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# IMPROVING MONITORING AND MAINTENANCE OF BATTERY ENERGY STORAGE SYSTEMS THROUGH A CLOUD-BASED IOT SERVICE

Master of Science Thesis
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# ABSTRACT

Anton Nguyen: Improving monitoring and maintenance of battery energy storage systems through a cloud-based IoT service
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The increasing use of battery energy storage systems has increased the need for advanced remote monitoring and maintenance solutions, as the complexity of the systems, operational reliability requirements, and battery life cycle management require accurate, continuous data collection. A cloud-based internet of things system is a key part of this, but its ability to support predictive maintenance, reporting, and lifecycle management had not been studied before. The aim of this study was to investigate how this system can improve the monitoring and maintenance of battery energy storage systems, what data the system currently produces, and what development needs are associated with building performance reporting and strengthening customer value.

The work was carried out in two phases. The literature review compiled a theoretical framework for the operation, monitoring, and maintenance of battery energy storage systems and analyzed trends highlighted in research in the field, such as predictive analytics and the importance of digital services. In the empirical part, the system was examined through system documentation, observation, and staff interviews. The aim of the interviews was to deepen understanding of maintenance needs and reporting development opportunities, as well as to identify factors affecting customer value. The interview themes were formed on the basis of a literature review and preliminary system analysis. The empirical data was analyzed using thematic analysis. The analysis focused in particular on system architecture, collected measurement signals, operating processes, reporting practices, and limitations identified by users.

The results showed that the system effectively supports basic monitoring, alarm tracking, and fault diagnostics, but its functionalities are focused on descriptive and diagnostic analytics. Significant shortcomings were found in data coverage, long-term trend analysis, user interface clarity, and reporting process automation. Literature review, interviews and system observations highlighted the need for a wider range of signals, such as module and cell-level data and cycle and energy histories, in order for the system to support predictive maintenance and more reliable life cycle analysis.

In conclusion, the study showed that the system provides a strong foundation for remote monitoring of battery energy storage systems, but there is room for improvement, particularly in terms of data scope, analytics capabilities, user interface, and automated reporting. Further development of the system could enable predictive analytics, improve usability and efficiency, and increase customer value by providing transparent, real-time, and automated performance reporting.

Keywords: battery energy storage system, BESS, battery management systems, Internet of things, predictive maintenance, data-driven maintenance

# TIIVISTELMÄ

Anton Nguyen: Akkupohjaisen varastointijärjestelmän valvonnan ja huollon parantaminen pilvipohjaisen IoT-palvelun avulla
Diplomityö
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Akkupohjaisten varastointijärjestelmien yleistyminen on lisännyt tarvetta kehittyneille etävalvonta- ja huoltoratkaisuille, sillä järjestelmien monimutkaisuus, toimintavarmuusvaatimukset ja akun elinkaaren hallinta edellyttävät tarkkaa ja jatkuvaa tiedonkeruuta. Pilvipohjainen esineiden internet -järjestelmä on tässä keskeinen osa, mutta sen kykyä tukea ennakoivaa huoltoa, raportointia ja elinkaaren hallintaa ei ole aiemmin tutkittu. Tämän tutkimuksen tavoitteena oli selvittää, miten tämä järjestelmä voi parantaa akkupohjaisten varastointijärjestelmien valvontaa ja huoltoa, mitä tietoja järjestelmä tuottaa tällä hetkellä ja mitä kehitystarpeita liittyy akkupohjaisten varastointijärjestelmien suorituskyvyn raportointiin ja asiakasarvon vahvistamiseen.

Työ toteutettiin kahdessa vaiheessa. Kirjallisuuskatsauksessa koottiin teoreettinen viitekehys akkuenergian varastointijärjestelmien toiminnalle, seurannalle ja huollolle sekä analysoitiin alan tutkimuksessa esiin nousseita trendejä, kuten ennakoivaa analytiikkaa ja digitaalisten palveluiden merkitystä. Empiirisessä osassa pilvipohjaista IoT-järjestelmää tutkittiin järjestelmädokumentaation, havainnoinnin ja henkilöstöhaastattelujen avulla. Haastattelujen tavoitteena oli syventää ymmärrystä huoltotarpeista ja raportoinnin kehittämismahdollisuuksista sekä tunnistaa asiakasarvoon vaikuttavia tekijöitä. Haastattelujen teemat muodostettiin kirjallisuuskatsauksen ja alustavan järjestelmäanalyysin perusteella. Empiiriset tiedot analysoitiin temaattisen analyysin avulla. Analyysissä keskityttiin erityisesti järjestelmäarkkitehtuuriin, kerättyihin mittaussignaaleihin, toimintaprosesseihin, raportointikäytäntöihin ja käyttäjien havaitsemiin rajoituksiin.

Tulokset osoittivat, että järjestelmä tukee tehokkaasti perusvalvontaa, hälytysten seurantaa ja vianmääritystä, mutta sen toiminnallisuudet keskittyvät kuvailevaan ja diagnostiseen analytiikkaan. Merkittäviä puutteita havaittiin datan kattavuudessa, pitkän aikavälin trendianalyysissä, käyttöliittymän selkeydessä ja raportointiprosessin automatisoinnissa. Kirjallisuuskatsaus, haastattelut ja järjestelmän havainnointi korostivat tarvetta laajemmalle signaalivalikoimalle, jotta järjestelmä voisi tukea ennakoivaa kunnossapitoa ja luotettavampaa elinkaarianalyysiä.

Yhteenvetona voidaan todeta, että tutkimus osoitti järjestelmän tarjoavan vahvan perustan akkuenergian varastointijärjestelmien etävalvonnalle, mutta parantamisen varaa on erityisesti tietojen kattavuudessa, analytiikkakyvykkyyksissä, käyttöliittymässä ja automatisoidussa raportoinnissa. Järjestelmän jatkokehitys voisi mahdollistaa ennakoivan analytiikan, parantaa käytettävyyttä ja tehokkuutta sekä lisätä asiakasarvoa tarjoamalla läpinäkyvää, reaaliaikaista ja automatisoitua suorituskykyraportointia.

Avainsanat: akkupohjainen varastointijärjestelmä, BESS, akun hallintajärjestelmät, esineiden internet, ennakoiva kunnossapito, tietopohjainen kunnossapito

# USE OF ARTIFICIAL INTELLIGENCE IN THIS WORK

Artificial intelligence (AI) has been used in generating this work:

☐ No
☒ Yes

I hereby declare, that the AI-based applications used in generating this work are as follows:

| Application | Version |
|---|---|
| MOT Kielipalvelu | |
| Scopus AI | |
| ChatGPT | GPT-4o |
| ChatGPT | GPT-5 |

## Purpose of the use of AI

AI was utilized in this thesis for suggestions regarding spelling and phrasing. AI was utilized to identify and retrieve relevant academic sources and quick insights from curated peer-reviewed literature. The use of AI facilitated more efficient and comprehensive research of existing studies and ensured that key materials were not overlooked during the source search and selection phase.

## Parts of this work, where AI was used

AI has been used in the above-mentioned way throughout the thesis.

## Acknowledgement of risks

I hereby acknowledge, that as the author of this work, I am fully responsible for the contents presented in this thesis. This includes the parts that were generated by an AI, in part or in their entirety. I therefore also acknowledge my responsibility in the case, where use of AI has resulted in ethical guidelines being breached.

# PREFACE

The work was carried out at Merus Power in Ylöjärvi from April 2025 to December 2025.

The early years of my studies were marked by exceptional circumstances. Teaching quickly shifted to remote learning, events were canceled, and social interaction became more challenging than usual. Fortunately, the situation improved over time, and my university experience evolved into an incredible journey filled with numerous cherished memories and meaningful connections. I have had the pleasure of making many new friends, and I hope that we can stay in touch in the years to come. As my studies approach their conclusion, I'm delighted to present this thesis, which represents the culmination of the last six and a half years.

I would like to express my sincere gratitude to my supervisors for their guidance and constructive feedback throughout the project. I would also like to express my gratitude to the representatives of Merus Power, whose expertise and support made the interviews and data collection necessary for this thesis possible. Their contribution was invaluable to the progress and completion of the research.

I especially want to thank my family for their encouragement to pursue my education, setting ambitious goals, and for being there through challenging times. I would like to express my sincere gratitude to all the wonderful people I have met during my studies, as well as to the various student associations I have been involved in, which have contributed to both my academic development and personal growth. Special thanks go to Uranaisten Opiskelijaseura and Sähkökilta. Their support has been priceless and has carried me through the most demanding phases of this journey.

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Anton Nguyen

# CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# LIST OF SYMBOLS AND ABBREVIATIONS

| | |
|---|---|
| $A_{\text{av}}$ | Average availability |
| $A_{\text{iE}}$ | Energy-related availability |
| $A_{\text{iP}}$ | Power-related availability |
| $E_{\text{actual}}$ | Actual available energy capacity |
| $E_{\text{contractual}}$ | Contractual energy capacity |
| $E_{\text{nominal}}$ | Nominal energy capacity |
| $\eta_c$ | Coulombic efficiency of the battery |
| $\eta_e$ | Energy efficiency of the battery |
| $I(t)$ | Current as a function of time |
| $i_{\text{discharge}}(t)$ | Discharge current as a function of time |
| $P(t)$ | Power as a function of time |
| $P_{\text{actual}}$ | Available PCS power |
| $P_{\text{contractual}}$ | Contractual nominal power |
| $P_{\text{demand}}$ | Power demand of the battery |
| $P_{\text{max}}$ | Maximum power available |
| $P_{\text{output}}$ | Power output of the battery |
| $Q$ | Electric charge obtained by integrating current over time |
| $Q_{\text{max}}$ | Maximum storable battery capacity |
| $R_{\text{BOL}}$ | Internal resistance at beginning-of-life |
| $R_{\text{current}}$ | Current internal ohmic resistance |
| $R_{\text{EOL}}$ | Internal resistance at end-of-life |
| $T$ | Total evaluation period |
| $t_i$ | Evaluation interval |
| $t$ | Time variable |
| $t_0$ | Starting time or initial condition |

| | |
|---|---|
| AC | Alternating Current |
| Ah | Ampere-hours |
| AI | Artificial Intelligence |
| BESS | Battery Energy Storage System |
| BMS | Battery Management System |
| C-Rate | Charge Rate |

| | |
|---|---|
| CBM | Condition-based Maintenance |
| CM | Corrective Maintenance |
| DC | Direct Current |
| DOD | Depth of Discharge |
| EMS | Energy Management System |
| EPS | Electric Power System |
| EV | Electric Vehicle |
| HVAC | Heating, Ventilation, and Air Conditioning |
| IoT | Internet of Things |
| KPI | Key Performance Indicator |
| kWh | Kilowatt-hour |
| LIB | Lithium-Ion Battery |
| MIC | Monitoring, Information Exchange and Control System |
| ML | Machine Learning |
| MTTF | Mean Time to Failure |
| MTTR | Mean Time to Repair |
| MWh | Megawatt-hour |
| PCC | Point of Common Coupling |
| PCS | Power Conversion System |
| PdM | Predictive Maintenance |
| PM | Preventive Maintenance |
| RCM | Reliability-centered Maintenance |
| Redox | Reduction-oxidation |
| RTE | Round-Trip Efficiency |
| RUL | Remaining Useful Life |
| SCADA | Supervisory Control and Data Acquisition |
| SOB | State of Balance |
| SOC | State of Charge |
| SOE | State of Energy |
| SOF | State of Function |
| SOH | State of Health |
| SOP | State of Power |
| SOS | State of Safety |
| SOT | State of Temperature |
| TBM | Time-based Maintenance |
| TMS | Thermal Management System |
| VRE | Variable Renewable Energy |

# 1. INTRODUCTION

The accelerating shift toward renewable energy sources, such as solar and wind power, presents new challenges for grid stability due to their inherent intermittency and unpredictability. To address these fluctuations in power generation and maintain reliable grid operation, battery energy storage systems (BESS) have emerged as essential infrastructure. BESSs can improve the flexibility, resilience, and stability of the power system by implementing various grid-supporting control strategies. They also provide operational flexibility, facilitating the balance between electricity generation and demand. [1–6] Lithium-ion batteries (LIB), in particular, have gained prominence in stationary energy storage applications owing to their high energy density, declining costs, and improvements in safety and cycle life [1, 7, 8].

As deployment of large-scale BESSs expands globally, the demand for smart monitoring and maintenance becomes increasingly critical. Modern BESS architecture integrates several systems responsible for monitoring, control, and protection functionalities. Among these, the monitoring, information exchange, and control (MIC) acts as a central node by coordinating communication across devices, managing system states, and handling critical logic functions, including alarms and trip events [9]. In parallel, battery management systems (BMS) serve a vital function in enhancing overall battery performance and maintaining system reliability by continuously monitoring key battery parameters [10–13].

The integration of advanced digital platforms integrating cloud computing and the Internet of Things (IoT) technologies has further advanced the capabilities of these systems. These solutions offer real-time insights into battery performance, support predictive maintenance, and improve early fault detection. These developments contribute significantly to extending the operational lifespan and enhancing the reliability of energy storage assets. [14–16]

The thesis is conducted in collaboration with Merus Power Oyj, a Finnish technology company headquartered in Ylöjärvi. The company's operations are divided into two main technological areas: energy storage solutions and power quality solutions. Merus Power specializes in designing, manufacturing, and delivering innovative and scalable BESSs and power quality solutions tailored for both industrial and utility-scale applications, enabling a sustainable and more energy-efficient future. The company operates globally, serving customers in the industry, electricity generation, and renewable energy sectors. [17]

The purpose of this study is to provide both theoretical and practical information on how cloud-based IoT service and reporting of energy storage systems can be further developed to better meet today's requirements, and how this development work can be integrated into the company's business models and maintenance services. The research is conducted from a cross-sectional perspective, focusing on the company's cloud-based

IoT service. The main objective of the thesis is to systematically examine how the company's cloud-based IoT service can enhance the monitoring and maintenance of BESSs. The review is based on an analysis of available data signals and data collection methods to identify the most significant gaps in data coverage, as well as in quality. The current state analysis is carried out through observation and interviews with the target company's key stakeholders. Based on this analysis, the study seeks to identify both the strengths and the shortcomings of the current system. Various ways to use the collected data to improve maintenance are presented, with the aim of improving system reliability, reducing maintenance costs, extending equipment lifetime and improving customer value.

The findings are used to propose a performance reporting framework that the company could automate as part of its broader after-sales and service in the future. The reporting framework is intended to provide a clear and comparable view of key BESS performance indicators (e.g., state of charge (SOC), state of health (SOH), efficiency and availability) so that both technical maintenance personnel and other stakeholders, such as customers, have an up-to-date view of the systems operation, availability and performance. The work also addresses the customer value generated by the solution, i.e., what kind of benefits and added value the reporting system creates from both a business and technical perspective.

This thesis primarily focuses on BESSs, a form of electrochemical energy storage, with the scope limited to LIBs. In the context of this thesis, the focus is on large-scale and grid-scale BESSs used in commercial, industrial, and utility-level applications. These systems typically have storage capacities in the megawatt-hour (MWh) range, consist of a high number of interconnected battery cells, and operate as part of a wider electrical grid or large facility energy management system. They require continuous monitoring, advanced data analytics, and integration with operational processes to ensure reliable and efficient operation. The thesis examines cloud-based IoT service solutions specifically designed for such systems, enabling real-time data collection, performance evaluation, and predictive maintenance to enhance system reliability, efficiency, and customer value.

The research questions in this thesis can be summarized as follows:

- How can the company's cloud-based IoT service improve the monitoring and maintenance of battery energy storage systems?
- What data signals are currently available and how do they serve to effectively monitor the system?
- How should a performance reporting system be built to meet the needs of both maintenance staff and customers and improve customer value?

The structure of this thesis follows a logical progression from theory to empirical analysis and development proposals. This thesis consists of 6 chapters and the contents of the chapters can be summarized as follows.

The study begins with the introduction in Chapter 1, which presents the background, objectives, research questions, and delimitations of the work. Before the actual research phase, Chapter 2 outlines the research design, including the underlying philosophy, research approaches, strategies, methodological choices, time horizon, techniques and procedures, and the overall research process.

The results of the literature review are presented in two main chapters. These chapters

define the key research concepts of the study and theoretical foundations and present previous research findings. Chapter 3 provides a theoretical background on BESSs and their management. It covers the roles, applications, and challenges of BESSs, the characteristics of lithium-ion batteries, the functions of BMSs, and key battery performance parameters.

This is followed by Chapter 4, which examines the monitoring and maintenance. It reviews various maintenance strategies alongside cloud-based monitoring and role of the IoT in BESS monitoring. Chapter also examines data-driven maintenance approaches. It introduces fault detection, digital twins, and predictive maintenance, emphasizing the challenges related to their implementation in real-world systems.

Building on this foundation, Chapter 5 presents the empirical analysis of the company's cloud-based IoT service, focusing on its purpose, architecture, collected data, identified gaps, and current capabilities. Based on these findings, the chapter also proposes a new performance reporting framework designed to improve monitoring and maintenance of BESSs, enhance reliability, and increase customer value. Finally, Chapter 6 concludes the thesis by summarizing the key findings, outlining the theoretical and practical contributions, and suggesting directions for future research.

# 2. METHODOLOGY

This chapter presents the research design and methodology. In this thesis, the methodological choices are presented using the research onion model by Saunders et al. [18, p. 130, 174], which guides the selection of data collection and analysis methods. Saunders et al. [18] provides a structured framework for research design, represented as a series of nested layers. The model helps researchers systematically consider and justify their methodological choices throughout the research process. This structured approach guides the research process from philosophical starting points to concrete data collection methods and ensures the transparency and rigour of the research objectives.

