculated at the control center and sent to each local EMS. In a highly decentralized architecture, the central EMS may not exist, therefore, EMS functions are only performed at the local EMSs.

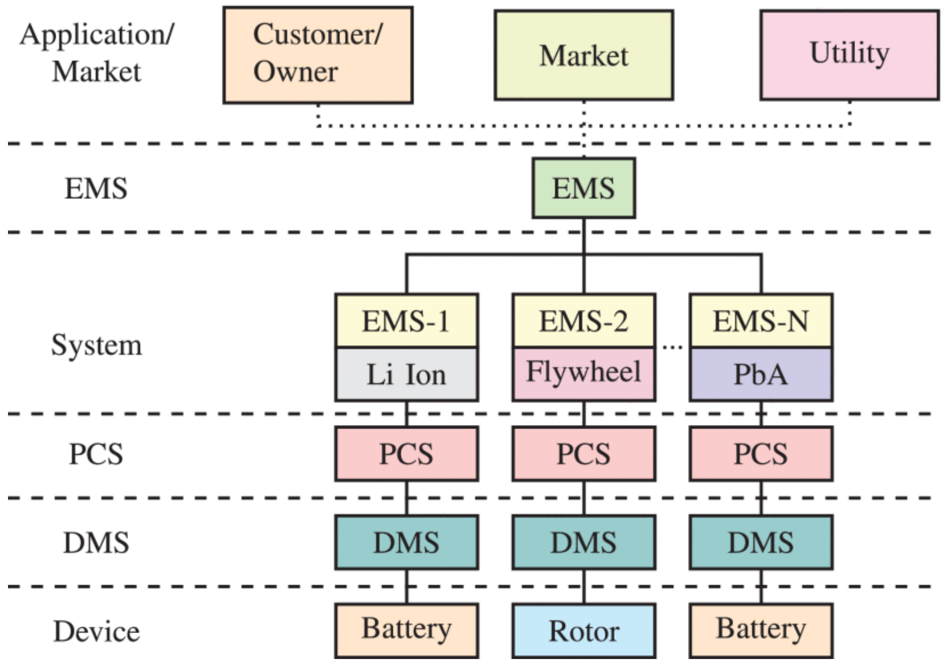

Figure 2. Energy Management System Hierarchy Architecture

1.2. Storage Device Management

The DMS includes a set of functions (software) that are responsible for: 1) safe operation, 2) monitoring and state estimation, and 3) technology specific functions (such as conditioning cycles to prolong life in some battery technologies) (see Figure 3). These DMS functions are designed to maintain safe operation and high performance of the storage device as well as to provide operating data to the EMS and PCS. They are often implemented on a DMS device (hardware) that is capable of sensing, monitoring, control, and communication.

Figure 3. Device Management System Functions

1.2.1. Ensuring safe operation of energy storage device

Grid-scale ESSs can store a significant amount of energy. Therefore, safety mechanisms, either passive or active, are required to prevent that energy from causing a hazard.

1.2.1.1. Passive Safety

Passive safety includes the protection measures that do not do any work until they are triggered to action. They are used to minimize the damage to the storage device and to the environment in worst-case scenarios including short-circuits, thermal runaway, and hazardous chemical leakage. Energy storage devices are typically protected against short-circuit currents using fuses and circuit breakers. Thermal isolation or directed channeling within electrochemical packs is often employed to prevent or slow the propagation of thermal runaway in Lithium-ion (Li-ion) batteries. Vanadium redox flow batteries (VRFB) are designed to prevent the leakage of the electrolyte into the environment through secondary and tertiary containment. Enclosures for flywheels are often reinforced and located underground to contain the destructive kinetic energy released by a catastrophic failure.

1.2.1.2. Active Safety

Active safety includes the protection measures that have control and monitoring capabilities. They are used to protect storage device against undesirable working conditions such as over-charge, over-discharge, and over-temperature that significantly reduce the life of the device [3]. The fundamental unit of an active protection mechanism is the feedback control process where:

1. data is collected from the process being controlled,
2. the controller decides what protection actions are needed,
3. actions are implemented though actuators such as circuit interrupts, the power conversion system, or even fire suppression systems.

