Predictive-Maintenance Practices For Operational Safety of Battery Energy Storage Systems

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Changes in the demand profile and a growing role for renewable and distributed generation are leading to rapid evolution in the electric grid. These changes are beginning to considerably strain the transmission and distribution infrastructure. Utilities increasingly recognize that integration of energy storage in the grid infrastructure will help manage intermittency and improve grid reliability. This recognition, coupled with the proliferation of state-level renewable portfolio standards and rapidly declining lithium-ion battery costs, has led to a surge in the deployment of battery energy storage systems (BESS). Though BESS represented less than 1% of grid-scale energy storage in the United States in 2019, they are the preferred technology to meet growing demand because they are modular and scalable across diverse use cases and geographic locations.

As the number of BESS installations has increased, system integrators, utilities, government bodies, and professional organizations have put considerable effort into developing safety standards and best practices for engineering and commissioning. However, safety incidents in the field have still led to total BESS destruction and posed risk to first responders. Despite the efforts of the energy storage industry to improve system safety, recent incidents show the need for a greater recognition of the limitations of current practices. For example, much of the effort has focused on improving safety at the cell and pack level. Additionally, risks that manifest during operation and catastrophic failures arising from operator error or component failures have not received as much attention as factory testing of BESS.

This article advocates the use of predictive maintenance of *operational* BESS as the next step in safely managing energy storage systems. Predictive maintenance involves monitoring the components of a system for changes in operating parameters that may be indicative of a pending fault. These changes signal the need for maintenance while the fault is still recoverable. Many industries, including utilities, use this maintenance approach for assets such as power plants, wind turbines, oil pipelines, and photovoltaic (PV) systems. However, this approach has yet to be fully explored and utilized for BESS. Predictive monitoring is complementary to and should not replace safer system designs, which are essential for real time mitigation of catastrophic failures. However, when applied to BESS, predictive monitoring can initiate actions that potentially prevent catastrophic failures from occurring. The following article reviews current safety practices in BESS development, provides examples of predictive maintenance approaches in other industries, notes the key components of an effective approach, and describes methodologies to identify leading fault indicators.

Current Recommendations and Standards for Energy Storage Safety

Between 2011 and 2013, several major grid energy storage installations experienced fires (figure 1). As a result, leading energy storage industry experts recognized that technologies and installations were beginning to outpace existing standards. In addition, while several energy storage technologies were available in the marketplace, lithium-ion based storage systems made up an increasing number of the installations. Of even greater importance, deployments were beginning to grow faster in behind-the-meter residential and commercial applications. As such, a stronger focus on the safety of lithium-based storage systems took hold due to the fire potential of the batteries.

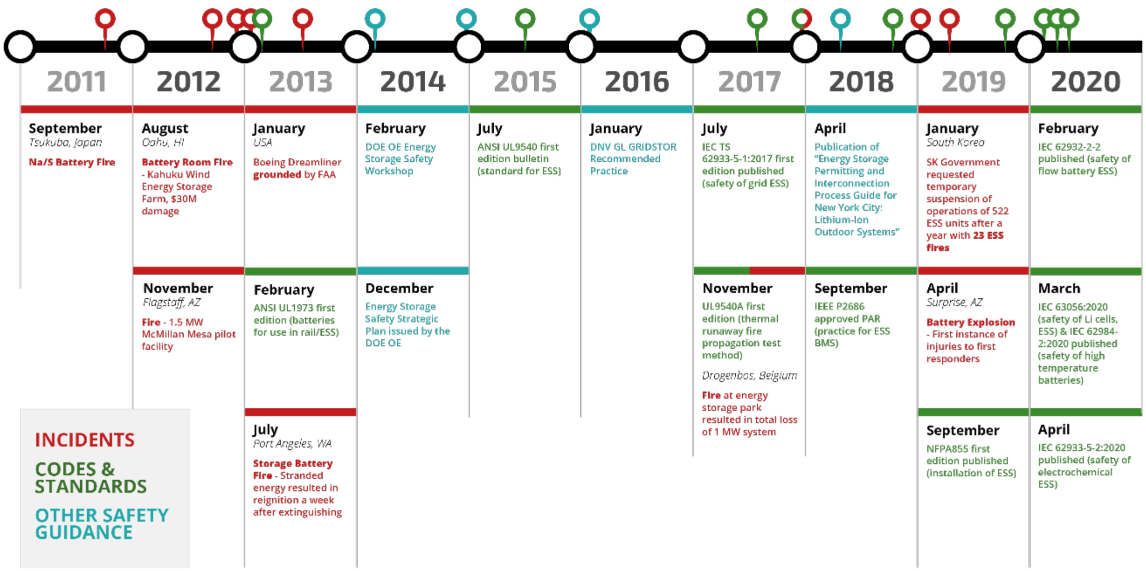


figure 1. Timeline of grid energy storage safety, including incidents, codes & standards, and other safety guidance.