The research onion consists of six layers that include research philosophies, research approaches, methodological choices, research strategies, research time horizon, and techniques and procedures. The philosophy that is used in this thesis is pragmatic, the approach is inductive, the method is multi-method qualitative, the strategy is case study, the time-horizon is cross-sectional, and the techniques and procedures cover data collection and data analysis. Data collection is carried out with interviews and observations of the company's cloud-based IoT service, including the analysis of available data signals and documentation. Data analysis is thematic analysis. The methodological choices applied in this thesis are illustrated in Figure 2.1 and are explained in more detail in the following sections. Next, we will examine the methodological choices of the study one by one, proceeding from the outermost layer of the research onion model toward its core.

### Research philosophies

Research philosophy forms the outermost layer of the Saunders research onion and reflects the researcher's underlying beliefs about how reality should be studied. It refers to a system of assumptions and beliefs concerning the nature of knowledge and how it is developed within the research process. [18, p. 130-131, 159] Research philosophies can be distinguished based on where the assumptions fall on the continuum between objectivism and subjectivism [18, p. 159]. According to Saunders et al. [18, p. 144-145], the five most widely used research philosophies are positivism, interpretivism, postmodernism, critical realism, and pragmatism.

This thesis adopts a pragmatic research philosophy, selected due to the practical nature of the research problem. Pragmatism allows the use of both qualitative and quantitative methods in a single study [19]. In pragmatism, reality is shaped by practical consequences, and research design is primarily guided by the research problem and question. [18, p. 151] According to Saunders et al. [18, p. 151], Kelemen and Rumens [20] define pragmatic research as a research philosophy that emphasizes the practical application of ideas and the relevance of concepts only when they support effective action. Rather than prioritizing theoretical distinctions, it focuses on solving real-world problems through

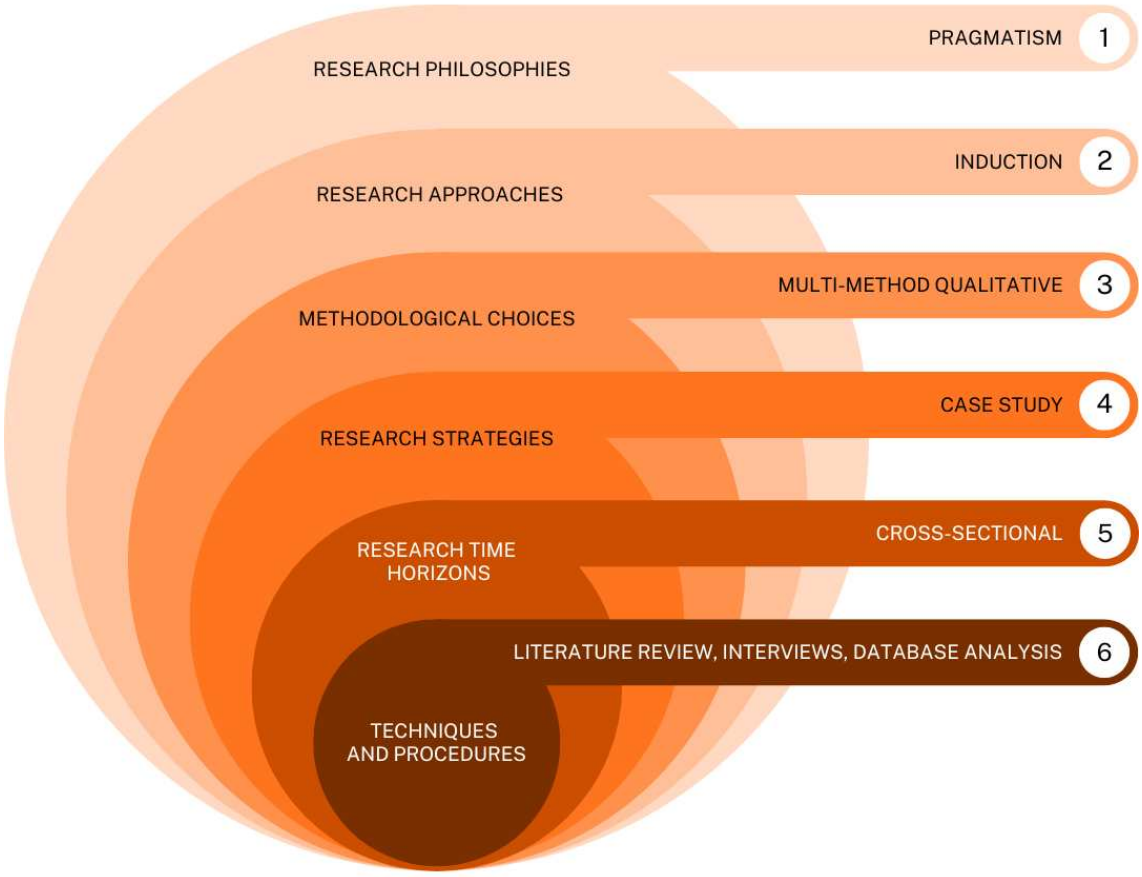



***Figure 2.1.*** *The scientific framework of the thesis (adapted from Saunders et al. [18, p. 130, 174]).*

research that produces actionable outcomes [18, p. 150-151]. Pragmatic research philosophy involves ontological, epistemological, and axiological assumptions [18, p. 150-151]. Ontology concerns the nature of reality, epistemology refers to assumptions about what constitutes valid and acceptable knowledge and how it is communicated, and axiology involves values and ethics, requiring researchers to reflect on how their own values influence topic selection, methodological choices, and data interpretation, and to make those values explicit as a foundation for research decisions and ethical judgment. [18, p. 133-134]

### Research approaches

The second layer of the research onion is referred to as “approaches to theory development", which outlines how researchers connect theory to their research. It involves choosing between deductive, inductive, or abductive approaches, depending on how theory is developed or tested in the study [18, p. 152]. This study uses an inductive approach

to theory development.

In deductive reasoning, the research begins with existing theory, from which logical conclusions are drawn and tested through data collection. If the premises are true, the conclusion must also be true. In inductive reasoning, the researcher starts with observations and builds theory from the data. The conclusion is supported by the data but is not guaranteed, as it involves interpretation beyond what is directly observed. Abductive reasoning begins with a surprising observation or conclusion, and the researcher identifies a plausible set of explanations for that outcome. If the proposed explanations logically lead to the observed conclusion, they are considered reasonable. [18]

### Methodological choices

Research methods are generally classified as either qualitative, quantitative or mixed methods research [18, p. 175-176][21]. A method refers to a systematic approach that a researcher uses to address and answer the research questions that have been set for the study [21]. According to Saunders et al. [18, p. 174] one way to distinguish quantitative research from qualitative research is to consider the type of data involved. Quantitative research is associated with numerical data, while qualitative research deals with non-numerical data such as videos, speeches, or interviews. Alford et al. [22, p. 156] defined a quantitative study as one that aims to understand and produce knowledge about the real world through quantitative research. Quantitative research involves the systematic collection and analysis of numerical data to understand phenomena and their relationships. It typically starts with a hypothesis or theory and uses experimental designs to test these hypotheses. The goal is to measure variables accurately and analyze data to identify patterns, correlations, and causal relationships. [22, p. 156-167] Qualitative research is commonly linked to an interpretive philosophy, as it focuses on understanding socially constructed and subjective meanings related to the studied phenomenon. It is often conducted in natural research settings to enable trust, participation, and in-depth understanding [18, p. 179]. Mixed methods research combines quantitative and qualitative data collection techniques and analytical procedures within the same study [18, p. 181]

Pragmatism does not prescribe a single method but emphasizes the use of approaches that best address the research problem. The choice between qualitative, quantitative, or mixed methods depends on the research question, context, and intended outcomes, making pragmatism a flexible foundation for methodological decisions. [18, p. 151] Therefore, this thesis adopts a multi-method qualitative research methodology, as it enables the integration of insights from both interviews and literature reviews to comprehensively address the research questions. This approach allows for a deeper understanding of the company's cloud-based IoT service for BESSs by combining empirical perspectives from practitioners with conceptual knowledge from existing research. The use of multiple qualitative methods ensures that the analysis captures both the contextual depth and interpretive details of the studied subject.

The research purpose of this thesis is both exploratory and descriptive, with an evaluative component. The exploratory element investigates what data signals are available and how they are currently utilized. The descriptive element provides an overview of the current monitoring architecture, data coverage, and reporting practices. Finally, the evaluative element assesses how effectively the system supports predictive maintenance and

customer value, forming the basis for proposing a performance reporting framework.

### Research strategies

The next layer is called research strategy. This thesis uses a case study research strategy, which is well suited for intensive and in-depth research into a phenomenon in its real-life context [18, p. 197]. . Strategy refers to a planned course of action aimed at achieving a specific goal. Therefore, a research strategy is a plan that defines how a researcher intends to approach and answer a research question. [18, p. 189-190] A case study aims to provide a comprehensive and multifaceted understanding of a specific case by examining it holistically. To achieve this, case studies typically draw on a variety of data sources, such as interviews, observations, statistical data, documents, or other contextual materials. What makes a case study distinct is that the case is a bounded example of a broader phenomenon, situated within a particular context that the researcher can clearly define and justify. The purpose is not to produce broad generalisations but to generate in-depth insights and illustrative descriptions that deepen understanding of the phenomenon, which may then be applied or adapted in other contexts. [21]

A case study allows the interaction between the company's cloud-based IoT service and its organizational context to be examined comprehensively. Case study research provides rich empirical insights by drawing on both qualitative and quantitative data from multiple sources [18, p. 197]. In this thesis, these sources include system documentation, IoT signal data, interviews with key stakeholders, and direct observation of monitoring and reporting practices. This combination enables the study to identify what is happening in the current monitoring and reporting processes, why these practices exist in their current form, and what their implications are for future action. The case study strategy is particularly appropriate for this research because the objective is not only to describe and evaluate the current system but also to propose practical development measures. By integrating multi-method qualitative evidence, the case study approach supports a holistic understanding of the dynamics of the monitoring system and provides a foundation for the design of a reporting framework that addresses technical, business, and customer value perspectives.

### Time horizons

In Saunders et al. [18] research onion model, the time horizon refers to the temporal scope of the research, which determines whether the research is conducted at a single point in time (cross-sectional) or over a longer period (longitudinal). The choice depends on the objectives of the research, the available data, and the nature of the phenomenon being studied.

This thesis uses a cross-sectional model because the main focus is on analyzing the current state of the company's cloud-based IoT service for BESSs. The study examines existing data signals, evaluates their coverage and quality, and examines current reporting practices and maintenance approaches during a specific period defined by the thesis schedule.

A cross-sectional approach is appropriate because the aim is not to observe changes over time, but to produce a snapshot analysis that reveals the current shortcomings and development opportunities of the system. This enables the formulation of practical and

immediately applicable improvement proposals, such as improvements to predictive maintenance and the design of a performance reporting framework.

Although longitudinal studies could provide valuable insights into the development of monitoring and reporting systems, the scope and schedule of this thesis do not allow for long-term observation. However, the recommendations provided in this thesis are forward-looking and designed to support future development and scalable implementation as part of the company's broader after-sales and maintenance activities.

### Techniques and procedures

The data collection techniques used in this thesis adopts qualitative approaches in order to provide a comprehensive understanding of the company's cloud-based IoT service for BESSs. By integrating multiple qualitative findings, the study builds a holistic picture of the current performance of the monitoring system and its development needs. This combined analysis forms the foundation for proposing a reporting framework that can support predictive maintenance, improve system reliability, and enhance the value delivered to customers.

Firstly, qualitative data is collected through semi-structured interviews with five participants representing different roles within the company, including service and maintenance experts, software development specialists and sales representatives. The interview framework, presented in Appendix A, was divided into six thematic sections: background and role, current monitoring and maintenance practices, data quality and usefulness, performance reporting, customer value and business integration, and future development. This ensured that both technical and business perspectives were captured. The semi-structured format allowed to follow a consistent line of questioning while leaving space for participants to elaborate on issues they considered most important.

Secondly, observations were made of the company's IoT monitoring platform, which provides historical and real-time measurements of system performance. Examples include energy usage statistics, state variables, efficiency, and availability. These data points are retrieved from system logs and monitoring dashboards to evaluate the current capabilities of the monitoring system. The data is analyzed using descriptive statistical methods, focusing on trends, variability, and completeness of key performance indicators. This analysis helps to identify the usefulness of available signals for improving maintenance and highlights gaps where additional or improved data would be beneficial. Observations complement interviews by examining how system data is used in practice, particularly in maintenance and reporting processes.

The qualitative material is analysed using thematic analysis, in which interview transcripts and observation notes are systematically coded to identify recurring patterns and themes. Following initial familiarization with the data, relevant segments were coded and organized into broader thematic categories representing shared concepts across the interviews. The results are presented under six key thematic areas: (1) use of the monitoring system in practice, (2) critical data signals and their reliability, (3) system limitations and technical challenges, (4) performance reporting practices, (5) customer value and business integration, and (6) development needs and future outlook. Thematic analysis of the interviews and observations enabled identification of discrepancies between the current system and desired outcomes, while the observational data also provided contextual

validation of the interview findings, particularly in relation to maintenance workflows and reporting processes.

### Research process

The research begins with a literature review to establish foundational knowledge of cloud-based IoT services and predictive maintenance in BESSs. This review identifies key concepts, existing technological frameworks, and gaps in current solutions, while providing the theoretical background needed to understand the technical and business context of the study. It also supports the formulation of the research questions and informs the selection of data sources, analytical methods, and evaluation criteria for the proposed development work.

After the literature review, the research consists of a systematic analysis of the company's existing cloud-based IoT service, including an evaluation of available data signals, their coverage, and quality. This is followed by semi-structured interviews with key stakeholders to gather insights on current maintenance practices, reporting needs, and customer value expectations. The findings are then used to identify development areas and to propose a framework for a performance report.

# 3. OVERVIEW OF BATTERY ENERGY STORAGE SYSTEMS

The most profound transformation in the electricity sector is the replacement of fossil fuels in electricity generation by variable renewable energy (VRE), i.e., wind and solar energy [3]. The proliferation of VRE generation makes energy storage more attractive because VRE generation is intermittent: its output varies over time and is imperfectly predictable. [3, 23]

To ensure a stable and reliable power supply, electricity demand and generation must be continuously in equilibrium. Imbalances between supply and demand can be costly and lead to long-term inefficiencies in electricity generation and distribution. [24] As the integration of VRE sources continues to grow, the need for flexible and reliable solutions to balance supply and demand becomes increasingly critical [3]. Consequently, energy storage systems (ESS) are becoming essential components in the evolution of modern power systems and will play a key role in the construction, development, and transformation of modern power systems, enabling greater flexibility, reliability and integration of renewable energy sources [3, p. 173-174][25, 26]. ESSs enhances system flexibility by decoupling electricity generation from consumption, enabling surplus energy to be stored during periods of low demand and dispatched when needed to meet higher demand [27]. In addition to time-shifting applications, ESSs can participate in energy and reserve markets by providing ancillary services such as frequency regulation and load balancing. [6] This allows ESSs to not only stabilize short-term supply-demand fluctuations but also contribute to market-based mechanisms that support overall grid reliability and economic viability [3, 6]. This functionality is especially important in systems with high VRE penetration, where supply fluctuations can be rapid and unpredictable [3].

There are various classification schemes for ESSs, reflecting the diversity of underlying technologies and their applications. According to the Massachusetts Institute of Technology [3] and Sabihuddin et al. [28], these technologies can be broadly categorized into four main types: electrochemical, chemical, thermal, and mechanical. Each of which is technologically mature to varying degrees and ready for large-scale deployment [3]. Alternatively, Nadeem et al. [29] propose a more detailed classification system that divides ESS into six categories: mechanical, thermal, chemical, electrochemical, electrical, and hybrid systems.

In this chapter, BESS and their management are examined to provide the necessary technical background for the thesis. The chapter begins with an overview of BESS technologies, including the key components, operating principles, and typical applications in large-scale environments. Particular attention is given to LIB technology, which is the most widely used chemistry in large-scale and grid-scale systems. The focus on BESS is justified by their central role in the energy transition, as they enable the integration

of VRE sources, support grid stability, and improve energy efficiency. Moreover, BESS represent the technological context of the case company's core business, making them directly relevant to the research objectives of developing cloud-based IoT service, predictive maintenance, and performance reporting solutions.

## 3.1 Key components of battery energy storage systems

BESS is an advanced energy storage technology that stores electrical energy by means of electrochemical materials and releases it when needed. This process involves storing energy in the form of electrochemical potential during charging, and then releasing it as electrical energy during discharging, thanks to the reversibility of the underlying chemical reactions. [23] BESSs have become increasingly suitable for electric power system (EPS) applications due to significant advancements in battery technology. An EPS, as defined by International Electrotechnical Commission [30], includes "all installations and plants provided for the purpose of generating, transmitting and distributing electricity". These advancements have led to reduced costs, improved performance, and an extended lifespan [7]. BESS units play a crucial role in modern energy systems by balancing supply and demand, supporting renewable energy integration, and enhancing EPS reliability [31]. LIBs have reached a level of commercial and technological maturity that offers high energy and power density, fast response times, scalability, modularity, and declining capital costs due to mass production, largely driven by the electric vehicle (EV) market. These features make them suitable for a wide range of EPS-scale services. [7, 8]

A typical BESS comprises of battery modules, MIC, BMS, power conversion system (PCS), supervisory control and data acquisition (SCADA) system, energy management system (EMS), and auxiliary systems such as thermal management system (TMS), protection and safety systems, EPS connection and other auxiliary devices. The performance of BESSs heavily depends on the design and configuration of these systems, especially the battery packs and PCS. [1, 31–35] The schematic diagram of a typical BESS is shown in Figure 3.1. A complete BESS subsystem includes a PCS, main BMS, and batteries. The BESS subsystem can operate independently when connected to MIC. [2] As shown in Figure 3.1, a BESS typically consists of one or more BESS subsystems.