For example, a BMS active protection mechanism will disconnect a battery module if its voltage/current/temperature limits are violated or a DMS will take a flywheel off-line if its rotor speed exceeds a threshold.

1.2.1.3. Fault Diagnosis

Some faults are easy to diagnose, such as when a smoke detector activates. Others are more difficult, such as an internal short circuit in a Li-ion battery. Early fault identification or fault prediction can enable a DMS to anticipate when a device failure may occur in the future by identifying the precursors to such events. Fault diagnosis methods can be classified into knowledge-based methods, model-based methods, and data-driven methods [4]. This is an active area of ongoing research [5].

1.2.2. Monitoring and State Estimation

The DMS measures quantities such as voltages, currents and temperatures, and estimates the quantities or device's states that cannot be measured directly. The following sections describe the three principal states of an energy storage device.

1.2.2.1. State-of-Charge Model

The state-of-charge (SOC) is the ratio between the remaining energy and the maximum energy capacity of an ESS while cycling [6]. In a small number of energy storage technologies, the SOC can be measured directly, but in general the SOC can only be estimated through other measurable parameters. For instance, the SOC of a pumped hydro plant can be determined directly from the reservoir level while the SOC of electrochemical batteries such as Li-ion or lead-acid batteries, can only be estimated through voltage and current measurements.

The parameters needed for estimation of the SOC differ for various energy storage technologies. Table 1 summarizes the required parameters for estimating SOC of several common storage technologies. In some cases, the SOC can be estimated using a simple model. In other cases, a more sophisticated model may be required, but there is a trade-off between accuracy and computational cost. A simple model is easy to develop and implement but might lead to large errors, whereas a more sophisticated model would provide better accuracy at the expense of higher computational requirements and more difficulty in development and implementation. A comprehensive overview of SOC modeling can be found in "Battery Energy Storage Models for Optimal Control" [6].

Table 1. Measurable Quantities for SOC Calculation

Technology	Measurable parameters for SOC calculation
Compressed air energy storage (CAES)	Pressure, volume, temperature, discharge profile
Electrochemical batteries	Voltage, current, temperature, age
Flywheels	Rotor speed, moment of inertia
Pumped hydro	Reservoir level
Superconducting magnetic energy storage (SMES)	Current, inductance
Ultra-capacitors	Voltage, capacitance/impedance, temperature
Vanadium redox flow battery	Voltage, temperature, electrolyte concentration

1.2.2.2. State-of-Heath Model

The state-of-health (SOH) is the present health divided by the initial health of an energy storage device [6]. Health is measured differently in different technologies, but energy capacity is the most commonly used proxy parameter. At some critical SOH, the battery becomes unusable or unreliable for given applications and should be replaced. The SOH of an electrochemical cell can be estimated from the ratio of its current capacity to its rated capacity. In lead-acid batteries for example, at approximately 80% of initial capacity the batteries start to become increasingly unreliable for backup power applications and should be replaced to continue to supply this service. Thus, 80% of rated capacity is considered to be 0% SOH for many applications and battery types. The most straightforward method for estimating SOH of batteries is to measure the impedance, as it is generally proportional to the capacity loss [7] [8] [9]. In many cases, this method has high error when the capacity loss and impedance are not well correlated. Model-based methods [10] [11] and data-driven methods [12] [13] can be employed to provide more accurate estimation.

1.2.2.3. Thermal Models

In many energy storage systems designs the limiting factor for the ability to supply power is temperature rather than energy capacity [6]. This is clearly the case in thermal storage technologies, where temperature can be used as a direct measurement of SOC, but this is also the case in many battery systems. Batteries can reach a high temperature limit long before they reach a low voltage limit on discharge, meaning that the EMS needs a thermal model of the batteries to correctly predict battery operational limitations.