In 2014, the U.S. Department of Energy (DOE) in collaboration with utilities and first responders created the Energy Storage Safety Initiative. The focus of the initiative included "coordinating DOE Energy Storage Systems Safety Working Groups with over 150 stakeholders from industries such as electric utilities, standards organizations, and manufacturing companies." These working groups "explored gaps in safety R&D; enabled the development of codes, standards, and regulations (CSR); and educated first responders on energy storage system safety." This was an initial attempt at bringing safety agencies and first responders together to understand how best to address energy storage system (ESS) safety. In 2016, DNV-GL published the GRIDSTOR Recommended Practice on "Safety, operation and performance of grid-connected energy storage systems." Other efforts included a collaboration between the New York State Energy Research and Development Authority, SmartDG Hub (led by The City University of New York), and New York City (with technical assistance from DNV GL, a testing and consulting company) which, in 2018, produced a permitting guidebook for BESS, titled "Permitting and Interconnection Process Guide for NYC Lithium-Ion Outdoor Systems."

At the same time, many organizations were also developing or improving codes and standards to guide the design and installation of ESS. Tables 1 and 2 categorize these standards into five groups: Components; Integrated Systems; Installation and Commissioning; Operations and Maintenance; and Incident Preparedness. Despite the breadth of these standards, none provide significant guidance on whole system preventive and predictive maintenance. Two of the most notable standards in the United States are Underwriters Laboratories (UL) 9540 (Standard for Energy Storage Systems and Equipment) and National Fire Protection Association (NFPA) 855 (Standard for the Installation of Stationary Energy Storage Systems).

UL 9540 (first edition with the American National Standards Institute, ANSI, in 2015) covers the safety of electrochemical, chemical, mechanical, and thermal ESS. The document also incorporates ESS equipment for control, protection, power conversion, communication, and fire detection and suppression. UL 9540A, first edition in 2017, created a test method for evaluating thermal runaway fire propagation in BESSs.

The effort to develop NFPA 855 began in 2016 as ESS technology usage began to increase due to consumer, business, and government interest. NFPA received more than 600 public inputs and 800 public comments during the development process for the document, and the first edition was published in 2019. NFPA 855 focuses on mitigating risk by examining where ESS are located, how installations are separated, and suppression systems in place. The document considers ventilation, detection, signage, listings, and emergency operations associated with the ESS, and provides extensive requirements for ESS fire safety.

A working group of the International Electrotechnical Commission (IEC), TC 120/WG 5 “Electrical Energy Storage Systems/Safety considerations,” has also developed two standards for integrated systems. IEC TS 62393-5-1:2017 specifies safety considerations (e.g. hazards identification, risk assessment, risk mitigation) applicable to any grid-integrated ESS. The recently published IEC 62933-5-2:2020 focuses specifically on electrochemical ESS, especially safety measures to mitigate hazards such as fire, explosion, and retention of toxic gases and liquids.

Efficient safety testing and evaluation of grid-scale BESS in accordance with the above standards is a key part of the development process for new systems. Typically, test facilities are outfitted for module or rack-level propagation studies. Figure 2 shows an example of a unique indoor test facility for a complete system at the National Laboratory for Advanced Energy Storage Technologies (NLAB) of the National Institute of Technology and Evaluation (NITE) in Japan. This NLAB “Large Chamber” is used to test containers up to 53 ft (16 m) in length under controlled thermal and wind velocity conditions (the first facility in the world to do so).

Guidelines under development include IEEE P2686 “Recommended Practice for Battery Management Systems in Energy Storage Applications” (set for balloting in 2022). This recommended practice includes information on the design, installation, and configuration of battery management systems (BMSs) in stationary applications. The document also covers battery management hardware (e.g. grounding and isolation), software (e.g. algorithms for optimal control), and configuration. More recently, the Modular Energy Storage Architecture (MESA) alliance, consisting of electric utilities and energy storage technology providers, has worked to encourage the use of communication standards, advance interoperability, and reduce the engineering effort to integrate an ESS into a utility. MESA is developing two standards: one defining communication between ESS components and another defining communication requirements for utility-scale ESS. These standards include parameters for inverters, meters, general ESS, battery-based ESS, and Li-Ion ESS under various operations.

table 1. Pre-installation codes and standards.