Battery cells are the core of the storage system [32][34, p. 130] and grid-scale BESSs require a high quantity of battery cells to achieve the necessary capacity and meet system-level performance demands [26]. Battery capacity, denoted in ampere-hours (Ah), refers to the amount of electrical charge a battery can store and deliver. To meet specific voltage and capacity requirements, individual battery cells are configured into modules, to form serviceable units, and further assembled into battery packs through series and parallel connections, which are integrated into a complete battery unit [37]. Additionally, this battery unit function allows part of the BESS to be easily disconnected during maintenance and inspection, which helps to minimize power outages and ensure the annual availability of the system [38]. Each unit includes essential supporting systems such as BMS, ventilation devices and other ancillary equipment [37].

The BMSs serve a central role in ensuring the operational safety, reliability, and efficiency of BESSs [15, 39, 40]. Its core responsibility is to continuously monitor and manage the behavior of battery cells and modules, preventing operational conditions that may cause degradation, malfunctions, or safety hazards such as over-charging, over-discharging,

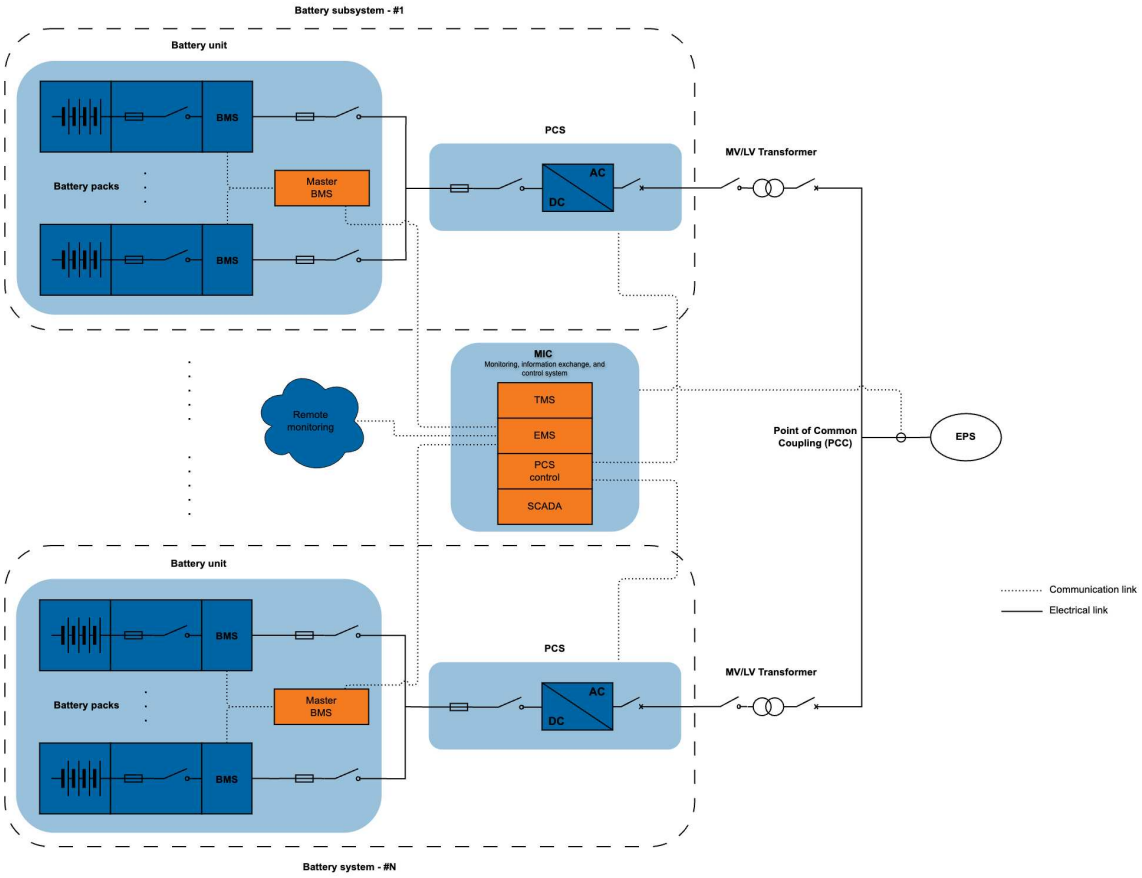



***Figure 3.1.*** *Schematic diagram of a typical BESS (adapted from [9, 36]).*

and thermal stress [32, 39, 41]. The basic functions of BMS are illustrated in Figure 3.2.

The BMS acquires real-time data from sensors and meters located at the cell and module levels. These data typically include parameters such as voltage, current, and temperature, which are used to estimate internal state variables, such as SOC and SOH. [42] These measurements are essential for managing power and temperature, as well as for charging and discharging operations, monitoring health status, and estimating the lifespan of the battery. [15, 32, 39–41, 43] The effectiveness of the BMS depends significantly on the accuracy and speed of data acquisition, which directly influence its performance [44]. Furthermore, the BMS enables communication between the internal data of the battery and external data collection systems, enabling real-time monitoring and control [15, 32, 40]. When integrated with additional safety mechanisms, the BMS enables coordinated protective actions, thereby enhancing the overall safety and reliability of battery systems [15].

The main BMS gathers data from all the BMSs within the battery unit. The main BMS also calculates or collects the battery state variables, and available charging and discharging power from the BMSs. Based on this data, the main BMS updates the status of the entire battery unit. The main BMS performs final battery protection if another system does not comply with current or status limits. [9] Additionally, the main BMS also exchanges operational data with the EMS and PCS to support coordinated, system-level functionality and decision-making [42].

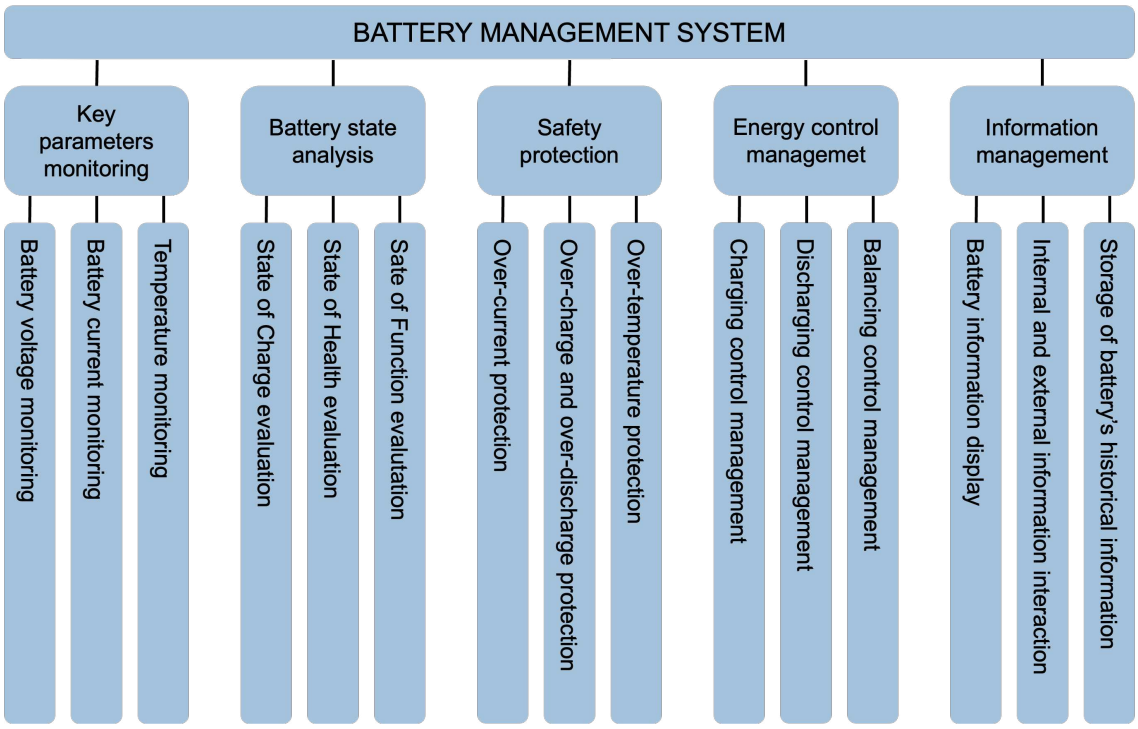



***Figure 3.2.*** *Basic functions of the BMS (adapted from [39]).*

An EMS is essential for ensuring the efficient, relible and safe operation of BESS, when deployed as flexible assets capable of delivering multiple EPS services. The primary objectives of the EMS are to maximize overall benefits of the system, including enhanced performance and cost reduction. An effective EMS must support different use cases and adapt to various regulatory environments. Within the BESS, the EMS manages power flow according to battery constraints and enables the implementation of operational strategies such as frequency regulation, peak shaving, and load balancing, which are critical for maintaining EPS stability. [32] In addition, the EMS can influence the efficiency and aging of the BESSs by optimizing the distribution of power demands to different battery units. [32, 33, 42]

The EMS typically operates within the broader limits defined by the BMS, but in practice, it may linearize or disregard certain conditions such as variations in cell voltages or temperature differences. When charge and discharge decisions involve balancing battery life with economic optimization, the BMS operational constraints are set as wide as possible within the safe operating area. Conversely, if the EMS depends on the BMS to ensure the designed lifetime of the battery, the BMS constraints are configured more narrowly to limit degradation, which may result in a significantly smaller operating window compared to the full safe operating area. [45]

Proper management of system operations requires that all subsystems within the BESS be able to communicate with each other, which mandates that each part have a compatible communication interface [42]. EMS receives battery-related parameters from the BMS and integrates additional inputs from various external sources. These may include electrical measurements at the point of common coupling (PCC), weather forecast data, market-related information, and control signals issued by distribution system operators (DSO), transmission system operators (TSO), and aggregators. [6]

The TMS controls all heating, ventilation, and air conditioning (HVAC) functions related to the system containment. TMS is responsible for maintaining the temperature of battery cells and battery packs within specified operating limits and ensuring that temperature differences within the battery pack are kept to a minimum. Temperature differences between cells can result in unbalanced current flow and accelerated aging, reducing system performance and service life. [32]

In EPS connected systems, additional electronics such PCSs and inverters are required to interface the direct current (DC) output of the batteries with the alternating current (AC) of the EPS at the PCC. PCSs may include DC/DC converters and/or DC/AC inverters, DC and/or AC filters, and a step-up transformer. PCS units are responsible for managing the bidirectional energy flow, electrical isolation, ensuring power quality, and adapting to the EPSs dynamic specifications. [6] The transformer is optional and can be omitted if the system output voltage and EPS connection voltage are the same [32]. The PCS receives commands from the EMS and interfaces with BMS [42].

SCADA provides a user interface for the system user. All control and operating modes, essential settings, and measurement data are displayed on the SCADA interface. [36]

## 3.2 Role and applications

BESSs are used in a wide range of EPS applications, which can be broadly grouped into four categories: energy arbitrage, ancillary services, transmission and distribution infrastructure services, and customer energy management services. As a further matter, BESSs support the transition to low-carbon energy systems by enabling greater penetration of VRE while maintaining reliability and efficiency. [3] Applications of BESSs by category are shown in Table 3.1.

Energy arbitrage refers to shifting electrical energy from low-value times or locations to high-value ones. It involves buying electricity during periods of low demand and low prices, storing it, and then selling it back to the EPS or using it during periods of high demand and high prices. [3] BESSs can optimize this process to generate profit by taking advantage of price volatility in electricity markets [6]. Studies have shown that energy arbitrage is economically feasible in various markets. However, the profitability of energy arbitrage depends on market conditions, regulatory frameworks, and the cost of battery degradation. [3, 6, 46]

Ancillary services provided by energy storage assets to the bulk power system generally operate for short periods of time, but they require very fast response times ranging from less than a second to several minutes. These services are crucial for maintaining grid stability and reliability. One such service is frequency regulation, which involves using storage to mitigate fluctuations caused by momentary imbalances between electricity generation and demand. This function is often performed automatically on a near-continuous basis, particularly in systems dominated by VRE. [3] In these systems, it substitutes for the inertia traditionally provided by spinning generators connected to transmission networks [3, 6]. Frequency control is typically implemented through droop control, whereby BESS adjust its power output in response to frequency deviations, thereby helping to stabilize the grid. However, BESSs are often constrained by their maximum and minimum SOC, which can limit their ability to provide continuous frequency control. [6]

***Table 3.1.*** *Applications of BESSs by category. [1–6]*

| Category | Applications / Services |
|---|---|
| Energy arbitrage | Electric energy time-shift |
| | Optimization of electric capacity |
| Ancillary services | Frequency control |
| | Voltage control |
| | Peak shaving |
| | Load following |
| | Supplemental reserves |
| | Black start capability (emergency back-up/black start) |
| | Integration of renewable energy sources |
| Transmission and distribution infrastructure services | Transmission system stability |
| | Transmission voltage regulation |
| | Transmission congestion relief |
| | Transmission and distribution facility deferral |
| | Distribution system reliability improvement |
| Customer energy management | Customer energy management |
| | Renewable energy management |
| | Power quality and reliability improvement |

Peak shaving and load following involve reducing the maximum power observed by the grid by flattening generation and load profiles [6]. Load following resembles frequency regulation but operates over longer time frames, from 15 minutes to 24 hours [3]. This addresses broader variations in supply and demand. Furthermore, BESSs can play a crucial role in the future paradigm of voltage management [6]. Voltage support maintains stable voltage levels across transmission and distribution networks. Black start capability enables a power station to restart independently, without relying on the transmission grid, in the event of a large-scale outage. Additionally, supplemental reserves provide extra power to the grid in less than 10 minutes and are used to maintain frequency stability during unexpected load changes or emergencies. [3, p. 6-7]

Energy storage can reduce infrastructure costs by deferring investments in transmission and distribution networks by peak shaving and load following. The feasibility of BESSs as a potential solution for deferring network upgrades depends heavily on the systems capacity, siting and operational management of BESS. Deferring network upgrades refers

to storing energy close to generation or demand sources and transferring it at a steady rate to avoid the need for capacity expansion or new transmission lines. [6, 25]

Customer energy management services, such as improving reliability and reducing peak demand, can be supported by small storage systems installed on customers' premises. These distributed systems can also be used to deliver energy services at the bulk power system level when coordinated by aggregators. [3]

## 3.3 Challenges

One of the primary challenges limiting the wider deployment of BESSs is performance degradation due to frequent charge–discharge cycles of batteries and side reactions. This degradation not only reduces system efficiency and lifespan but also introduces economic uncertainty related to system reliability, operational costs, and return on investment. Therefore, real-time monitoring, predictive diagnostics, and effective control strategies are essential to ensure optimal system performance and safety throughout the operational life of BESS units. [16]

Each component of the BESS system is exposed to its own aging or failure process. Understanding these degradation processes is essential for developing reliable BMS lifetime prediction methods and implementing reliable data-based control and condition monitoring strategies both at the local controller level and on cloud-based management platforms. [31, 47] The Table 3.2 outlines common symptoms and possible diagnoses across these subsystems.

Battery aging is primarily characterized by two mechanisms: calendar aging and cycle aging. [48, 49] Calendar aging refers to the natural decline in the electric charge of a battery over time, even when the battery is not in active use. This type of degradation is largely influenced by temperature and the SOC of the battery during storage. In contrast, cycle aging is associated with the operation of the battery and depends on usage parameters such as charge–discharge cycles, depth of discharge (DOD), charge/discharge rates, thermal environment, and mechanical stress induced by repeated cycling. [48]

Aging or failure of the BESS system typically results in recognizable symptoms in various subsystems. At the cell level, problems such as abnormal voltage or temperature readings and physical deformations may indicate system degradation or internal faults. Cells and modules may exhibit symptoms such as enclosure deformation and local overheating at connection points, often caused by loose connections or enclosure aging. This can lead to increased contact resistance and abnormal heating, which can damage the battery packs [50]. Packs might exhibit uneven temperatures or the presence of gases (e.g., CO or $H_2$), suggesting problems in cooling systems or internal cell faults. At the unit level, abnormalities such as uneven temperature distribution, irregular linkage current, or insulation problems can occur due to imbalances between packs or issues in connections and cabling.

The BMS plays a crucial role in fault detection, data acquisition and communication; however, the BMS itself is vulnerable to failure. Symptoms include data acquisition problems, unresponsive communication, and outdated monitoring metrics.

Faults in the PCS electrical circuits can result in voltage or current deviations, abnormal frequency responses, or poor power quality indicators, such as increased total harmonic

***Table 3.2.*** *The aging and fault symptoms of BESS subsystems [31].*

| Item | Subsystem | Symptom Description | Diagnosis |
|---|---|---|---|
| Battery system | Cell | Voltage and temperature abnormal, deformation | Cell aging or fault |
| | Module | Module deformation, excess heat at link point | Link loosen, module enclosure aging |
| | Pack | Temperature difference, excess CO/$H_2$ | Cooling devices abnormal, cell fault |
| | Unit | Temperature difference, linkage current or insulation | Packs imbalance, connection and cable abnormal |
| BMS | Acquisition | Data and information abnormal | Slave BMS fault |
| | Communication | Data do not refresh | Communication fault |
| PCS | Electrical performance | AC and DC power quality, e.g., total harmonic distortion, current ripple, frequency and voltage deviation | Electrical circuit or control system fault |
| | Mechanical performance | Over-heating, abnormal noise | Heat-sink, fan or water cooling system fault |
| Auxiliary devices | Air conditioning | Battery house temperature abnormal | AC fault or temperature setting incorrect |
| | Ventilation | Vent flow and disruption insufficient | Fans fault or air flow problem |
| | Fire extinguish | Gas detector abnormal, fire fighting miss operation | Fire extinguish system fault |

distortion. On the other hand, mechanical performance issues such as overheating or unusual noise suggest failures in thermal management components like heat sinks, fans, or water-cooling systems.