1.2.3. Technology Specific Functions

1.2.3.1. Equalization of Battery Cells

For multi-cell battery packs, unequal cell voltages increase the risk of over-charge/over-discharge. To prevent these problems, the DMS must monitor and periodically equalize the battery cell voltages. There are two classes of cell equalization (i.e., cell balancing) methods:

Passive balancing – includes two steps: 1) fully charge the battery pack, and 2) remove the excess charge from the cells with highest voltages through passive resistors until their voltages reduce to a reference value. This method is relatively inexpensive, but it is potentially inefficient and does nothing for abnormally low voltage cells. Also, if the cooling system cannot effectively dissipate the heat from the passive resistors, it increases the cell temperature thereby reducing the battery life.

Active balancing – the charge is transferred from higher voltage cells to lower voltage cells. Switched capacitors, inductors/transformers, and power electronics (converters) can be utilized to redistribute the charge between cells. The advantages of this method are that it is more efficient, it reduces heat generation, and it addresses both high and low voltage cells. However, it involves more expensive components, more complicated controls, and increases the instrumentation cost. It also introduces additional failure mechanisms into the module design.

1.2.3.2. Electrolyte Rebalancing of Vanadium Redox Flow Batteries

For VRFBs, electrolyte rebalancing between the two half-cells is important to prevent differential ion transfer across the membrane and side reactions lowering the efficiency of the battery [14]. The electrolyte imbalance is often detected by comparing the SOC of both half-cells. Once the electrolyte imbalance is quantified, a chemical reductant can be added to the positive electrolyte to balance the oxidation states [14].

2. Power Conversion Control

The majority of energy storage devices employ a direct current (DC) interface. Therefore, a PCS is required to integrate with the alternating current (AC) power grid. The purpose of the PCS is to provide bi-directional conversion and electrical isolation.

Power conversion system architectures are described in more details in Chapter 13: Power Conversion Systems. The PCS management system often includes at least two levels of control: primary and secondary. The primary control (low level) includes the module level controllers that generate the drive and gate signals for the power converters' semiconductor switches given the operating mode from the secondary control and the states of PCS and energy storage device. The secondary control (high level) specifies the operating mode of the system given the power commands (e.g., charge and discharge rate) from the EMS and the energy storage states (e.g., SOC and temperature) from the DMS. Because the primary control of PCS is covered in Chapter 13, this chapter only describes the operation of the secondary control.

2.1. Secondary Control

The secondary control performs the high-level management that determines the operating mode for each of the power converters. The three most common modes are: charging, discharging, and standby.

2.1.1. Charging Mode

Charging mode occurs when the EMS commands the energy storage device to charge. This mode can include a power level, in which case the charge current is controlled to deliver the commanded power. Depending on the SOC of the device, a different charging stage is selected. Figure 4 shows a three-stage charging scheme for batteries. The three stages are [15]:

- Bulk charge (current control) – used for fast charging when the SOC is low
- Absorb charge (voltage control) – used to prevent overcharging the battery when the SOC is higher than a certain level
- Float charge (voltage control) – used when the battery is close to fully charged