Components	
Secondary cells and batteries containing alkaline or other non-acid electrolytes - Safety requirements for secondary lithium cells and batteries for use in electrical energy storage systems	IEC 63056:2020
High-temperature secondary batteries – Part 2: Safety requirements and tests	IEC 62984-2:2020
*Recommended practice for battery management systems in energy storage applications	IEEE P2686, CSA C22.2 No. 340
*Standard communication between energy storage system components	MESA-Device Specifications/SunSpec Energy Storage Model
Molded-case circuit breakers, molded-case switches, and circuit-breaker enclosures	UL 489
Electrochemical capacitors	UL 810A
Lithium batteries	UL 1642
Inverters, converters, controllers, and interconnection system equipment for use with distributed energy resources	UL 1741
Batteries for use in stationary, vehicle auxiliary power, and light electric rail applications	UL 1973
Integrated Systems	
Electrical energy storage (EES) systems - Part 5-1: Safety considerations for grid-integrated EES systems - General specification	IEC TS 62933-5-1:2017
Electrical energy storage (EES) systems - Part 5-2: Safety requirements for grid-integrated EES systems - Electrochemical-based systems	IEC 62933-5-2:2020
Flow battery energy systems for stationary applications – Part 2-2: Safety requirements	IEC 62932-2-2
Recommended practice and requirements for harmonic control in electric power systems	IEEE 519
Interconnection and interoperability of distributed energy resources with associated electric power systems interfaces	IEEE 1547
*Standard communications specification for utility-scale energy storage system	MESA-ESS
Explosion protection by deflagration venting	NFPA 68
Explosion prevention systems	NFPA 69
Standard for energy storage systems and equipment	UL 9540
Test method for evaluating thermal runaway fire propagation in battery energy storage systems	UL 9540A

table 2. Installation and post-installation codes and standards.

Installation and Commissioning	
Installation of stationary energy storage systems	NFPA 855
Transportation testing for lithium batteries	UN 38.3
Safety of primary and secondary lithium cells and batteries during transport	IEC 62281
Competency of third-party field evaluation bodies	NFPA 790
Standards for securing power system communications	IEC 62351
Fire suppression	NFPA 1, NFPA 13, NFPA 15, NFPA 101, NFPA 850, NFPA 851, NFPA 853, NFPA 5000, IBC, IFC, state And local codes
Ventilation and thermal management of batteries for stationary applications	IEEE/ASHRAE 1635, IMC, UMC, state And local codes
Egress/access/illumination (operating and emergency), physical security, fire department access, fire and smoke detection/containment	NFPA 1, NFPA 101, NFPA 5000, IBC, IFC, state And local codes
Buildings, enclosures, and protection from the elements	IEC 60529, UL 96A, NFPA 5000, IBC, state And local codes
Signage	ANSI Z535, IEEE C-2, NFPA 1, NFPA 70E, NFPA 101, NFPA 5000, IBC, IFC, state And local codes
Emergency shutoff	IEEE C-2, NFPA 1, NFPA 101, NFPA 5000, IBC, IFC, state And local codes
Spill containment, neutralization, and disposal	NFPA 1, IPC, UPC, IFC, IEEE1578, state and local codes

Electrical safety	IEEE C-2 (National Electrical Safety Code), NFPA 70E, FM Global DS 5-10, DS 5-1, DC 5-19
Communication networks and systems for power utility automation	IEC 61850
Seismic requirements, design, and testing	IBC (International Building Code), CBC (California Building Code), OSHPD, IEEE 693, ACI 318-05, ACSE 7-10
Recommended practice for commissioning of fire protection and life safety systems	NFPA 3
Building and systems commissioning	ICC 1000
Operations and Maintenance	
Electrical safety in the workplace	NFPA 70E
Recommended practice for electrical equipment maintenance	NFPA 70B
Hazardous materials code	NFPA 400
Incident Preparedness	
Guide for substation fire protection	IEEE 979
Guide to the fire safety concepts tree	NFPA 550
Standard system for the identification of the hazards of materials for emergency response	NFPA 704
Guide for fire and explosion investigations	NPFA 921

figure 2. An example of a full-scale ESS testing facility, the NLAB Large Chamber, operated by NITE, Japan.

Gaps in Current Approaches to Safety

Despite the depth of these collective efforts to understand and mitigate the causes of BESS failure, catastrophic failures continue to occur in the field. In 2019, South Korea initiated a study to determine the leading causes of 23 BESS fires that had occurred since April 2017. The country's Ministry of Industry formed an investigation committee of academics, research institutions, laboratories, and ESS industry experts. In the initial cases examined, cells or battery modules were not believed to be the root cause of the failure. As reported in the press at the time, the investigation identified four main causes of failure:

1. ***Lack of battery protective systems for electric shock***: Systems were not able to properly protect DC contactors against electrical hazards arising from overvoltage or overcurrent.