Auxiliary systems, such as HVAC, are also important for maintaining optimal environmental conditions. Faults in these systems, ranging from incorrect temperature settings to insufficient air flow or faulty gas detectors, can lead to serious safety risks, such as thermal overload or fire.

A comprehensive understanding of these types of faults supports a framework for predictive maintenance and real-time condition monitoring algorithms, which are essential for ensuring the safe, efficient, and continuous operation of large-scale BESSs [31]. The implementation of artificial intelligence (AI) algorithms for the purpose of smart operation and maintenance constructs an effective approach to mitigating the safety risks associated with BESSs [51].

## 3.4 Lithium-ion batteries in BESSs

Over the past two decades, LIBs have become the leading rechargeable battery technology due to their high energy and power densities [3]. Although LIBs come in a variety of chemistries, their principle of operation remains the same [52]. These electrochemical energy storage devices rely on reduction-oxidation (redox) reactions [3]. These reactions occur at two electrodes, anode and cathode, separated by an electrolyte, enabling the controlled flow of electrons and ions to store or release energy. The typical cell consists of a graphite-based anode (negative electrode) and a cathode (positive electrode) composed of lithiated metal oxides, e.g., lithium iron phosphate. The electrolyte solution, which facilitates the movement of lithium ions, usually contains lithium salt dissolved in organic carbonate solvents. [3, 37] Typical electrolytes are based on organic solvents, which are flammable and volatile [37, 53]. The electrodes are separated by a thin polymeric film, commonly polyolefin, which acts as a physical barrier to prevent short circuits while allowing ionic conductivity. These materials are crucial for determining the energy density, overall performance and favored applications of different types of the battery. [3, 37] The standard operating voltage of commercial lithium-ion cells typically ranges between 3–4 volts, though variations exist depending on the specific cell chemistry. Cells can be assembled into different physical configurations, most commonly cylindrical, prismatic, or pouch formats, by stacking multiple layers of electrodes and separators within a sealed housing. [3, 37, 54]

Among commercially available rechargable (secondary) battery technologies, LIBs are widely recognized for their superior performance characteristics, making them highly suitable for various applications including portable electronics, EVs, and large-scale BESSs. LIB technology is the most suitable for various applications because of their exceptionally high energy and power density, high cell voltage, long lifespan, long cycle life, low self-discharge, low pollution, good thermal and electrochemical stability and excellent high-temperature and low-temperature resistance along with a superior round-trip efficiency that typically exceeds 95%. High energy density allows for more energy to be stored in a smaller volume and high power density is essential for applications that require rapid energy discharge. [26, 55–60] In particular, lithium-ion technology remains a favorable option for BESS applications, primarily due to its extended cycle life and adaptable charge–discharge performance [61]. Moreover, LIBs are considered maintenance free and do not suffer from memory effects. This means they do not lose their maximum capacity when repeatedly charged after being only partially discharged. [62–64] However, the use of critical materials such as cobalt and lithium impacts the overall cost of LIBs, which limit their widespread adoption [65]. Continuous research and development are therefore essential to reduce costs and enhance the performance and safety of LIBs, ensuring their viability for a broader range of applications.

Despite their advantages, LIBs are subject to inevitable aging processes driven by elec-

trochemical side reactions that occur during charge and discharge cycles. These aging mechanisms gradually lead to a decline in the usable energy and power capability of the battery while increasing internal resistance of the battery, ultimately affecting performance and reliability [32, 48, 49, 66]. A battery is typically considered to have reached the end of its useful life when its SOH declines below 80% of its initial value or when its internal resistance has doubled compared to its original state [48, 67].

Battery degradation is a multifaceted process influenced by thermal, electrochemical, and mechanical factors, and in severe cases it may compromise system safety by contributing to failures such as thermal runaway, fires, or explosions [37, 47, 68]. As a result, considerations for degradation must be incorporated during both the system design phase such as oversizing the initial capacity and during operational planning, including limits on maximum cell discharge power [32].

Thermal runaway in LIBs is a significant safety concern primarily because of the high flammability and volatility of organic solvents in liquid electrolytes. Effective monitoring, cooling systems, material innovations, and safety devices are essential to mitigate these risks and ensure safe operation of LIBs. [37] In parallel, research is ongoing to develop safer alternatives, including solid-state electrolytes, gel polymer electrolytes, ionic liquids, and flame-retardant formulations. [53, 69] Understanding these mechanisms and implementing effective mitigation strategies is crucial for enhancing the safety, performance, and longevity of energy storage systems.

## 3.5 Key battery parameters

### 3.5.1 Availability and performance

#### Availability

Availability refers to the ability of the BESS to remain operational and capable of delivering stored energy when required. According to *SFS-EN 13306:2017* [70], availability is defined as the ability of an item to be in a state to perform its required function when needed, under specified conditions and assuming the provision of necessary external resources. In the context of BESSs ensuring high availability is critical for supporting energy demand during peak load periods, compensating for fluctuations in renewable generation, and maintaining supply during grid disturbances. Achieving this requires effective system maintenance, continuous real-time monitoring, and timely fault detection and resolution. Sustained high availability enhances the reliability of energy delivery and contributes to overall grid stability. [71]

In the contractual framework used by the company, availability is evaluated by comparing the actual performance of both the PCS and the energy capacity against their contractual requirements. The power-related availability factor $A_{\text{iP}}$ is calculated as the ratio between the available PCS power $P_{\text{actual}}$ and the contractual nominal power $P_{\text{contractual}}$. Similarly, the energy-related availability factor $A_{\text{iE}}$ is defined as the ratio of the actual available energy capacity $E_{\text{actual}}$ during the evaluation interval to the contractual energy capacity $E_{\text{contractual}}$. The overall availability for each evaluation interval $t_{\text{i}}$ (typically 1 hour) is determined by taking the minimum of these two factors, ensuring that the system is only considered available when both sufficient power and energy capacity are provided. The

annual availability is then calculated by summing the interval-specific minimum availability values across the total evaluation period $T$ (8,760 hours) and expressing the result as a percentage. This formulation ensures a comprehensive and contractually aligned assessment of system performance over time. Availability can be calculated with Equations 3.1-3.3.

$$A_{\text{iP}} = \frac{P_{\text{actual}}}{P_{\text{contractual}}} \tag{3.1}$$

$$A_{\text{iE}} = \frac{E_{\text{actual}}}{E_{\text{contractual}}} \tag{3.2}$$

$$\text{Availability \%} = \frac{\sum \min\left(A_{\text{iP}}, A_{\text{iE}}\right) t_{\text{i}}}{T} \times 100\%. \tag{3.3}$$

### Capacity

Capacity $Q$ refers to the total amount of electrical charge that can be stored and released by a battery from a fully charged state to its cut off voltage [72, 73]. It is typically expressed in Ah and is calculated as the integral of the discharge current over time, given by

$$Q = \int_0^t i(t)\, dt, \tag{3.4}$$

where $i(t)$ denotes the discharge current as a function of time and $t$ represents the elapsed discharge duration [73, 74].

Capacity is not constant as it decreases over time due to aging processes influenced by factors such as charge–discharge current, operating temperature, DOD, and the number of cycles [72, 73]. Due to these variations, the term “battery capacity” is used in different ways in the literature [72]. The most common definitions include nominal capacity or rated capacity, which is the rated capacity specified or the capacity at the beginning of life defined by the battery manufacturer. Effective capacity or available capacity is the remaining charge capacity the battery can provide at a given point in its life. At the start of the battery life, the nominal and available capacities are equivalent. Dynamic capacity represents the instantaneous ability to deliver charge and varies with operating conditions and fluctuates during charging and discharging cycles. [72][75, p. 31-33]

### Energy rating

The energy rating of a battery refers to the amount of energy it can store and release, typically expressed in kilowatt-hours (kWh) or MWh. The duration for which the battery can supply power depends on the energy consumption level of the connected load.

### Round-trip efficiency

Round-trip efficiency is defined as the ratio of the energy output during discharge to the energy input during charging. It quantifies the overall efficiency of the energy storage cy-

cle, representing the fraction of input energy that is successfully recovered and delivered by the system. [3]

### 3.5.2 Battery state estimation

The field of battery state estimation has already grown significantly, with numerous approaches reported in the literature, according to Hu et al. [76]. In large-scale applications such as EVs and stationary BESSs, lithium-ion battery packs typically consist of thousands of individual cells connected in series and parallel to achieve the required voltage and capacity levels. These configurations introduce increased safety demands and more complex state monitoring requirements. [77]

As noted by Jose and Shrivastava [43] and Tan [39], battery management comprises several key assessments, including SOC, SOH, state of energy (SOE), state of power (SOP) and state of function (SOF). In addition to the commonly referenced states, Hu et al. [76] introduce further estimations such as state of temperature (SOT), state of safety (SOS) and state of balance (SOB), underscoring the need for comprehensive monitoring. Hu et al. [76] emphasize that battery state estimation has evolved into a broad research domain, with numerous methodologies documented in the literature.

Accurate determination of these parameters is essential for effective charging strategies, thermal regulation, and overall health management of batteries [76]. Estimation of these parameters relies on battery characteristics, including voltage, current, temperature, and internal resistance or impedance, obtained through direct measurement. However, these parameters typically exhibit nonlinear dependencies on both the measured variables and operating conditions including temperature and charge/discharge rates. Consequently, model-based approaches are frequently integrated to enhance the accuracy of state estimation algorithms, particularly in high-power and high-energy applications. [77]

Each of these state variables evolves on different time scales due to the multi-physics nature of electrochemical battery systems. Fast-changing states such as SOC, SOE, and SOP are influenced by rapid electrochemical reactions and require real-time estimation. Temperature-related dynamics, reflected in the SOT, change on an intermediate time scale and depend on the thermal structure and heat transfer properties of the system. Conversely, SOH is governed by slowly evolving degradation mechanisms such as capacity fade and increased internal resistance, typically assessed over longer time frames. The overall safety state SOS integrates information from all these dimensions to evaluate the risk status of the system and guide safety-critical operational decisions. [76]

#### State of charge

The SOC is a key indicator used to represent the available energy in a battery. Accurate estimation of the SOC is essential for battery management, as it reflects the remaining usable energy during operation. This information is critical for optimizing charging and discharging strategies and ensuring the battery operates within safe and reliable limits. [76] Due to the complex nature of electrochemical processes and the strong coupling between internal variables, SOC cannot be directly measured in real-world applications. As a result, real-time SOC estimation has become a core function of modern BMSs and a significant focus of ongoing research efforts aimed at improving the accuracy and reliabil-

ity of battery state monitoring. [76]

Various problem formulations can be used to express the SOC. In general, SOC refers to the proportion of the remaining capacity of the battery relative to its maximum available capacity. The remaining capacity describes the amount of charge still available to supply electrical loads, while the maximum capacity denotes the total charge the battery can store based on its electrochemical characteristics. [76, 77] The value of SOC is expressed as a percentage from 0% to 100%, where a value of 100% means the battery is fully charged, while 0% indicates complete discharge [13].

One of the most commonly used techniques for estimating SOC is the coulomb counting [72] due to its simplicity and ease of implementation [72, 78]. The coulomb counting method continuously monitors the battery current and integrates it over time to compute the accumulated charge [77]. The dynamic behavior of SOC over time can be expressed mathematically through an integral formulation that incorporates current flow, coulombic efficiency, and nominal capacity

$$SOC(t) = SOC(t_0) + \int_{t_0}^{t} \frac{I(t)\,\eta_c}{Q_{\text{max}}}\,dt, \tag{3.5}$$

where SOC($t$) denotes the state of charge at time $t$, while SOC($t_0$) is the initial SOC at time $t_0$. The variable $I(t)$ corresponds to the time-dependent current flowing into or out of the battery and $\eta_c$ is the coulombic efficiency, defined as the ratio of the energy required for charging to the discharge energy required to restore the original capacity. [76, 78]

Inaccurate initial SOC values and cumulative measurement errors can lead to significant estimation inaccuracies in practical applications [79]. Conventional techniques are susceptible to variations in temperature and battery degradation, which can compromise their accuracy [80]. As a consequence of these issues, a variety of approaches for estimating the SOC has been reported in the literature [13, 72, 78], each with different levels of complexity, accuracy, and suitability depending on the battery type and application. The researches by Ul Hassan et al. [72], Hannan et al. [78] and Nyamathulla and Dhanamjayulu [13] examines these approaches, including voltage-based approaches, coulomb counting, model-based estimations, and increasingly, data-driven and hybrid techniques, emphasizing that no single method is universally optimal.

### State of health

The SOH is a conceptual metric that reflects the extent of degradation of a battery relative to its condition at the beginning of service life [64]. It is used to assess battery ageing and to estimate the remaining useful life (RUL) [77, 80], thereby indicating when a battery can no longer meet the power, energy, or standby requirements of its intended application [64]. Reaching this condition typically signals the need for maintenance actions or battery replacement [64].

The SOH is commonly expressed as a percentage representing the ratio of the current maximum capacity of the battery to the original rated capacity [77, 81]. As such, it provides a quantitative measure of the current condition of the battery and serves as a basis for performance assessment and lifecycle decision-making. Accurate SOH estimation is therefore essential for monitoring the health of individual cells and ensuring the reliable

and stable operation of the overall power system [82].

According to Berecibar et al. [67], in some cases, the increase in internal resistance may have a more significant impact on battery performance than the loss of capacity. Therefore, a reliable estimation of the SOH should take into account both the capacity degradation and the rise in internal resistance. The SOH of the battery can be quantified using internal resistance as

$$SOH = \frac{R_{\text{EOL}} - R_{\text{current}}}{R_{\text{EOL}} - R_{\text{BOL}}} \times 100\%, \tag{3.6}$$

where $R_{\text{current}}$ denotes the current internal resistance of the battery, $R_{\text{BOL}}$ represents the internal resistance of the battery in a new (beginning-of-life) condition and $R_{\text{EOL}}$ is the internal resistance measured when the battery reaches its end-of-life threshold [13, 79].

In addition to capacity degradation and internal resistance, some researchers define the SOH as the ratio between the remaining usable cycles and the total expected life cycle of a battery. However, this definition presents practical limitations. Due to the high degree of uncertainty associated with real-world battery usage, it is difficult to predict the exact operating conditions throughout the lifespan of the battery. As a result, accurately estimating the number of remaining charge–discharge cycles is not feasible, which reduces the practical applicability and reliability of this SOH definition. [39]

According to Nyamathulla and Dhanamjayulu [13], a variety of techniques have been developed to estimate the SOH of batteries, aiming to accurately assess their degradation and RUL. These methodologies can be broadly categorized into model-free or experimental-based, model-based, and data-driven methods [13]. Hybrid approaches that combine data-driven modeling with physics-based understanding have shown significant potential for improving the accuracy of SOH estimation [80].

#### State of power

Predicting power capability is a key aspect of battery management, as it indicates the amount of power the battery can deliver in the immediate future. Power capability refers to the rate at which energy can be transferred from the battery pack to the load without exceeding the design limits of the cells or associated electronics, and it is inherently an instantaneous quantity. This capability is typically assessed using the SOP or SOF, which quantify the available power relative to the rated value.

The SOP is defined as the ratio of peak power to nominal power [83], indicating the amount of power it can deliver to or absorb from the connected system within a predetermined time interval [76]. In the context of BESSs, the system can be, for example, an EPS. In essence, the SOP represents the instantaneous power capability of a battery. Due to the underlying electrochemical and thermodynamic behaviour of the battery, SOP estimation is constrained by factors such as terminal voltage, current, temperature, maximum available capacity, and SOC [84].

### State of energy

By analogy, SOC can be expressed as SOE, which represents the ratio between the remaining available energy and the total stored energy [74]. Unlike SOC, SOE is a more generalized metric that can be applied to any type of energy storage device [74]. For energy storage technologies that do not rely on charge-based mechanisms, such as mechanical or thermal storage, SOC is not physically meaningful, and a more general indicator is required. SOE can also be formulated dynamically as

$$SOE(t) = SOE(t_0) + \int_{t_0}^{t} \frac{P(t)\,\eta_e}{E_{\text{nominal}}}\,dt\,, \tag{3.7}$$

where SOE($t$) is the SOE value at time $t$, SOE($t_0$) is the SOE value at initial time $t_0$, $P(t)$ denotes the power at time $t$ and $E_{\text{nominal}}$ represents the nominal energy of the battery. The term $\eta_c$ denotes the energy efficiency of battery. [76, 85]

### State of temperature

The SOT describes the thermal condition of a battery and reflects the internal temperature or the temperature distribution within the cell. It arises from the balance between heat generated by electrochemical reactions and heat dissipated through conduction, convection, and, to a negligible extent, radiation. Accurate SOT estimation is essential because thermal inhomogeneity within large-format cells can accelerate degradation and affect safety. Depending on the modeling approach, SOT may be represented by core, surface, or average temperature values. Models are used to capture the relevant thermal dynamics, supported by appropriate parameterization and experimental reference measurements. [76]

### State of function

The SOF refers to the operational capability of a battery pack under a set of predefined constraint conditions. It plays a vital role in application-specific performance evaluation, especially when standard state parameters such as SOH, SOC, or voltage alone are insufficient to determine whether the battery system can meet the functional demands of a given application in real-world conditions. [13] The SOF can be calculated as

$$SOF = \frac{P_{\text{output}} - P_{\text{demand}}}{P_{\text{max}} - P_{\text{demand}}}, \tag{3.8}$$

where $P_{\text{output}}$ denotes the battery power output, $P_{\text{demand}}$ is the power demand, and $P_{\text{max}}$ indicates the maximum power available under baseline conditions. While SOC is used to reflect the real-time charge level of the battery and SOH captures the degradation relative to a new cell, these metrics alone may not fully represent the functional capability of the battery under constrained conditions. Consequently, in such scenarios, the SOF functions as a more comprehensive indicator for assessing the operational performance of the battery system. [13, 43]

#### State of safety

The SOS is a quantitative indicator used to assess how safely a LIB or battery system is operating at a given moment. The SOS indicator reflects the proximity of the battery to critical failure thresholds by integrating multiple parameters such as voltage, current, temperature, internal impedance and external deformation. [76, 86] Accurately estimating SOS is challenging due to the complex interactions between operational parameters and failure mechanisms, especially under variable environmental and load conditions [76].