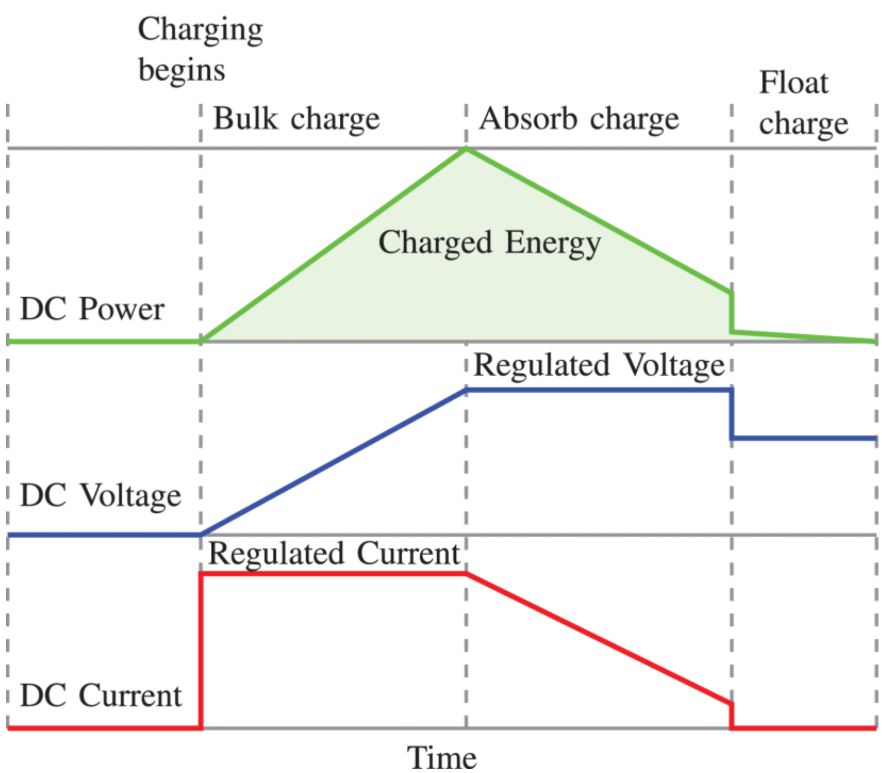

Figure 4. Three-stage Charging Scheme for Batteries

This charging scheme can also be applied to ultra-capacitors. The charging time for an ultra-capacitor is much shorter compared to a battery because a much higher current can be tolerated during the bulk charge stage (see Figure 4). Similarly, the charging scheme for flywheels includes:

- Torque control mode (bulk charge)
- Speed control mode (absorb charge)
- Power control mode

2.1.2. Discharging mode

This mode occurs when the EMS commands the energy storage device to discharge at a power level to provide certain grid services. Two critical factors that must be considered for an electrochemical battery are: (1) a higher discharge current reduces the energy capacity, and (2) SOC lower/upper limits are often required to increase cycle life.

2.1.3. Standby mode

Standby mode occurs at the end of charging period when the maximum SOC limit has been reached. While in this mode, the energy storage device is not significantly charging or discharging. For an electrochemical battery, float charge might be used to compensate for the self-discharge. For a flywheel, a small charge current is used to maintain its nominal speed.

2.1.4. Advanced inverter functions

For most applications, the above basic operating modes are sufficient to fulfill the EMS commands. However, there has been a push to incorporate advanced inverter functions within the PCS's operating modes, primarily to enable increased penetrations of distributed solar generation. Examples of these functions include:

- Volt-var (voltage support)–regulate voltage by controlling reactive power output of the PCS
- Volt-watt–regulate voltage by controlling real power output of the PCS
- Constant power factor–maintain a constant power factor at the PCS's output

Depending on the evolution of these capabilities, some grid control functions may reside in the PCS secondary control going forward. After the operating mode is specified by the secondary control, control references are calculated and passed to the primary controller.

3. Communication Interface

To coordinate operations between different subsystems of an ESS, each subsystem must be equipped with a communication interface. Fundamental requirements for a communication interface of an ESS can be found in existing standards such as IEC 61850-7-420 and Modular Energy System Architecture (MESA) (see Figure 5). Commercial systems often follow standardized communication protocols. Modbus TCP is commonly used in a large number of devices in today's market because of its simplicity and flexibility. DNP3 plays an important part in modern SCADA systems, which are widely used in power systems. Subsystems/devices often use different communication protocols and, therefore, must be capable of integrating with a wide range of devices/systems with different protocols. An example of such a platform is VOLTTRON developed by PNNL [16].