2. ***Insufficient management of the operating environment***: Most of the installations were in mountains or coastal areas. These environments exposed the BESSs to harsh conditions, including large temperature swings and high humidity, that could damage insulation and cause fires.

3. ***Faulty installations***: Human error during installation could have led to system faults resulting in ESS fires.

4. ***Lack of ESS integrated control and protection systems***: Gaps in the integration of the BMS and energy management system (EMS) may have caused the fires.

The conclusions of the investigation raise the question: When it comes to the next stage of failure analysis for ESS, how can the industry further improve operations to reduce incidents in the field? Some of the issues noted in the South Korea investigation were not captured by standards, and there was no mechanism for identifying and fixing problems or design issues after the installation.

Currently, the industry certifies ESS based on defined sets of codes and standards. This certification focuses on overall design review of the core ESS, testing for adherence to standards before shipment, and commissioning once the unit is installed in the field. Ideally, the certification process ensures that the overall system design is sound, the factory testing ensures that the unit was constructed correctly, and the commissioning test ensures that there are no faults created or discovered immediately after the unit is installed at the site. Nevertheless, gaps remain in maintaining the unit after installation and identifying potential failures that may occur in the longer term. In short, there is not much guidance on what to do on Day 2, once a project is completed.

Continuous monitoring of the system after installation is needed to facilitate maintenance and ensure problems are identified early so that they are addressed before they lead to cascading failure. Systems can be monitored by a BMS, but designs are not standardized, and owners/operators may not have ready access to critical information. Also, the inability of management systems to “connect the dots” among large quantities of data may be causing systems to fail. IEEE P2686 may address some of these gaps. Still, current failure response mechanisms usually lead to total BESS destruction. ESS hazard mitigation techniques are primarily designed to protect human safety, which certainly needs to be the focus. These responses (e.g. water quenching) will often render the system unrecoverable, making the mitigation just as catastrophic (in a technical sense) as the initial event. Thus, we advocate development of a framework for predictive maintenance of *operational* BESS as the next critical step in safe deployment of ESS.

Improving Operation Through Predictive Maintenance

Preventive and predictive maintenance are mature concepts for operational systems in industry. Operators complete preventive maintenance on a routine or timed schedule (weekly, monthly, annually, etc.) based on average or expected lifetime statistics for equipment. By contrast, predictive maintenance is carried out when needed based on the actual condition of the equipment. Components are monitored for changes in operating parameters that may be indicative of a pending fault, and these changes prompt intervention.

Some organizations have offered general guidance on preventive maintenance for BESS. For example, an Energy Storage Safety 101 presentation during a May 2020 meeting of the California Energy Storage Alliance recommended semi-annual steps such as visual inspections of the overall system, examining the HVAC (cooling), and checks on the ESS software control and communications. They also proposed an annual process similar to commissioning. A 2019 *Energy Storage News* report on operations and maintenance noted that the Smarter Network Storage Project, a 6 MW/10 MWh battery system, receives a 6-month check-up to ensure optimal performance (including identifying battery degradation levels, pushing software upgrades, and inspecting the power conversion system). In the same report, a representative of an ESS integrator noted that a lot of their maintenance involved software updates. BMSs implement safety functions and controls that depend on algorithms, sensor data, and system parameters. Furthermore, BMSs and inverters must communicate to coordinate control actions and responses to faults and warnings. Therefore, any software or firmware update glitches in either of those components can impact the effectiveness of safety features, leading to potential BMS malfunction and damage to batteries. Periodic software patching also ensures that systems are protected from known cybersecurity vulnerabilities.

Though helpful, preventive maintenance may be an oversimplification of what is required for maintaining complex systems and preventing failures. Here, we define a complex system as one with many interacting components where it is difficult to comprehensively model all the behaviors due to the dependencies, relationships, and all other interactions between these components. In complex systems, faults are less apparent and may not be visually identified or fixed by a routine procedure. Hence, complex operations for other systems (figure 3) often rely on predictive techniques, which are yet to be fully explored for BESS.