#### State of balance

According to Wang et al. [83], the SOB is a concept designed for the balance state characterization and regulation. It extends beyond assessing individual cell capacity balance to include the overall balance condition of the battery pack. The estimation of SOB incorporates multiple parameters, including cell voltage, pack voltage, temperature, internal resistance, and maintenance current. [83, 87]

### 3.5.3 Charging, discharging and life cycle parameters

#### Charge and discharge rate

The rate at which a battery is charged or discharged relative to its nominal capacity is defined as the charge and discharge rate, also known as the C-rate. While batteries capable of operating at high C-rates can deliver greater power output with respect to their nominal capacity, they are also subject to increased thermal stress and accelerated degradation, which can reduce overall cycle life. [71]

#### Depth of discharge

The DOD is a critical parameter influencing the performance and lifetime of batteries. According to Rufer [74] DOD represents the amount of electrical energy extracted from a battery relative to its total capacity, typically reported as a percentage. Operationally, the DOD is also defined as the difference between the upper and lower SOC limits within a charge–discharge cycle, and it is commonly expressed as a percentage [71]. For instance, cycling a battery between 80% and 30% SOC corresponds to a DOD of 50%. Battery cycling refers to the repeated process of charging and discharging, where one full cycle consists of a complete discharge followed by a recharge.

DOD is closely linked to the cycle life of a battery. The term cycle life describes the number of cycles a battery can complete before reaching a defined end-of-life criterion. As discussed in Section 3.4, this criterion typically corresponds to a reduction in usable capacity to approximately 80% of the initial value or a substantial increase in internal resistance, often approximated as a doubling of the original value. Referring to aging of LIB (see Section 3.3), higher DOD levels accelerate degradation mechanisms and results in cyclic aging becoming the predominant aging process, leading to a shorter cycle life. Conversely, low DOD cycles often result in minor cyclic aging effects and calendric aging is expected to be dominant [32]. Thus, understanding and managing DOD is essential for optimizing battery longevity and ensuring reliable operation across diverse applications.

### Remaining useful life

The RUL is similar to SOH and refers to the estimated remaining time a battery can continue to operate within its intended functional parameters before reaching a predefined failure threshold [64, 88]. According to Ansari et al. [88], the RUL prediction of LIBs depends on number of cycles and battery capacity. While SOH assesses the extent of degradation relative to the maximum allowable limit, RUL prediction extends this evaluation by estimating both the current state and the expected future rate of degradation [64]. To enhance reliability and minimize safety risks, the RUL is commonly estimated using either model-based techniques or data-driven techniques. [88]

### Energy throughput

Energy throughput refers to the total amount of energy that a battery stores and releases within its lifetime. Throughput is typically measured in kWh or MWh referred to as charging and discharging. It represents the cumulative energy exchanged through charging and discharging processes. [89, 90] Monitoring energy throughput enables the optimization of charging and discharging strategies, for example by adjusting the DOD, in order to reduce degradation and extend battery lifetime. It also provides a quantitative basis for assessing when a battery is approaching the end of its useful life, which supports timely replacement decisions and ensures sustained system performance and reliability. [89]

# 4. MAINTENANCE AND CONDITION MONITORING

Neglecting maintenance or relying on outdated equipment often leads to reduced production quality and inefficiencies, which in turn cause lower productivity, higher product costs, and diminished profitability. Efficient and proactive maintenance practices are therefore essential to operational strategy, as they directly affect cost control, productivity, and process efficiency. By strengthening these areas, effective maintenance can substantially improve a company's competitiveness and profitability in an increasingly demanding market environment. [91] Therefore, effective and reliable maintenance planning and scheduling are crucial for optimizing the operation and management of physical assets, in this case BESSs.

This chapter examines the maintenance and condition monitoring from the perspective of BESSs to identify approaches that best support reliability, efficiency, and life cycle optimization. Firstly, the chapter reviews different types of maintenance strategies, including corrective, preventive and predictive, with a focus on their applicability to large-scale and grid-scale BESSs. Each maintenance type is described in terms of its objectives, and potential benefits, as well as its limitations in practical use. This chapter examines how advanced technologies can enhance the maintenance and condition monitoring of battery energy storage systems. It explores how the effective use of data and analytical capabilities enables more accurate diagnostics, timely maintenance actions, informed decision-making, and value creation. In addition, the chapter addresses the role of cloud-based IoT services in strengthening monitoring and control functionalities, thereby supporting predictive maintenance, extending system lifetime, and improving overall operational efficiency. Finally, the chapter discusses how data-driven maintenance integrates continuous data collection, fault identification, and predictive analytics to form intelligent maintenance workflows. The objective is to demonstrate how these data-centric approaches contribute to prolonged system lifetime, reduced maintenance costs, and improved operational performance in BESSs.

## 4.1 Maintenance strategies

The maintenance concept is defined by the standard *SFS-EN 13306:2017* [70], as follows: "combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function." On the other hand, a maintenance strategy refers to a management approach designed to achieve maintenance goals and objectives [70, 91]. The maintenance strategy includes decisions on when, where, and how maintenance tasks are performed and what resources are needed. Depending on the specific needs and characteristics of the system or object being maintained, different types of maintenance strategies can be applied. These strategies provide distinct benefits and are selected according to

the particular needs and conditions of the organization. [91, 92] The maintenance strategy can be categorized based on the timing of repairs in relation to equipment failure [93]. A multitude of authors have classified maintenance strategies in divergent ways. The two fundamental strategies are unplanned (reactive) maintenance and planned (proactive) maintenance [94]. The primary types of maintenance concepts identified in the literature include corrective maintenance (CM) and preventive maintenance (PM) [70, 91, 93, 95], which can be further categorized into distinct approaches such as time-based maintenance (TBM), and condition-based maintenance (CBM) [91]. Some of the most common designations are illustrated in Figure 4.1.

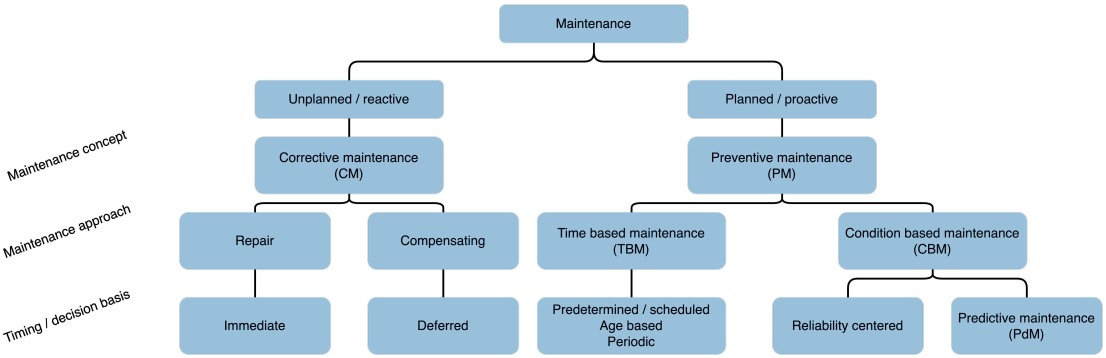
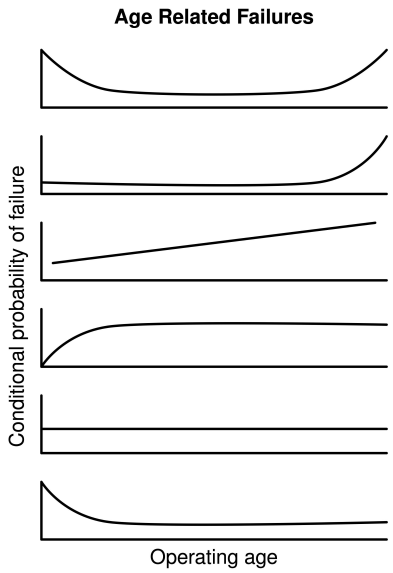



***Figure 4.1.*** *Hierarchy of maintenance strategies [70, 91, 96, 97].*

Identifying the failure pattern is essential for selecting the most technically viable maintenance or failure management strategy. This requires a comprehensive understanding of the failure events and the associated faults they produce [98]. According to NASA Office of Safety and Mission Assurance [99], study based on failure data revealed that traditional scheduled maintenance policies were often ineffective in reducing failure rates, despite their high cost. This was because, for many components, the likelihood of failure did not increase with operational age, which means that fixed-interval maintenance alone was not an adequate strategy [99]. The probability of failure can be modeled using various curves, as shown in Figure 4.2, where the time element serves as the fundamental unit of measurement, with adjustments made to account for factors such as cycles, elapsed hours, hours utilized, and distance traversed. The vertical axis is employed to denote the conditional probability of failure. The figure summarizes the results of three different studies on failure probability behavior as a function of time. Failure has been categorized into six types.

The distinction between failure patterns in simple and complex components plays a key role in maintenance planning. Simple, single-part items, such as tires, brake pads, compressor blades, and structural elements, often show a clear link between aging and reduced reliability, especially when affected by wear, fatigue, or designed for limited use. These typically align with failure types A and F. In such cases, applying age-based limits, such as thresholds based on operating time or stress cycles, can help improve the reliability of the overall system. In contrast, complex systems tend to follow more variable failure behaviors, often represented by types B, C, D and E, where reliability depends on multiple conditions. Complex systems frequently encounter early-life failures, also referred to as infant mortality, followed by a phase where the probability of failure either stabilizes or rises steadily. In contrast to simple components, these systems rarely exhibit a distinct wear-out phase. In many cases, scheduled overhauls can unintentionally raise the overall




| | UAL 1968 | BROMBERG 1973 | U.S. NAVY 1982 |
|---|---|---|---|
| Type A Bathtub | 4% | 3% | 3% |
| Type B Wear-out curve | 2% | 1% | 17% |
| Type C Fatigue wear curve | 5% | 4% | 3% |
| Type D Initial break-in period | 7% | 11% | 6% |
| Type E Constant failure rate curve | 14% | 15% | 42% |
| Type F Infant mortality | 68% | 66% | 29% |

***Figure 4.2.*** *Conditional probability of failure curves (adapted from [98, 99])*

failure rate by reintroducing early-life failures into an otherwise stable system. Research has demonstrated that random failures of all recorded equipments and components account for approximately 77% to 92% of all failures, while age-related failures represent only 8% to 23%. [99]

### 4.1.1 Corrective maintenance

According to the standard *SFS-EN 13306:2017* [70], CM refers to "maintenance activities performed after a fault has been identified, with the objective of restoring the item to a condition in which it is capable of fulfilling its required function." CM is most suitable for non-critical and easily repairable equipment [93]. In circumstances where failures do not inflict significant risks, adequate downtime is acceptable, and the asset value is relatively low, adopting a CM approach can be an acceptable and cost-efficient option. [96]. However, for components whose failure could result in considerable downtime or operational disruption, a more proactive maintenance strategy is required [93].

CM is generally recognized as inefficient due to the high costs and downtime associated with unexpected failures. While CM provides short-term cost advantages and operational simplicity, it may result in higher long-term expenses due to unplanned equipment failures, increased safety risks, and production downtime. [91, 93, 95]

### 4.1.2 Preventive maintenance

As defined in the standard *SFS-EN 13306:2017* [70], PM refers to "maintenance actions performed with the aim of evaluating and/or mitigating degradation, thereby reducing the likelihood of an item failing." PM aims to prevent failures and is designed to extend the life of equipment, reduce unplanned downtime, and minimize the need for unplanned repairs [91, 93, 100]. However, PM cannot fully eliminate the risk of unexpected failures, particularly in components not included in the maintenance schedule [93]. When not supported by failure data, fixed-interval scheduling can result in unnecessary part replacements and

increased costs [91, 93, 100]. Furthermore, there are two main reasons why frequent replacement of parts may be disadvantageous. First, substituting original components can potentially reduce the overall lifespan of the equipment due to risks such as installation errors, hidden defects, or incompatibility. Second, newly installed parts and consumables often have a higher probability of defects or early failure compared to components that have already proven reliable in operation. [93]

PM plays a crucial role in enhancing system reliability, ensuring safety, and maintaining continuous operations, despite its higher initial investment [91]. The optimal ratio between PM and CM is highly context-dependent and shaped by factors such as asset criticality, operational demands, and the organization's economic environment [95]. Both Stenström et al. [95] and Hamasha et al. [91] emphasize the need to account for user-related costs, such as delays, lost production, maintenance work, and life cycle costs including costs and benefits to society, owners, users and the environment, in maintenance planning to fully realize the value of preventive strategies. Chen et al. [82] states that CM and PM are traditional maintenance strategies that often result in lower system reliability, increased downtime, and higher overall maintenance costs.

### 4.1.3 Time-based and condition-based maintenance

TBM is a preventive strategy in which maintenance is predetermined or scheduled at regular intervals, regardless of the current condition of the equipment. According to *SFS-EN 13306:2017* [70], predetermined maintenance is defined as "preventive maintenance carried out in accordance with established intervals of time or number of units of use but without previous condition investigation." In contrast, scheduled maintenance is described as "maintenance carried out in accordance with a specified time schedule or specified number of units of use." The aim is to reduce the likelihood of unexpected failures by servicing equipment before issues arise. TBM also supports overall equipment effectiveness by promoting routine tasks. [91]

TBM estimates the expected lifespan of equipment using time-of-failure data or statistics. It operates under the assumption that the failure behavior of the asset is predictable and consistent over time. However, the duration of the operating period may not be a reliable indicator for assessing the condition of a product, as the rate of deterioration is influenced not only by time but also by various operational and environmental factors. As a result, TBM may lead to unnecessary interventions, interruptions to normal operations, and in some cases, unintended malfunctions due to maintenance-related disruptions. [91]

As stated in standard *SFS-EN 13306:2017* [70] CBM is "preventive maintenance that includes an evaluation of physical conditions, investigation, and potential subsequent maintenance actions." Mostafa et al. [96] describes CBM as a process that integrates technology and human skills. This integration utilizes a combination of all available diagnostic and performance data, operational parameters, maintenance history, operator logs, and design data to evaluate the probability of a potential failure. [91, 96] CBM activities are executed in accordance with the condition indicated by these measurements, rather than on a predetermined schedule. CBM aims to reduce unnecessary interventions and minimize disruptions to normal operations by enabling maintenance actions only when specific indicators of degradation are detected. When diagnostics are accurate, CBM supports timely decision-making to prevent potential failures, thereby improving opera-

tional efficiency and reducing overall maintenance costs. This approach is implemented exclusively in situations where indications suggest an impending failure that could impair the performance of the asset or result in a total loss of functionality [91].

As stated in Hamasha et al. [91] CBM may not always be the most economically viable option, particularly when equipment issues are minor or non-critical. In such instances, CM may be more appropriate. Conversely, TBM is considered the most effective strategy when the service life of machinery or components can be reliably predicted, allowing maintenance to be scheduled at optimal intervals. [91]

### 4.1.4 Predictive maintenance

As industries seek to optimize operational efficiency and reduce downtime, traditional maintenance approaches have shown limitations [93]. Conventional corrective and preventive strategies are often predicated on fixed schedules or post-failure actions, which do not account for real-time operating conditions or emerging signs of degradation. This discrepancy has prompted the emergence and implementation of PdM, a paradigm shift in maintenance management towards a proactive, data-driven approach. The standard *SFS-EN 13306:2017* [70] defines PdM as "condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item." PdM is a proactive approach that utilizes advanced digital technologies such as condition monitoring, data analysis, AI and machine learning (ML) [93, 101]. These technologies have significantly advanced the capabilities and adoption of PdM [93].

PdM encompasses a variety of techniques aimed to monitor system components in order to anticipate, forecast, and detect early signs of potential faults. This allows for timely maintenance before faults become critical, rather than relying on fixed schedules or post-failure intervention. [91, 93, 101] The selection of the appropriate PdM method for a specific problem or monitored equipment can be challenging due to the broad spectrum of available techniques [93].

As argued by Cakir et al. [102], PdM is the latest type of maintenance, offering the longest service life and reliability for equipment, as well as the most environmentally friendly and cost-effective solution. It is important to acknowledge that the aforementioned benefits are the result of the author's assessments, and their significance and relevance may vary depending on the characteristics of the system in question and the context in which it is implemented. Molęda et al. [93] explains that the digitization and transformation of predictive processes enhance the understanding of operational phenomena and support more accurate, evidence-based decision-making with reduced reliance on intuition. By integrating data from multiple sources and applying advanced analytics, organizations can implement new maintenance strategies, improve work and inventory planning, increase production efficiency, and enhance safety levels.