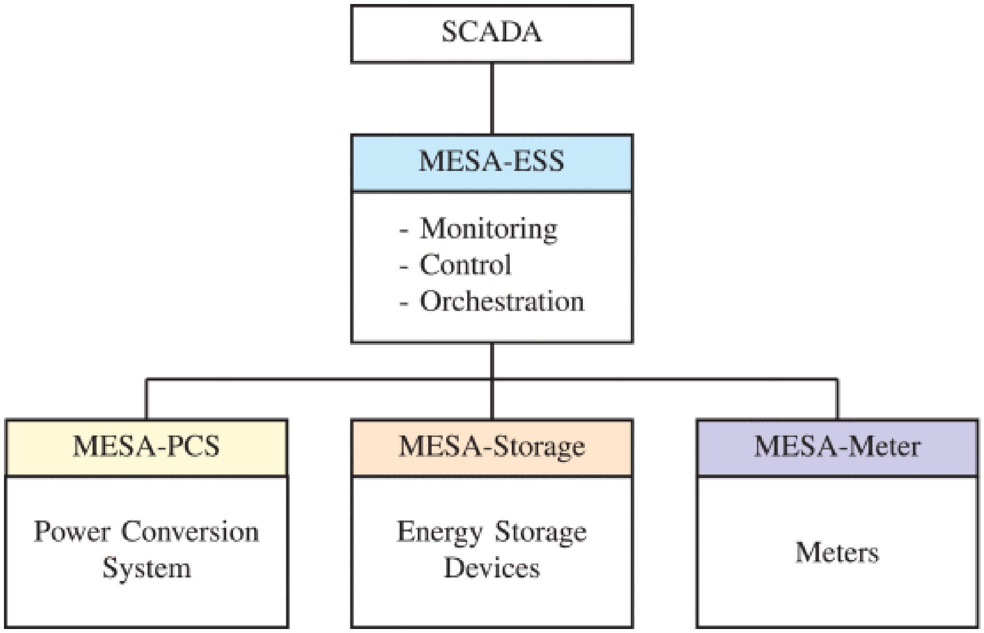

Figure 5. MESA Communication Basic Structure [17]

4. Optimal Operation of Energy Storage Systems for Various Applications

4.1. Market Applications

The United States has seven regions that operate electricity and grid ancillary services markets. In these regions the potential revenue of ESSs is dependent on the market products they provide. Generally, the EMS tries to operate the ESS to maximize the services provided to the grid, while considering the optimal operation of the energy storage device. In market areas, maximizing grid services is typically aligned with maximizing revenue. The operation of an ESS can be viewed as an optimization problem where maximizing revenue is the primary objective and the constraints are the market requirements and physical limitation of the ESS (e.g., SOC limits).

4.2. Behind-the-Meter Applications

Behind-the-meter ESS optimal operations can be enabled through the EMS. The objective of the EMS is to shift and shave the electricity usage of consumers by charging and discharging the ESS to minimize their bills [18]. The savings often come from demand charge reduction, time-of-use (TOU) energy charge reduction, and utilization of net-metering energy. Optimization techniques used for market applications can also be used to achieve this objective while ensuring that storage device constraints, such as maximum capacity, storage efficiency, running cost, charging/discharging rate, etc., are satisfied. Most behind-the-meter optimization algorithms are distributed or decentralized because centralized approaches are invasive to users and do not scale well [19].

5. Summary

This chapter provided an overview of EMSs needed for operating ESSs. Since ESSs as grid assets are quite new, most system operators are still learning to efficiently operating them. The grid operators need robust EMSs that can manage multiple technologies, and grid services in evolving market structures. As the regulatory environment for energy storage is evolving quickly, there are also challenges in developing generic models that work across market structures and technologies. Even with recent progress, storage valuation/optimization continues to be challenging. Many related areas require additional research. Examples of these areas include: 1) storage models that fully reflect the performance and cycle life characteristics of ESSs, 2) optimization approaches for stacked benefits, 3) energy management systems that enable the integration of massive deployment of distributed energy resources.

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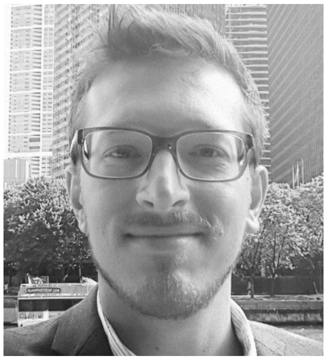

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