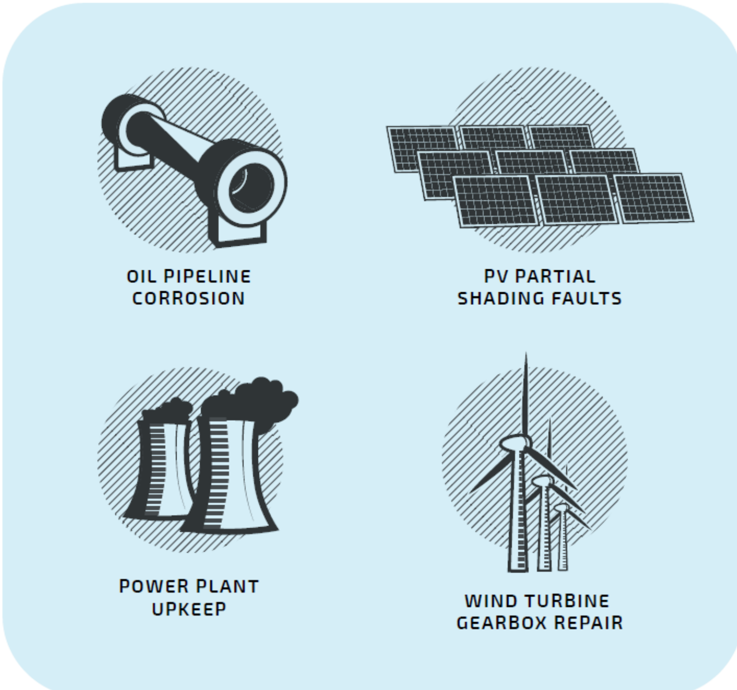


figure 3. Applications of predictive maintenance for other systems.

Predictive analysis involves understanding how all the components in a system fail, and then actively monitoring the components for failure criteria. A 2019 report by GlobalData, "Predictive Maintenance in Power," noted several successful implementations of this approach in the utilities sector:

- The monitoring and diagnostics center at the utility American Electric Power identified warning signs of failure and initiated repair work of a gas turbine blade before breakdown. This resulted in savings of about $19 million.
- Duke Energy used predictive analytics for early detection of a crack in a turbine rotor. This resulted in savings of over $7.5 million.
- Southern Company applied predictive analytics to power station models to decrease unexpected maintenance and maintain data quality reliability. This resulted in savings of approximately $4.5 million.
- Many wind turbine operators now use predictive analytics to monitor the health of the gearboxes. The cost of gearbox failure can be upwards of $350,000 per incident.

Despite these and other successes, both business and technical challenges hinder broader adoption of predictive maintenance in BESS. From the business perspective, the energy storage industry is relatively young. Thus, business priorities and budgets do not always motivate investment in "soft" engineering such as data analytics and AI-based services. The nascence of the industry also means reduced data on fault patterns, especially due to limited public knowledge exchange, making data analytics more difficult. Furthermore, pressure to keep the cost per kWh as low as possible means less investment in sensors and infrastructure to process large volumes of data.

In terms of technical challenges, predictive maintenance techniques tend to be used for mechanical systems where factors such as “wear and tear” can be readily measured and monitored. For electronic systems, predictive practices may be more difficult to apply. Rather than wear out, electronic components are more likely to have a binary failure profile. An issue with one component may manifest itself downstream and result in a failure of another component, requiring data collection from multiple points to identify a pending failure.

Implementing predictive monitoring in conventional BESS hardware is also difficult due to limitations in communication channel availability and processing power of battery/energy management devices. In a BESS, predictive monitoring would involve processing data from battery racks and the overall system to identify failure indicators. Ideally, the BMS of an energy storage device should have the ability to assist in this area. However, current BMSs are not all designed to recognize faults occurring outside of the immediate impacts on the battery itself (e.g. cells, modules) and may not have the throughput to process all the data. Predictive analysis must also depend on data from the energy management system (EMS) to understand the system behavior. Current EMSs are often intended for dispatching/controlling multiple grid resources. They do not include the necessary monitoring and safety functions to manage single or multiple BESSs. EMSs often lack direct communication with BMSs and any fault detection by the BMS may not get communicated to the EMS, limiting prevention actions from system operators. Current standards have not addressed this issue.

A properly designed monitoring approach for operational ESS will create indicators that can provide characteristics such as those in table 3. The overall goal is clear: identify indicators of potential faults and preemptively intervene on an operational ESS without making the intervention itself a problem. However, the links and causal relationships between fault indicators and the potential of those indicators to lead to larger faults are not readily apparent at this early stage of the BESS industry. Ultimately, stakeholders must establish a methodology for identifying indicator-fault relationships that can be tracked and monitored in these systems.

table 3. Key characteristics of indicators for predictive monitoring.