According to Molęda et al. [93], the analysis of process parameters involves using actual measurement data to derive indicators that reflect equipment performance or health status. By tracking these indicators over time, changes in the condition of the equipment can be effectively assessed. This method is commonly integrated with technologies such as the IoT, ML, and big data analytics. The large volumes of data generated by modern industrial systems provide valuable input for predictive maintenance applications. Perfor-

mance indicators can be directly computed from operational data. [93] For example, the efficiency of a BESS can be assessed by comparing the electrical energy output to the energy input over a given period. Additionally, a health index model can be constructed based on historical operational data.

### 4.1.5 Reliability-centered maintenance

Rausand and Høyland [97] define reliability-centered maintenance (RCM) as a systematic approach to analyzing system functions and failure modes, with the goal of prioritizing PM tasks in a safe and cost-effective manner. In RCM, the focus is on the functions of the system rather than on individual components. The objective is to reduce maintenance costs by concentrating only on the most critical system functions and eliminating or avoiding maintenance activities that are not strictly necessary. For existing maintenance programs, this often leads to a reduction in the number of PM tasks. [97]

Reliability-centered maintenance is a process aimed at improving equipment availability by focusing on its reliability and maintainability. Reliability refers to the ability of an asset to perform its intended functions at a specified time under given conditions. Maintainability refers to the ability of an asset to be restored to operational condition through maintenance activities. The availability of an asset is a combination of its reliability and maintainability. Reliability can be measured by the mean time to failure (MTTF), and maintainability by the mean time to repair (MTTR). [97]

Average availability $A_{\text{av}}$ can be calculated as:

$$A_{\text{av}} = \frac{\text{MTTF}}{\text{MTTF} + \text{MTTR}} \tag{4.1}$$

This formula illustrates how RCM increases availability by reducing unnecessary PM actions, thereby shortening the average repair time. RCM also focuses on the most critical maintenance tasks to ensure that reliability levels remain high.

The concept of RCM was originally developed to meet the needs of the aviation industry and was later adopted in the nuclear power sector to guide maintenance activities. RCM supports decision-making and can be used as a foundation for designing preventive maintenance programs. [97]

### 4.1.6 Prescriptive maintenance

Prescriptive maintenance goes beyond predicting failures. Prescriptive maintenance is a maintenance strategy that uses real-time data, models, and predictive analytics not only to forecast equipment failures but also to recommend optimal actions to prevent or mitigate them. [103, 104] It leverages sensing technologies, expert knowledge modeling, and predictive data analytics based on historical and real-time data to forecast potential failures and suggest corrective measures. This approach enables not only failure prediction but also decision-making that optimizes system performance and reliability. [103]

Prescriptive maintenance employs machine learning, statistical modeling, and optimization algorithms to support maintenance decision-making, reduce downtime, and enhance asset performance, making it particularly valuable in the dynamic operation of complex

systems [104]. According to Giacotto et al. [104], the exact scope of prescriptive maintenance remains somewhat ambiguous, as various authors have proposed differing definitions without reaching a unified view. For the purpose of establishing a common basis for discussion, these authors describe prescriptive maintenance as a proactive maintenance strategy that leverages IoT technologies, asset health prognostics, and prescriptive analytics to recommend courses of action aimed at optimizing maintenance activities and maximizing asset availability [104].

## 4.2 IoT and cloud-based monitoring

The IoT refers to a network of interconnected digital and mechanical devices equipped with unique identifiers that communicate and share data without requiring manual intervention [105, p. 2]. These devices, ranging from everyday consumer products such as smartwatches to industrial equipment, are connected through the internet, enabling real-time data collection, analysis, and automation. IoT transforms objects into active participants in communication networks, allowing them to exchange information and act autonomously. [105, p. 7-15] The growing adoption of IoT platforms in industrial contexts has significantly transformed the way systems are monitored, maintained, and optimized. However, as the number of available platforms continues to grow, so does the variability in their capabilities, architectures, and alignment with industrial needs. [106]

In industrial contexts, IoT is increasingly viewed as a closed-loop system, where sensors continuously collect operational data (e.g., temperature, vibration, images, or velocity) that is stored, processed, and analyzed to support decision-making. This enables applications in areas such as maintenance management, optimization, operations research, safety, and security, across diverse domains including transport, energy, finance, agriculture, and smart infrastructure. [107]

A key application of IoT is in condition monitoring and predictive analytics. By leveraging continuous data streams, IoT-based monitoring enables accurate diagnostics and forecasting of equipment health, thereby preventing unplanned downtime and prolonging system life. Advanced analytics, including statistical techniques, signal processing, and ML methods, are increasingly integrated to identify patterns, predict failures, and optimize performance. IoT-based predictive maintenance offers significant benefits, including reduced equipment replacement, enhanced safety, improved availability, and greater efficiency. [107]

Furthermore, the integration of cloud technologies expands the capabilities of IoT-enabled condition monitoring by facilitating scalable data storage, collaborative applications, and remote access to system information. Cloud-based SCADA systems support real-time publishing of data, multi-location monitoring, and collaboration across distributed assets such as wind farms, irrigation networks, and industrial plants. This architecture allows for pervasive analytics and faster decision-making, reinforcing the role of IoT in advancing Industry 4.0 through smarter, connected, and more resilient systems. [107]

### 4.2.1 Remote monitoring

Remote system monitoring refers to the capability to observe and quantify the behavior of a system located at a distance from the user. Such monitoring is enabled by the inte-

gration of operational data and in-site sensor measurements into a centralized platform. This approach replaces labor-intensive manual practices of recording system behavior and responding only after failures occur, enabling instead a more proactive and preventive strategy for service and maintenance. When systems are situated in highly remote or inaccessible locations, remote monitoring becomes particularly critical, as it ensures operational continuity and reduces the need for on-site activity. [108]

Incorporating remote monitoring and control systems into BESS infrastructure allows operators to track key battery parameters continuously, receive alerts about operational anomalies in a timely manner, and manage battery functions remotely. This connectivity improves system supervision efficiency, enables predictive maintenance, and streamlines diagnostic procedures. These capabilities are essential for ensuring the reliable operation of battery systems, especially in distributed or large-scale applications. [15]

The importance of remote monitoring becomes evident when comparing the two maintenance pathways illustrated in Figure 4.3. In systems without remote monitoring, maintenance is inherently reactive. A fault results in the immediate loss of system functionality, after which technicians must diagnose the issue with limited historical information. Component replacement introduces procurement delays, extending the MTTR and generating considerable operational losses. These challenges are exacerbated when assets are located in remote or inaccessible environments. [108]

In contrast, systems equipped with IoT-enabled remote condition monitoring benefit from continuous data acquisition from operational controls, sensors, and auxiliary systems. This data supports real-time health assessment and enables the prediction of failure modes and component-level MTTF through analytics. Spare parts and personnel can be prepared in advance, and maintenance can be scheduled during planned downtime. As a result, failures are prevented proactively, system availability is improved, and the economic justification for remote monitoring becomes clear through reduced MTTR and measurable return on investment. [108]

### 4.2.2 The role of IoT in energy storage system monitoring

The integration of IoT technologies into BESSs systems has become a key enabler of advanced real-time monitoring, optimization and control [16]. IoT devices, such as sensors and communication modules, are used to collect data from the battery system and transmit it to cloud-based platforms. This approach supports continuous monitoring of battery health. [15] BESSs equipped with a wide range of IoT devices can send operational data directly to centralized data centers or SCADA systems [15], facilitating centralized and scalable management of multiple battery systems from a single control point [16]. By facilitating communication between decentralized BESS units and grid management platforms, IoT technologies enhance the controllability, scalability, and security of modern power systems. This integration enables real-time oversight, continuous system health monitoring and supports data-driven decision-making at both the local and system-wide levels. [16]

A fundamental function of IoT-based systems is real-time data acquisition. This is achieved through the integration of embedded IoT sensors, which monitor essential parameters such as voltage, current, and temperature, ensuring uninterrupted data collection. Once the data is collected, it is wirelessly transmitted to cloud service plarforms, allowing oper-

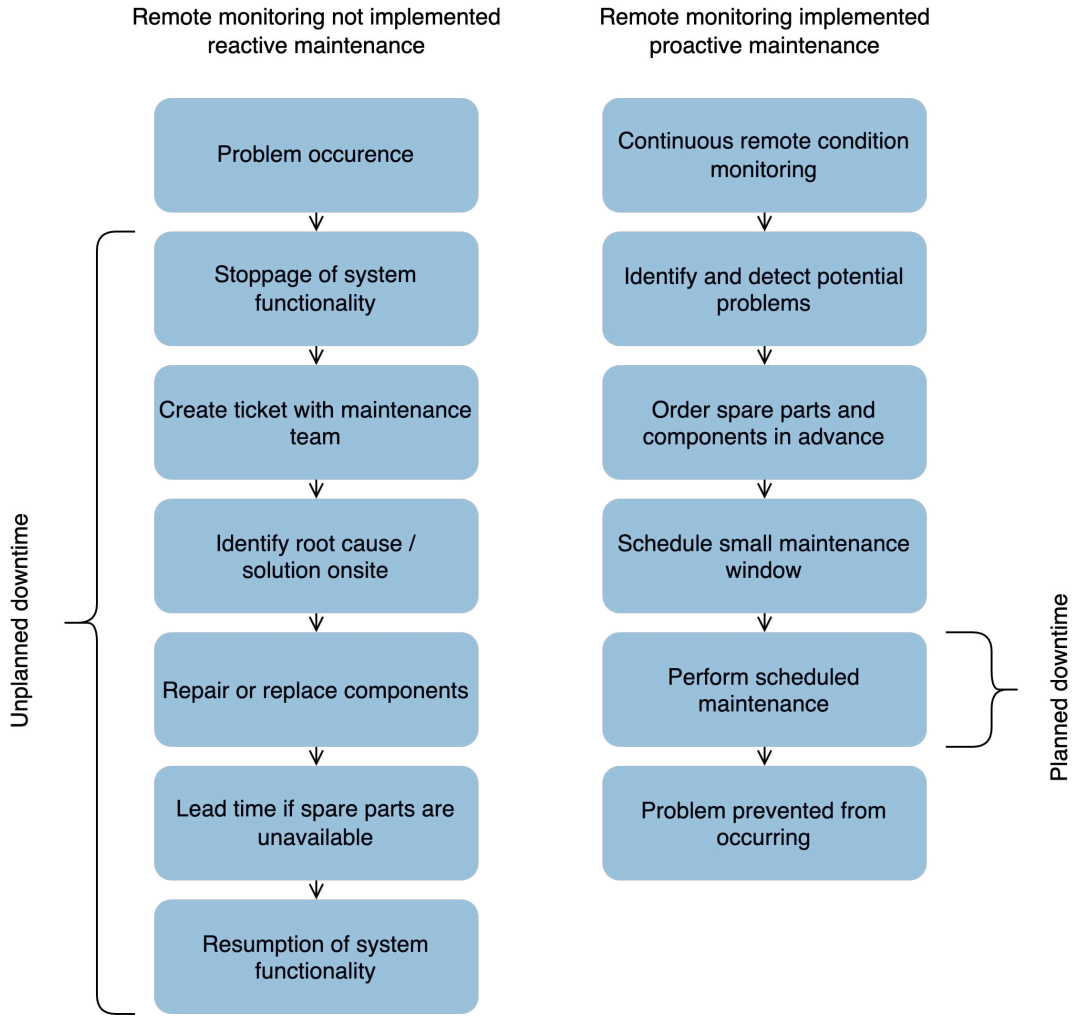



***Figure 4.3.*** *Comparison of user journeys without and with remote monitoring (adapted from [108]).*

ators to access the information remotely. This facilitates constant observation of system performance and enables rapid response to any abnormal conditions. [15]

Following data transmission, cloud-based analytics systems process the data to detect potential issues or performance degradation. This enables predictive maintenance and performance optimization by utilizing ML algorithms to predict potential faults and battery health metrics such as RUL and capacity retention. If anomalies or deviations are identified, the system can issue warnings and initiate corrective actions, such as activating cooling mechanisms or implementing load reduction strategies. [15].

The increasing complexity of modern battery systems, particularly in high-demand applications such as EVs and grid-scale BESSs, has created a need for enhanced functionality. At the system component level, modern BMSs are increasingly built upon IoT and cloud-based infrastructures. As Khan et al. [15] and Adhikaree et al. [109] notes, integrating IoT technologies and cloud computing into BMSs improves their functionality by enabling accurate real-time and remote health monitoring and control of battery cells, modules and packs. It creates a foundation for advanced BMS capabilities including predictive analytics through data-driven modeling approaches, fault diagnosis, and adaptive

control strategies, enhancing operational safety, and minimizing performance variability across the system [10, 15, 109]. By incorporating these technologies, BMSs become more responsive and intelligent, contributing to the overall efficiency and reliability of energy storage infrastructures [16].

## 4.3 Data-driven maintenance

Data-driven maintenance represents a transformative approach in industrial maintenance, leveraging advanced technologies to optimize maintenance schedules, reduce costs, and improve equipment reliability. According to Jasiulewicz-Kaczmarek et al. [110]. the term "data-driven" means the fact that implemented activities and processes are primarily stimulated by data, not by intuition or experience. Increasing easier access to data and awareness of the possibilities offered by data in the decision-making process drives enterprises to shift towards a new type of maintenance strategy called data-driven maintenance [110]. Unlike traditional time-based or reactive maintenance strategies, data-driven methods rely on continuous data collection, analysis, and interpretation to anticipate potential failures and schedule maintenance actions proactively [93]. In the context of BESS, this approach is particularly valuable due to the system complexity and the interdependence of their electrical, thermal, and control subsystems.

As outlined in Chapter 3, BESS are composed of numerous interconnected components, each with specific degradation patterns and operational characteristics. Building on this foundation, the current section focuses on how data-driven methodologies can be applied to monitor and predict these degradation processes, enabling more intelligent and predictive maintenance.

A key element of data-driven maintenance is the development of a fault and degradation database, which compiles detailed information on component-level aging and failure processes. By systematically recording and classifying these events, the database serves as a reference for identifying patterns in operational data. [93] When new data from a specific BESS installation aligns with known fault signatures, the system can automatically initiate model optimization or protective control measures. This enhances operational safety and enables maintenance actions to be taken before major failures occur.

The approach is further strengthened through the use of digital twin technology, which links the physical BESS and its local controllers with a cloud-based environment for data modeling, state estimation, and system optimization. The digital twin continuously receives sensor data from the operating system, allowing for real-time updates of the model and accurate estimation of system health and performance.

### 4.3.1 Fault detection and prognostics

To extend the RUL of a BESS, several maintenance practices and strategies can be employed. These practices focus on advanced management systems, PdM, and repurposing strategies. Accurate prediction of battery condition is essential for improving operational efficiency, reducing overall maintenance and operating costs, and preventing potential system failures. [48]

According to Molęda et al. [93], manual analysis performed by experts is usually highly accurate. However, it is very time-consuming and requires extensive knowledge of the

field. The complexity of the system has been identified as a factor that limits the applicability of root cause analysis. Therefore, it is worth considering the use of data-driven algorithms to automate or significantly simplify the process of identifing the underlying root causes of failures and to avoid their future occurrence. [93]

Determining the various states of batteries, such as SOH, SOS, SOC, SOT, SOP, and SOE, is imperative for effective battery management, particularly in diverse operating conditions. An accurate assessment of these states facilitates enhanced battery management and improves the prediction of battery RUL. [58] Kumar et al. [80] states that integrating SOC and SOH predictions with real-time health indicators contributes to the development of robust predictive maintenance frameworks. The availability and use of high-quality battery datasets, often collected from multiple sensors and under varying operational scenarios, play a crucial role in supporting these estimations. Leveraging existing datasets not only saves time in data acquisition but also enhances model accuracy and supports a better understanding of degradation patterns and aging mechanisms.

In this context, data-driven prognostic modeling has become essential for predictive maintenance. Advanced ML techniques, such as enhanced random forests and hybrid models, have demonstrated significant potential for accurately and flexibly forecasting SOC and SOH. By combining real-time health indicators with SOC forecasting, these models significantly optimize battery usage and prevent premature failure. [80] Overall, integrating rich battery datasets with ML approaches enables developing more robust and intelligent battery management systems.

**Data analytics**

The primary goal of adopting a predictive and data-driven approach is to enhance human capabilities. Organisations seeking to implement a data-driven approach must address the multifaceted challenges associated with such transformation. This involves developing a comprehensive regulatory framework and governance model that considers both organisational and technological dimensions. It requires identifying potential barriers, proposing feasible solutions, and analysing the roles, interests, and preferences of all relevant stakeholders. Furthermore, it is essential to evaluate the compatibility of existing business processes and technological infrastructures with the intended data-driven strategy. [111]

Data analytics refers to the process of discovering, interpreting, and communicating meaningful patterns in data to support informed decision-making and operational improvement [112]. According to Karim et al. [111] and Tekinerdogan and Akşit [112], data analytics can generally be divided into four categories: descriptive, diagnostic, predictive, and prescriptive. Descriptive analytics focuses on reporting what has happened, such as identifying when an asset has failed. Building on this, diagnostic analytics seeks to determine why the failure occurred by analyzing data to uncover root causes. [111, 112]

Predictive analytics is an advanced analytical approach that uses current and historical data to estimate the likelihood of future behaviors, trends and events, such as forecasting whether similar failures might occur in comparable assets. The most advanced form, prescriptive analytics, uses these predictions to recommend optimal actions or automate decision-making processes. [111, 112]

In maintenance applications, predictive analytics combines reliability and maintainability

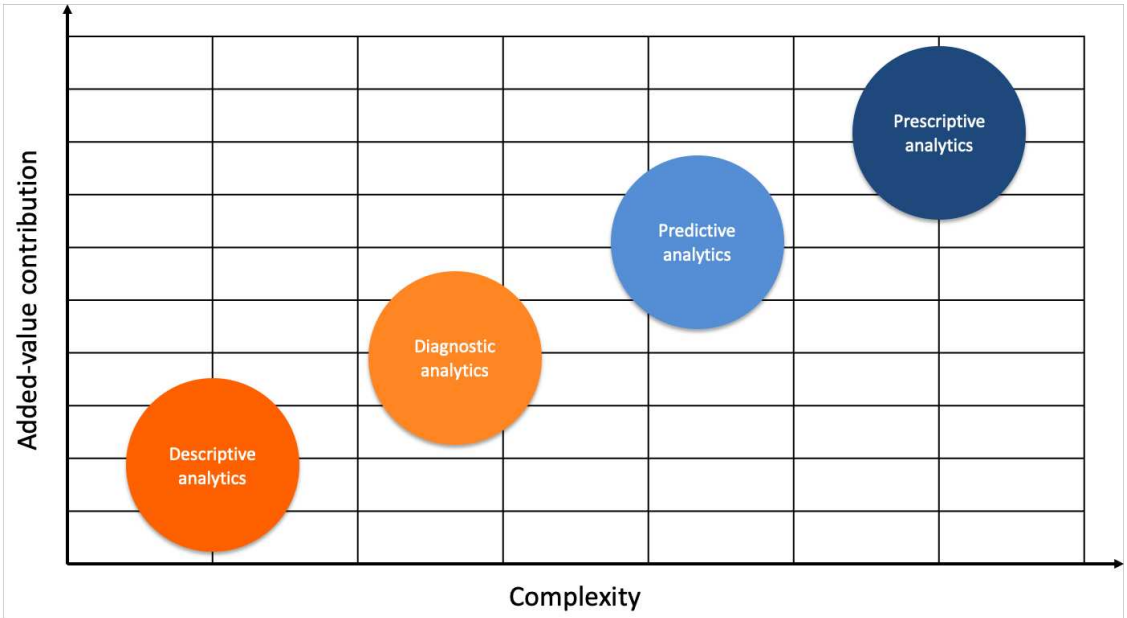



***Figure 4.4.*** *Types of data analytics (adapted from [111]).*

data with operational and business planning information, such as planned operations and maintenance. Predictive models are constructed using statistical methods and ML or deep learning algorithms, enabling the identification of patterns, estimation of probabilities, and forecasting of outcomes. Predictive analytics take advantage of large datasets and are capable of compensating for missing values by leveraging contextual data and observations. [111]

A wide variety of modeling approaches and estimation methods have been employed to support key battery management functions such as voltage and current monitoring, charge–discharge estimation, protection and cell balancing, thermal regulation, RUL and advanced battery state prediction [13]. Data-driven learning techniques include fuzzy logic controllers, neural network algorithms, support vector machines, genetic algorithms and nonlinear observers. Stochastic methods include Kalman filters, particle filters, and Markov models. Furthermore, there are more advanced methodologies, including deep learning architectures and hybrid methodologies. [13, 72, 111, 113]

The performance of data-driven methods is highly dependent on the quality and representativeness of the training dataset. If the training data does not sufficiently cover the operational conditions encountered during real-time use, the resulting model may produce inaccurate state estimates. This sensitivity to unseen data remains a key limitation in the deployment of data-driven battery management solutions. [13]

### Artificial intelligence and machine learning

Artificial intelligence is the ability of machines and systems to acquire and apply knowledge and act intelligently. AI is widely regarded as a powerful tool that can support, enhance, or even autonomously generate decisions traditionally made by humans [111]. ML is a subfield of artificial intelligence that allows systems to learn and improve from large data sets without explicit programming. ML involves developing algorithms that can

identify patterns in data and construct models for specific tasks. These algorithms facilitate accurate predictions and adaptive, intelligent behavior. Deep learning, a subset of ML, uses multi-layer neural networks inspired from the neural network in human brain to learn from large datasets and is highly effective for complex, high-dimensional data. [114] This is especially relevant where processes are influenced by hundreds or even thousands of physical variables [115], such as voltages, currents and temperatures [79].

According to Susto et al. [115], the growing availability of data is changing decision-making processes in several areas of operation, such as scheduling, maintenance management, and quality improvement. ML methods offer increasingly effective solutions in these areas, supported by advances in hardware, cloud-based solutions, and algorithms [115]. According to the findings of numerous studies conducted by Nyamathulla and Dhanamjayulu [13],Ul Hassan et al. [72], Ansari et al. [88], Wang et al. [79], and Ghazali et al. [40], various ML and deep learning algorithms are used to predict battery health, state estimation and RUL with high accuracy. Such predictive capabilities are critical for effective management and maintenance of the battery [40]. Ghazali et al. [40] also noted that integrating ML into battery monitoring has proven to be an efficient and effective way to predict battery lifespan. According to Nyamathulla and Dhanamjayulu [13] there has been significant interest in these methods and these methods are preferred because they offer increased accuracy, greater learning capacity, improved generalization performance, and faster convergence speed.

AI algorithms are increasingly being integrated into BMSs to enhance their capabilities in classification, regression, and optimization. With the growing availability and quality of operational data from large-scale battery systems, AI-based methods are gaining traction for integrated state estimation and predictive diagnostics within the battery research community. Various AI models have been used for battery state estimation. These methods are useful for estimating the SOH and predicting the RUL, both of which are critical for real-world applications. Because battery performance degrades progressively over time, it is essential to detect degradation early and model its trajectory for accurate life expectancy forecasting. [76]

As Ramgir [105, p. 233] asserts, a significant challenge facing AI is the issue of trust. Since humans are responsible for designing and training these systems, they also influence the ethical frameworks within which AI operates. This is particularly relevant in systems that rely on deep learning, where intelligence is derived from the training data. [105] In addition, AI-based methods frequently necessitate substantial datasets for training, and the training process is often time-consuming [76]. Consequently, the decision-making capabilities of AI are inherently shaped by the quality and nature of the input data. The reliability and ethical standing of AI systems is contingent upon the data to which they are exposed, as these systems are selected and curated by humans, thereby reflecting human choices and potential biases. [105]

**Digital twin**

Digital twins are increasingly recognized as a key enabling technology for Industry 4.0, closely connected to the IoTs and used to forecast the behavior of cyber-physical systems [116]. A digital twin is a virtual representation that mirrors the structure and behavior of a physical object or system. Digital twins provide a continuously updated virtual model of a physical asset, enabling remote monitoring, inspection, and analysis, particularly valuable

when the asset is difficult to access. The digital twin is dynamically linked to its physical counterpart through real-time data, capturing operational behavior and environmental interactions, with sensor data playing a central role in enabling it to reflect current conditions and respond accurately to changes. [111] The effectiveness of digital twins depend on model accuracy, computational efficiency, and the ability to integrate aging effects and scenario-based analyses for real-time or near real-time use [116].

Digital twins support the aggregation of high-fidelity data and are effective for managing complex and high-value systems. The primary objective is to enable informed decision-making by offering detailed insight into the current state of the asset and its likely future behavior. Depending on the application, digital twins facilitate real-time visualization, anomaly detection, diagnostics, predictive simulations, control system design, and confidence assessment of predictions. They also assist in estimating RUL, scheduling maintenance, and visualizing components that are otherwise inaccessible. [111]

The integration of IoT technologies is fundamental to digital twin operation, as IoT devices serve as the communication bridge between the physical asset and its digital replica, ensuring continuous synchronization and data exchange between the two representations. Digital twins are increasingly applied to enhance intelligence across business functions, operational decision-making, and maintenance strategies. By enabling real-time monitoring, simulation, and analysis, they contribute to sustainable and efficient asset management frameworks [111].

Digital twins allow real-time modeling and monitoring of BESSs, improving safety, reliability, and operational efficiency. For a BESSs digital twin can support multiple functions, including battery degradation assessment, enable online SOC and SOH forecasting for battery management, and provide monitoring, diagnostics, lifetime prognostics, fault detection and prediction, performance optimization, and cyber attack detection and mitigation. [31, 116] Integrating digital twin technology with reinforcement learning algorithms further enhances real-time state estimation and predictive maintenance, optimizing energy distribution and battery performance [117]. According to Tang et al. [31] the digital twin enables an effective framework for data-driven modeling and large-scale data analysis by linking distributed BESS stations and aggregating their operational data. Within this framework, the battery model and its associated parameters can be periodically updated and identified using ML-based algorithms [116].

# 5. ANALYSIS OF COMPANY'S CLOUD-BASED IOT SERVICE

The purpose of this study was to examine how the company's cloud-based IoT service can improve the monitoring and maintenance of BESS, with a focus on identifying development needs related to data collection, system usability, reporting practices, and customer value. This chapter presents a system-level analysis of the current state of the monitoring platform. Conducted from a cross-sectional research perspective, this analysis draws on observations, technical documentation, and supporting interview insights to evaluate the system architecture, data availability, usability in daily operations, and alignment with both technical and business expectations.

The chapter begins by describing the architecture of the cloud-based IoT service and the data collection process. It then analyzes how the system is used in practice and evaluates the availability and quality of collected data signals. Identified technical limitations and user-reported challenges are discussed in the context of daily operations. The chapter also examines current performance reporting practices and their relationship to customer value delivery. The sections aim to answer corresponding research questions about how the company's cloud-based IoT service currently supports monitoring and maintenance activities, what data signals are available and how effectively they serve system supervision, and how performance reporting practices should be developed to meet the needs of maintenance personnel and external stakeholders while strengthening customer value.

## 5.1 System purpose, architecture and data flow

This section describes the purpose and technical structure of the current cloud-based IoT service, including its main components, communication protocols, and the flow of data from field devices to the cloud platform. The focus is on how data is collected, transmitted, stored, and visualized.

The company's cloud-based IoT service serves as the central platform for remote monitoring of large-scale BESSs deployed in industrial and utility environments. Its core function is to collect high-frequency operational data from multiple on-site devices, aggregate and store this information securely in the cloud, and provide structured access to both technical experts and business users. The system plays a critical role in facilitating remote diagnostics, identifying early signs of performance degradation, supporting maintenance workflows, and generating performance reports for internal and external stakeholders.

Within the architecture of cloud-based monitoring systems, the industrial IoT edge gateway acts as a key intermediary between physical devices at the operational level and higher-level data platforms in the cloud. Its primary role is to enable reliable and secure

communication with cloud services and connected assets, such as sensors, controllers, or energy storage components, while also providing preliminary data processing capabilities at the edge of the network.

The edge gateway collects data from local devices, often using industrial communication protocols. It can perform tasks such as data filtering, aggregation, or buffering before transmitting selected information to the cloud. This approach helps reduce the amount of raw data sent over the network, improves response times, and allows the system to operate even in environments where internet connectivity may be intermittent or unreliable.

From an architectural perspective, the gateway supports the overall system by increasing decentralization and fault tolerance. By handling basic processing tasks locally, it reduces the dependency on constant cloud connectivity. In addition, edge gateways are typically capable of running lightweight software modules or containerized applications that support monitoring, alerting, or preprocessing functions. These capabilities align with the principles of edge computing, where computational tasks are distributed closer to the data source.

To extend the capabilities of edge gateways and enable scalable edge-to-cloud operations, the system architecture can incorporate a lightweight runtime environment for deploying and managing applications directly at the edge. This approach extends the analytical capabilities traditionally found in cloud environments to the edge of the network, allowing systems to respond more quickly to local events and operate effectively even in environments with limited or intermittent connectivity. Instead of transmitting all raw data to a central system, edge devices can clean, aggregate, and evaluate data locally, sending only relevant insights upstream. This reduces bandwidth usage and supports offline functionality when network connections are unstable.

In analyzing the company's cloud-based IoT monitoring system, it was identified that the analytics currently applied primarily align with descriptive and diagnostic approaches. In the context of the company's monitoring environment, descriptive analytics provides an overview of system performance and operational status by summarising key data signals and parameters such as SOC, SOH, voltages, currents, and powers. This form of analytics provides insight into past events and supports daily system supervision through dashboards and alarms.

Diagnostic analytics complement this process by helping to understand why an event occurred. This helps identify the relationships between observed anomalies, such as deviations in the SOC, voltage imbalances, and unexpected trips, and their potential root causes. This allows maintenance and engineering teams to evaluate the circumstances that led to performance degradation or faults.

Although more advanced stages, such as predictive and prescriptive analytics, have not yet been fully implemented, the existing combination of descriptive and diagnostic analytics establishes a solid basis for future development. These analytical layers already support condition monitoring, basic fault analysis, and informed decision-making within the company's cloud-based IoT service infrastructure.

In the IoT service architecture, time-series measurement data originating from various field devices is collected, stored, and maintained using a cloud-based relational database. The solution employs a PostgreSQL database to store momentary parameter values received from all connected devices. This structure enables high-resolution monitoring,

historical analysis, and integration with downstream systems. The measurement interval is fixed at 1-second resolution, momentary data messages are received every 30 seconds and becomes available every 3 minutes. Data retention policies vary by system type. Currently, the system retains data for 30 days for active harmonic filters, static var compensators, and static synchronous compensator systems, while for ESS solutions, data is stored for up to 13 months.

## 5.2 Monitoring system in practice

### 5.2.1 Workflows and system usage

The remote monitoring system plays a central role in daily operations related to BESS deployment, maintenance, and follow-up. Interviewees consistently described it as the primary interface for accessing operational data from battery systems, with functionalities including real-time monitoring, alarm and trip tracking, and basic performance review.

Usage of the system varies significantly across organizational roles, reflecting the diverse functional needs of different teams. The interviews confirmed that while the platform serves as a critical tool for technical personnel, its adoption and usability differ depending on the team's proximity to system operations.

The service and software development and cloud solutions teams are the most active users of the system. Service team rely on the platform daily for monitoring system health, diagnosing faults, and verifying stability following installation or software updates. On-field technicians and proactive system oversight rely on frequent access to real-time alarm data and historical trends. Several interviewees emphasized the importance for remotely detecting anomalies, analyzing the profile of measured variables, and reacting to alarms and trips.

The software development and cloud solutions team engage with cloud-based IoT service primarily for infrastructure monitoring, debugging, and continuous development of new features. Daily operations involve checking the operational status of monitoring system, verifying the health of backend components, and ensuring that solutions remain online and actively transmitting data.

Although the sales team does not operate monitoring system directly in their daily routines, the system is an essential component in customer-facing activities, particularly when presenting and selling operation and maintenance agreements. The remote monitoring system is a key component of the performance monitoring service that the company offers as part of its operation and maintenance agreements. Its ability to collect, store, and provide access to comprehensive system data guarantees transparency for external stakeholders, traceability, and continuous performance monitoring.

In operational contexts, the system is used to confirm the successful installation of components such as fans, and assess component condition prior to on-site visits. A frequently mentioned practice was using the system to verify the scope of detected issues, often in conjunction with alarm and trip history checks. Users also relied on the platform to review trends in key parameters such as SOC, SOH, and core electrical metrics including voltage, current, and power. For more targeted diagnostics, such as monitoring the temperature or condition of contactors, the system was considered useful, albeit not compre-

hensive. With respect to preventive maintenance, interviewees reported that the system is sometimes checked before scheduled maintenance visits, and that measurement data are occasionally used to anticipate emerging service needs.

One critical use case involved proactive verification of performance guarantees. In contracts where warranties are time-bound, interviewees reported the need for regular monitoring to ensure compliance. This ongoing verification process highlights the strategic role of the system as a reporting tool, serving not only internal operational needs but also external obligations and client expectations.

While monitoring system was broadly acknowledged as an essential tool, its practical use revealed several limitations that affect workflow efficiency and usability. Multiple interviewees highlighted that monitoring system can serve as a starting point for system evaluation, but not the sole tool relied upon. For deeper troubleshooting or access to more granular data, users frequently turned to complementary systems such as SCADA, citing their superior visual representation and more intuitive interface. In some cases, the monitoring platform was used only during mandatory reporting periods or excluded entirely from root cause analysis, indicating that its perceived value varies significantly across user groups. Although the system was not consistently regarded as the primary troubleshooting tool, it nonetheless contributes meaningfully to several technical and reporting related processes.

### 5.2.2 Performance reporting practices

Performance reporting is a critical function that supports both internal maintenance operations and external stakeholder communication. Currently, the reporting process is largely manual and time-intensive, despite the existence of a centralized monitoring platform that provides access to essential operational data. Reports are typically compiled on an annual basis; however, in certain projects, external stakeholders request monthly reporting intervals. Monitoring platform serves as the backend system from which this reporting data is drawn, even if the actual reports are compiled manually.

The primary metric reported to external stakeholders is system availability, which is defined contractually using a one-hour resolution, although company commonly calculates availability at a 15-minute resolution to ensure higher precision. Other metrics commonly included in performance reports are the SOC, temperature, voltage and current trends, number and severity of alarms and trips, and maintenance activities performed and scheduled.

Despite the ability of the monitoring system to collect and store much of the necessary data, report generation currently involves a significant amount of manual work, particularly in compiling and formatting data into a customer-facing format. Interviewees described the manual extraction of screenshots from key performance indicators (KPI), trends and dashboards as a routine yet inefficient step, particularly when preparing reports or sharing insights internally. This manual effort is perceived as inefficient and prone to inconsistency, highlighting the need for automation and export features. According to the interviewee, reporting could be significantly improved by introducing features such as rolling 12-month availability tracking, where operational start dates would be set within the system and reports would be generated automatically based on that timeline.

The current reporting output is also limited in terms of visualization and user-friendliness. Data visualizations on the monitoring platform are still seen as basic and often not intuitive, especially for non-technical users. Suggestions for improvement included adding trend graphs for key parameters such as temperature and SOH, as well as implementing clear, color-coded visual indicators (e.g., pie charts, gauges) to reflect system status in a more interpretable format. These improvements would not only make the reports more informative but would also enhance communication with external stakeholders who may lack deep technical knowledge of BESS systems.