Element	Description
Time element	• Days of warning rather than minutes or hours • Not all faults will have long lead times, but anything that can extend the timeframe can minimize destructive failures
Actionable warnings	• Point to components needing replacement • Allow time for examination of areas causing the warning to occur
Recoverable actions	• Safety measures intended to prevent catastrophic failure and threats to human safety can ultimately destroy the unit (“unrecoverable”) • “Recoverable” action must have minimal impact on the system

Creating a Predictive Maintenance Approach for BESS

The sophistication of approaches for identifying useful “flags” or fault indicators has evolved substantially. In the most basic, reactive approach, these indicators are based on near misses reported by employees. All data are significant and can be useful in preventing future failures. Hence, we recommend a culture where the reporting of near misses is encouraged. More rigorous approaches involve (a) leveraging indicator-fault links established during the system design phase and (b) combining with additional indicator-fault links from analysis of operational data in fielded systems. Identification of these links is an iterative process. During the design phase, system integrators develop the product based on institutional or historical knowledge. However, use cases the system encounters in the field could lead to new fault indicators. Thus, the predictive maintenance approach should be scalable to adapt to new "patterns" with minimal impact on the overall system cost and availability. The following section elaborates on this two-layer approach for identifying indicator-fault relationships during the design phase and based on data analytics on fielded systems.

Identifying Indicator-Fault Relationships During the Design Phase

It is expensive to retrofit a fielded system. Thus, the first step during the design phase is to make a deliberate decision to sense critical information and get as much data as possible to provide insight into various failure modes. Next, the process requires:

1. Creation of a comprehensive listing of *recoverable* battery system faults and linking of faults to leading indicators. This begins with thoughtful engineering consideration of the system design. However, the designer should complement this with collection of historical data from key developers, operators, and manufacturers.
2. Determination of whether indicators are already being tracked through current BMSs, EMSs, or any plant controllers.
3. Finalization of a list of indicators and criteria that need to be monitored to reduce field failures of BESS equipment.

This is a beneficial process to leverage, although there may be gaps when new failure modes are identified or the process does not account for design errors or field/environmental degradation that could lead to failures.

The industry has many well-established processes for system design, including various probabilistic risk assessment approaches (e.g. failure modes and effects analysis, fault tree analysis, etc.) and systems theoretic process analysis. It is important to note nuances from processes created from a system *safety* perspective. These processes are rooted in historical data, where the mechanism of a past failure is identified to improve designs and prevent a similar failure from occurring in the future. To contribute substantially to predictive maintenance, however, the system design process also needs to establish monitoring criteria that can be used in maintaining device operation.

Probabilistic risk assessment (PRA), built from a foundation of risk management, is the most widely used safety engineering method. A PRA approach identifies hazards, their deterministic causes and consequences, and provides a method of describing uncertainty. The process enables the calculation of expected risk (defined as probability of an event multiplied by the relative severity of its consequences) so that a developer can compare different design options. PRA uses fault tree analysis and event tree analysis to break a complicated system into subsystems and components when there is insufficient data to directly predict behavior. Risk is then increased or decreased based on how failures in components and subsystems operate together to generate accidents.

Additionally, failure modes and effects analysis (FMEA) is a systematic procedure for assessing reliability and how component failures can impact system safety. Developers begin an FMEA by compiling a list of each component or type of component in a system. Then they calculate the probability of each component failing in a variety of ways based on historical data. Table 4 shows a brief list of typical FMEA calculations for a BESS (adapted from an EPRI report on ESS safety). The probability and severity each receive a score of 1-10, with 10 corresponding to a more probable or severe event. Each failure mode is linked to a hazard effect, consequence, method of prevention, and method of detection. Identification of the detection method lays the foundation for predictive maintenance. It is apparent, however, that this conventional FMEA approaches system design from a safety perspective (preventing catastrophic failure) rather than detecting faults while they are still recoverable. The process creates a probability but does not provide leading indicators that are necessary to flag pending failures of the areas. Still, these processes are beneficial in understanding what areas to focus on when creating indicator-fault relationships.

table 4. Excerpt from a conventional, safety-focused FMEA for a BESS.

System or Component	Failure Mode	Hazard Effect	Consequence	Prevent	Detect	Probability, Severity	Value for Risk
BMS	System does not operate safely through normally expected temperature operating range	Fire	Safety incident	BMS testing	Independent temperature sensor	3,10	30
Battery Cell	Group of failures	Fire	Safety incident	Abuse testing	Fire alarm	3,9	27
Battery Pack	Group of failures	Fire	Safety incident	Abuse testing	Fire alarm	2,10	20
BMS	Battery damage due to BMS malfunction	Fire or loss of function	Safety incident	Fusing, inverter protection	EMS fault on BMS behavior	2,7	14
Inverter	Inverter fails to detect/react to over-temperature in insulated-gate bipolar transistors	Loss of function	Power output de-rating	Rely on supplier	EMS fault on inverter temperature rise or inverter fault	3,4	12

A more recently developed design tool, Systems Theoretic Process Analysis (STPA), views a system as a collection of interacting control loops. Accidents happen when the component interactions in these loops violate safety constraints. Unlike PRA-based tools, it does not rely on any component failure rate data. Thus, this methodology is valuable in the development of new, complex systems. STPA is conducted in four parts:

1. Identify the accidents and hazards to be prevented in the system
2. Draw all the control structures in the system
3. Determine unsafe control actions
4. Identify causal scenarios, or linkages between faults

This fourth step can lead to the relevant indicators for predictive maintenance. Resources in the "For Further Reading" section provide a more detailed explanation of this process.

Different companies prefer different methodologies during the system design phase. In the previous section, we provided a few examples rather than recommending a specific approach. Many methodologies are rooted in the (appropriate) foundation of protecting human safety, with hazard mitigation responses that tend to render the system unrecoverable. Predictive monitoring accepts that faults may occur through degradation due to long-term operation or from the impact of an external issue that may damage a component. Predictive maintenance requires identifying the cascading chain of faults that leads to failure and specifying which faults are recoverable.

Identifying Indicator-Fault Relationships with Data Analytics on Fielded Systems

The second layer of identifying indicator-fault relationships for predictive maintenance involves using field data. During the design phase, developers evaluate the system based on institutional or historical knowledge. However, they may not be aware of everything they need to consider. With data analytics, the goal is to process field data and examine them from different perspectives to identify new relationships. The original system design may not have coverage of all the necessary signals, so a developer may need to integrate different datasets to understand what is going wrong. Once a developer identifies a new indicator-fault relationship from post-processing of field data, it becomes another signal to respond to in real-time.

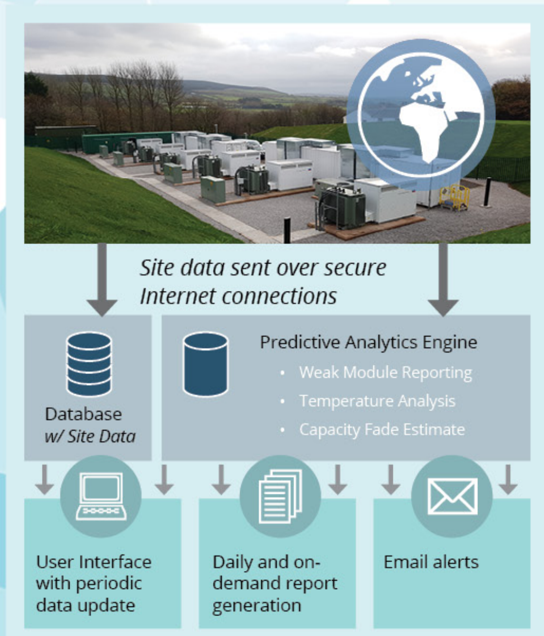
Figure 4 offers a case study for developing such a predictive maintenance approach from the system integrator NEC Energy Solutions. The company first used FMEA during the system design phase to identify critical components and failure pathways, and to determine data needs. Their cloud infrastructure enables data collection and storage from BESSs deployed around the world. Historical data from all sites is used in predictive analytics algorithms. One algorithm, used to identify anomalies in battery modules, parses historical data from each rack for a site and associates indicators in the rack data (e.g. cell voltages, current, battery capacity, operation hours) with system operations. These anomalies represent recoverable issues that could potentially lead to non-recoverable faults. Examples include capacity degradation or a cell short circuit/thermal runaway that causes a system fire hazard (to date, NEC installations have not experienced any catastrophic events or fire hazards). Notifications about this anomalous behavior prompt further analysis to remove any false positives. If the engineers identify a real anomaly, they place the offending battery rack out of service until the module is replaced. In summary, predictive maintenance has allowed NEC to identify misbehaving battery modules before they trigger safety hazards, negatively impact system availability, or reduce the system capacity. The approach has also led to a reduction in maintenance costs by allowing the service team to plan visits more efficiently in each geographic region.

CASE STUDY

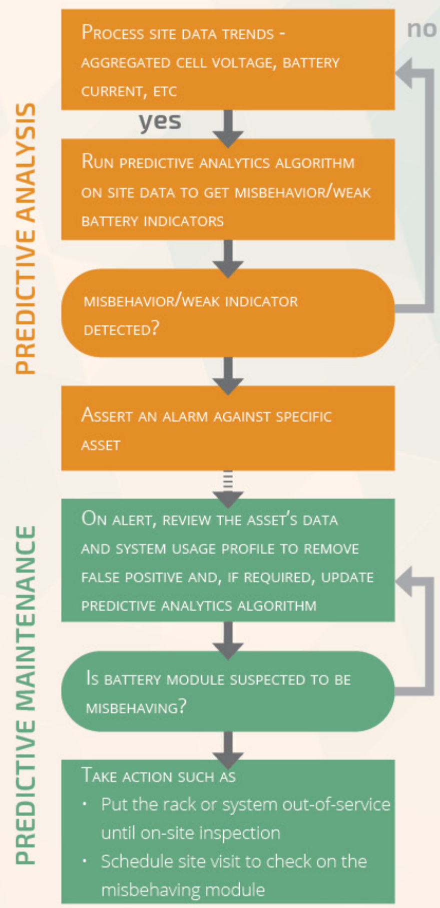
Predictive Maintenance Approaches for BESS

Example application of predictive analytics on real-time and historical BMS data to identify indicators of unusual behavior. These indicators prompt alerts which ultimately lead to predictive maintenance.

Information Flow



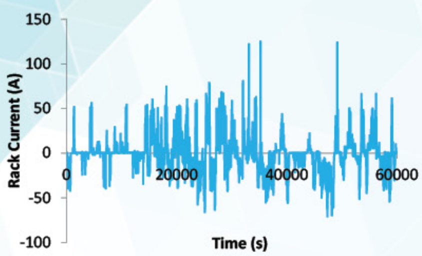
Action Sequence

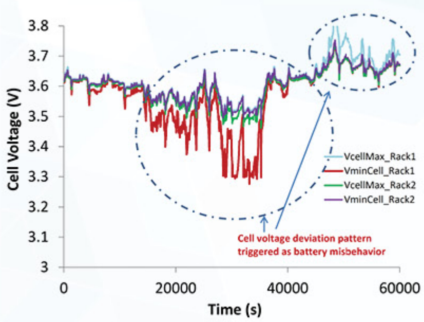


Battery Misbehavior Indicator Warning

In this example, predictive analytics identified a pattern where the cell voltage of a module in Rack #1 was abnormally deviating from the other cell voltages.

The service team was alerted to this pattern and they reviewed the data closely, subsequently replacing a battery module in this rack.





Results

Misbehaving battery modules were identified using predictive analytics algorithms before they could trigger safety hazards, negatively impact system availability, or reduce the system capacity. Furthermore, this approach helped the service team plan maintenance visits more efficiently in each geographic region, reducing the warranty costs.

figure 4. Predictive maintenance case study from NEC Energy Solutions.

Opportunities for Collaboration in Identifying Indicator-Fault Relationships

Since the goal of predictive maintenance is to reduce catastrophic outages of ESS and improve safety, the tools for the process must be available to all BESS operators. The most critical asset is a comprehensive list of indicator-fault relationships. System integrators can identify some of these relationships during the system design phase; however, substantial datasets for further analytics are not broadly available. In some cases, these data may be considered proprietary and, in general, companies have understandable reluctance about releasing fault data. Today, the only public energy storage database (maintained by the DOE) focuses primarily on installations, technologies, and applications of energy storage. Creating a clearinghouse of fault information and issues is a more complicated request.

Thus, we recommend that independent third-party stakeholders create a public database of causal links and fault data that companies can use to enhance predictive monitoring applications in their systems. This task may be daunting for individuals but may not be as difficult for organizations dedicated to supporting ESS safety. Safety of first responders is enough of a reason to encourage system integrators and others involved in system maintenance to collaborate in the public process of identifying these causal relationships and leading indicators.

Summary and Recommendations

This article recommends that the energy storage industry shift to a predictive monitoring and maintenance process as the next step in improving BESS safety and operations. Predictive maintenance is already employed in other utility applications such as power plants, wind turbines, and PV systems. This process complements current BESS codes and standards, and also contributes to broad efforts to design safer systems. Such an approach is necessary because:

- BESS failures are still occurring despite tremendous efforts to mitigate the key faults believed to be the contributing factor in the failures.

- When faults do occur, the steps taken to contain the failure (and protect human safety) usually result in the total loss of the unit.

- Current standards for BESS emphasize factory testing, commissioning, and emergency response rather than guidance for operation and maintenance.

The goal of a predictive process is to identify an indicator of a recoverable fault to initiate an inexpensive maintenance operation and prevent the initial fault from cascading into a catastrophic failure. However, creating the causal links between end-failure states and the key indicators is a daunting task, especially at this early stage of the BESS industry. This article described how system integrators may establish these links during the design phase and from data analytics on fielded systems. Despite challenges, the benefits of predictive maintenance approaches in reducing catastrophic failures and improving safety are too great to ignore. Even today, with companies such as NEC using only their own historical data, the approach is providing great value. Despite this success story, the industry would ultimately benefit from a public, professional consortium creating a database of all issues that lead to larger problems/warning signs of failure. This greater transparency would enhance safety without eroding commercial competitive advantages.

Acknowledgment

The authors gratefully acknowledge funding from the U.S. Department of Energy, Office of Electricity, Energy Storage Program, under the direction of Dr. Imre Gyuk. Sandia National Laboratories is a multi-mission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525. This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

For Further Reading

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