The current system uses fixed roles to control what users can do, grouped into engineering, trading, and management. Each group includes three levels: observer, operator, and admin. Observers can only view information, operators can view and make changes, and admins have full access, including user and system management. These roles are hard-coded and cannot be customized for individual external stakeholders. Employees are usually given admin or operator roles, while external stakeholders typically receive observer access. However, the monitoring system does not yet offer tailored views for different roles. Maintenance personnel need detailed technical data to support troubleshooting and proactive service, while external stakeholders benefit more from high-level summaries that show availability, reliability and performance of the asset. Role-based reporting would help serve both groups better.

## 5.3 IoT data availability and quality

### 5.3.1 Data availability and reliability

The company's cloud-based monitoring platform aggregates data from both in-house and third-party devices deployed in the field. These devices collect operational parameters such as voltage, current, power, temperature, and SOC, which are transmitted to the cloud for visualization, diagnostics, and historical analysis. The availability of real-time and historical data supports both daily operational decision-making and long-term performance evaluation. The collected data is stored on the cloud platform for a certain period, with a sampling interval of one second, enabling high-resolution temporal analysis during the retention period.

The accuracy of the measurements available through the cloud-based IoT service depends on the underlying hardware performing the data acquisition. Specifically, the measurement accuracy is determined by the characteristics of the device internal circuitry, including voltage transformers, which are critical for reliable sensing in electrical systems. The platform itself does not modify the accuracy but reflects the precision of the data sources it receives.

Measurement methods are device-specific and vary depending on the type of physical quantity being monitored. The company's proprietary equipment uses measurement methods which are optimized for device control. When third-party devices are integrated into the monitoring system, their measurement methodologies may differ, and relevant specifications should be reviewed in the manufacturer's documentation to understand the data characteristics and limitations. However, in the context of this research, it is not possible to assess the measurement methodologies of third-party devices in detail. This is primarily due to limited access to proprietary documentation and technical specifica-

tions, which are often restricted by manufacturers. Additionally, the scope of the study is confined to the system-level behavior and output of the cloud monitoring platform, rather than the internal mechanics of individual hardware components. As a result, the evaluation focuses on the aggregated data as presented by the system, without delving into the device-specific measurement techniques used by external equipment suppliers.

### 5.3.2 Missing data and additional data needs

The interviews brought attention to several missing signal types and measurement data, which were considered essential for effective monitoring, diagnostics, and life cycle management of the systems. The absence of these signals was seen to significantly limit both the technical depth of analysis and the operational reliability of the monitoring platform.

One specific limitation that was mentioned was the absence of device-specific identifiers, such as serial numbers, software and firmware versions, and system versioning information. Without this metadata, interviewees reported being unable to form a complete picture of system configurations. However, they did not have a clear consensus on how such registries should be interpreted or displayed within the system.

The absence of infrastructure-level monitoring signals, such as central processing unit load, memory usage, or disk space status, was also highlighted. This was particularly important for diagnosing gateway or system-level failures, where the problem may not originate from the batteries itself but from the supporting control hardware. Similarly, data communication health, such as cyclic redundancy check values for optical fiber connections were noted. While this information may be partially available through the company's EMS web interface, it is not directly accessible or integrated into the main monitoring system, limiting its usefulness in daily operations.

Frequently mentioned gap was the lack of module- or cell-level SOC and SOH visibility. While some aggregated values may be available, interviewees stated that deeper granularity is required to detect internal imbalances or early degradation patterns. In addition, the absence of cycle counting functionality was noted as a limitation, as it prevents long-term tracking of battery usage and degradation. This was seen to hinder the ability to estimate RUL, which is increasingly important for life cycle management and maintenance strategies. This aligns with findings in the literature, where accurate estimation of battery cycle life is emphasized as a critical factor for optimizing performance, reducing life cycle costs, and ensuring the safety and reliability of energy storage systems [118]. As noted by Alipour et al. [118], battery aging not only affects the total cost of ownership but may also lead to serious safety incidents. Similarly, no current measurements are available for key components such as contactors or fans, even though such data could inform predictive maintenance and thermal management strategies. Lastly, the inability to access historical data on charged and discharged energy was seen as a major limitation, as it restricts retrospective analysis and performance validation.

These limitations were considered critical, as they hinder the ability of the system to support data-driven decision-making, preventive maintenance planning, and the ability of the system to detect early degradation patterns. Together, these missing signals represent a substantial gap in the ability of the system to provide comprehensive situational awareness and support advanced monitoring use cases. Enhancing signal granularity and extending data retention would directly support life cycle assessment, degradation mod-

eling, and trend-based diagnostics. These findings are consistent with the observations of Nyamathulla and Dhanamjayulu [13], who emphasized that the performance of data-driven methods are highly dependent on the quality and quantity of the training dataset. Furthermore, AI-based methods often require large datasets for training [76].

### 5.3.3 Data restrictions

The interviews highlighted several data-related limitations that affect the long-term usability, reliability, and completeness of the monitoring system. One of the most frequently mentioned concerns was the limited data retention period, with some systems storing data for only 30 days. This was seen as inadequate, particularly for applications requiring long-term trend analysis, performance verification, or post-incident investigations.

Another critical issue identified was the loss of data following system updates or reboots. One interviewee reported that valuable operational data had been lost during such events, pointing to the absence of a robust integrated backup solution. Furthermore, the interviews revealed that historical performance data of batteries is not accessible after one year, limiting the ability to conduct long-term condition assessments or life cycle analyses. This was considered problematic in contracts involving performance guarantees. While some setups included a network attached storage based backup, this was not implemented consistently across all systems, resulting in unequal data security and recovery capabilities.

One interview highlighted concerns about the reliability of the data pipeline in the current monitoring system. Measurement signals pass through several processing and communication layers before reaching the monitoring interface. This multi-stage flow introduces several potential points of failure. It was reported that if there is a disruption at any stage, measurements may be lost entirely. In one case, incorrect frequency values appeared in the system due to a small calculation or interpretation error in one layer. These types of issues reflect how complex the current signal chain is and how minor computational error can lead to major data inconsistencies. A newer solution is being explored to reduce the number of signal transfer steps and improve reliability.

Participants also raised concerns about data gaps caused by communication issues or system-level disruptions within specific solutions. One interviewee noted that delayed or missing alerts have occurred in situations where a system stopped transmitting trend data packets, yet no alarm was triggered to indicate the interruption. These interruptions not only compromise the continuity of data records but also hinder accurate diagnostics and trend interpretation.

In addition, due to the 3 minute data buffering delay mentioned earlier, emerging anomalies or abnormal conditions can only be detected after this delay has passed. In the interviews, this delay was identified as a limitation, particularly in the context of real-time situational awareness. Although interviewees acknowledged that most operational scenarios do not require immediate responses, the delay still reduces the effectiveness of the system in early anomaly detection and rapid diagnostics, especially when compared to systems that offer near real-time streaming of critical parameters.

## 5.4 System limitations and implementation challenges

### 5.4.1 User interface and usability

Based on the interviews, several significant limitations and feature gaps were identified in the current monitoring system, particularly concerning the user interface and overall usability. These issues were consistently highlighted across different user roles, indicating a shared perception of the practical shortcomings of the system.

The user interface was not considered intuitive or user-friendly, which hinders its effective daily use. One commonly mentioned problem was the incompatibility of the user interface with mobile devices, which limits its usability in field work, remote work, and on-call service when a quick glance at the situation is needed. Interviewees emphasized that mobile access for alarm acknowledgment and system status checks would significantly improve flexibility and responsiveness.

Users expressed a preference for dashboards that offer instant overviews of site availability, performance status, and health metrics. Suggestions included color-coded indicators, KPI gauges for rapid assessment, and trend graphs that visually summarize key operational parameters. In contrast, interviews revealed notable shortcomings in the data visualization capabilities of the system. Trend charts were frequently described as visually cluttered and lacking appropriate scaling options, which limits their effectiveness for rapid analysis. Additionally, the absence of a comprehensive visual overview was highlighted, particularly when compared to SCADA systems, which technicians preferred for their clarity and structured presentation. A major limitation is the lack of a dashboard-style interface that would allow unified monitoring of all systems or sites. Finally, a specific technical limitation noted was the inability to easily detect imbalance between modules via the user interface. This kind of imbalance may have operational or maintenance implications, and interviewees expressed the need for clearer visual cues or automatic alerts related to such issues.

The interviewees stated that without prior experience or special training, it is difficult to find the necessary information because the structure of the system does not guide the user effectively. Another critical point of concern was the unclear naming of parameters, which caused confusion when interpreting technical values or navigating system states. To address this issue, it would be beneficial to clarify the definition of the parameter, thus enhancing the user's comprehension. The alarm and trip lists were also a recurring topic of criticism. They were described as cluttered, unable to be customized, and lacking visual prioritization, which made prioritization difficult in multi-site operations. Several interviewees suggested that categorizing or visually grouping alarms by type, severity or location. This would make them easier to interpret. At present, active alarms do not stand out clearly, making it harder to distinguish between ongoing and historical events.

From the sales perspective, improving the usability and visual presentation of remote monitoring system would further strengthen its role as a customer-facing tool. For example, having a simplified demo version or clearer dashboards could allow sales personnel to perform live demonstrations and better communicate the benefits of the system.

### 5.4.2 Missing features and technical challenges

The interviews also revealed several missing features that limit the overall functionality and long-term usability of the system. These shortcomings were widely perceived as barriers to achieving full operational efficiency and predictive maintenance capabilities.

A commonly cited limitation concerns maintenance documentation. The system does not currently support recording or storing maintenance actions, reports, or individual corrective and preventive tasks within the platform. This lack of integrated maintenance records was seen as an obstacle for traceability and knowledge sharing between teams. Similarly, the lack of a centralized event or maintenance calendar was noted, with interviewees expressing the need for scheduling and notification capabilities to support proactive planning and remind technicians of upcoming service intervals.

From an integration perspective, the system does not connect with ticketing or service management tools nor integrate with the company's EMS web interface, representing missed opportunities for streamlined workflows. Current practices require manual inspection of individual systems and, in some cases, cross-referencing between company's EMS and SCADA views, an approach considered inefficient and prone to error. In addition, monitoring platform is not currently integrated with other internal systems, such as maintenance planning tools or enterprise resource planning software. Integration of reporting functionalities with these systems could improve overall workflow efficiency and support better alignment between technical operations and business objectives.

Additional limitations include the lack of long-term trend visualization, as current functionality only supports short-term analysis, with data accessible for approximately six hours at a 1-second interval, 24 hours at 15- or 30-second intervals, and one day at a 1-minute interval. Longer periods are available with more at coarse resolutions, with up to 31 days of data for 15-minute, 30-minute, 1-hour, and 24-hour intervals. This is restricting the ability to detect gradual changes or assess performance over extended periods.

Interviewees also highlighted the absence of predictive analytics and AI-based diagnostics, which were considered essential for future development. Such features could enable failure anticipation, improving system reliability and customer value. Yuan et al. [48] posit that the extension of the RUL of BESSs can be optimized by the implementation of advanced condition monitoring, predictive maintenance strategies, and the accurate assessment of battery condition. Implementing AI-based anomaly detection, early warning indicators, and battery health prognostics would significantly strengthen the diagnostic capabilities of the system and contribute to reduced downtime and improved asset utilization. While predictive analytics relies on probabilistic models and cannot guarantee absolute accuracy, it serves as a critical tool for anticipating potential future events and supporting the development of effective maintenance strategies.

Building on the identified limitations in data availability, trend visibility, and analytical capability, several opportunities emerge for enhancing the monitoring system through AI, ML, and digital twin technologies. AI and ML methods could be applied to develop automated tools for anomaly detection, state estimation, and RUL prediction, reducing reliance on manual diagnostics and enabling earlier detection of degradation patterns. These models could support predictive maintenance workflows by identifying emerging faults before they escalate and by providing more informed maintenance scheduling.

Digital twin technology offers a complementary pathway for system development. By creating a virtual representation of the BESS that is continuously synchronized with real-time operating data, a digital twin could enable advanced diagnostics, degradation modeling, predictive simulations, and scenario analysis. Such a model would allow maintenance teams to assess system behavior under varying conditions, evaluate the impact of aging, and optimize control strategies without affecting the physical asset. Integrating advanced algorithms within the digital twin framework would further strengthen its capability to support decision-making, improve operational reliability, and extend lifetime of BESS. Implementation of these technologies would require increased data granularity, improved retention, and reliable real-time synchronization, but they offer substantial potential to enhance monitoring accuracy, support predictive maintenance, and increase the overall value delivered to both internal users and customers.

### 5.4.3 Automation deficiencies

The interviews revealed several limitations related to the lack of automation in the current monitoring and reporting processes. As mentioned, monthly reports are still compiled manually, which requires significant time and effort from personnel, also increasing the risk of human error. Moreover, there is no automatic reporting functionality available for external stakeholders, meaning that all external reporting must also be handled manually. Although report automation has been discussed, it has not yet been implemented in practice. As a result, even tasks such as exporting trend images must be performed manually by taking a screen shot, further highlighting the lack of automation in daily workflows. Furthermore, a related issue identified in the interviews was the presence of automatically confirmed alarms. Automatically confirmed alerts may interfere with the identification of actual events, creating confusion in operational monitoring.

### 5.4.4 Organizational challenges

The interviews revealed several organizational challenges hindering the effective development and utilization of the monitoring system. One concern that was mentioned was the lack of clarity around decision-making responsibilities, particularly in relation to predictive features. Participants questioned who is ultimately responsible for deciding which predictive capabilities to implement and who should serve as the primary point of contact for the cloud-based IoT service development team. The absence of clearly defined roles and responsibilities was seen as obstructing coherent development efforts and contributing to delays and inefficiencies.

Another theme that emerged was difficulty in prioritizing development needs, especially when user feedback and internal demands exceed the available development capacity. Interviewees pointed to bottlenecks in the development process, particularly related to the limited resources of the cloud-based IoT service development team, which constrain the implementation of requested features and improvements.

A notable concern was the absence of a structured feedback loop from users to developers. Presently, the users of the platform lack the tools to provide systematic and actionable feedback, which hinders the translation of field experience into concrete development tasks. Consequently, the valuable insights derived from day-to-day operations are not being incorporated into the development of the system, thereby further reinforcing the dis-

connect between usage and improvement. Establishing more systematic mechanisms for capturing user insights, prioritizing feature requests, and coordinating cross-team development would help ensure that improvements align with operational and customer-facing needs.

According to Karim et al. [111], when organizations fully recognize and utilize the potential of their data assets, decision-making becomes more evidence-based, accurate, and strategically grounded. Achieving this potential requires the integration of several technological, organisational, and human factors. These include selecting analytics technologies that are aligned with organisational objectives and the maturity of available data, fostering a data-driven culture that encourages critical thinking, curiosity, and continuous improvement, and developing data literacy and analytical competence through consistent practice and applied learning. Equitable and efficient access to data across organisational levels is equally important, alongside maintaining high standards of data governance, privacy, and security. Furthermore, ongoing training and professional development are essential to strengthen employees' proficiency in data analysis and interpretation. [111] In comparison with these recommendations, the findings of this study suggest that several of the foundational conditions for data-driven decision-making are still emerging within the organisation, which partly explains the current limitations in analytics capability, reporting processes, and system development.

## 5.5 Business impact and customer value

The interviews highlighted multiple dimensions of value creation through the monitoring system, encompassing customer value, internal organizational benefits, and emerging business opportunities. The system supports transparency, service quality, and customer trust, while also enabling internal efficiency through automation, better diagnostics, and strategic use of data. These dual benefits highlight the role of the system as both a customer-facing tool and a platform for operational improvement.

### 5.5.1 Internal value and business opportunities

Based on the interviews, several key themes emerged regarding the organizational and internal value generated by the monitoring system, particularly in relation to operational efficiency, employee enablement, and strategic positioning. A notable benefit is the ability to tie performance-based bonuses to system availability. This provides a direct financial incentive to maintain high BESS availability, making accurate and real-time monitoring an essential operational tool.

Early warning and predictive capabilities was identified playing a critical role in enhancing operational efficiency by enabling faster response times, thereby improving service outcomes and minimizing the downtime. The proactive identification of anomalies allows teams to intervene before issues escalate, which not only supports risk mitigation but also facilitates systematic fault resolution rather than reactive troubleshooting. Additionally, the integration of real-time diagnostic data into maintenance strategies contributes to cost optimization by reducing unnecessary service visits and enabling targeted interventions. These benefits were consistently recognized in daily operations, where the value of timely responses and data-driven decision-making was repeatedly emphasized.

From a risk management perspective, the current system supports diagnostics that reduce operational risks, such as unexpected outages or component failures. Importantly, the presence of smart and predictive features was seen not only as a technical asset but also as a competitive differentiator in the marketplace.

The reduction in manual work through automation was also emphasized as a major benefit. As reporting and diagnostics tasks become increasingly automated, operational efficiency improves, freeing up resources for more value-adding activities. This automation could also contribute to an easier onboarding process for new employees. Intuitive, visual tools reduce the learning curve, allowing new team members to engage with the system more effectively from the start.

In addition to these internal benefits, the interviews revealed several business opportunities linked to the capabilities of the system. Interview findings highlighted the strategic potential of intelligent system functionalities in business-to-business public relations and market positioning. Several participants emphasized that features such as predictive diagnostics, real-time dashboards, and transparent reporting not only enhance operational performance but also serve as differentiators in a competitive landscape. These capabilities were perceived as valuable tools for reinforcing the company's image as a provider of modern, data-driven solutions. Moreover, the possibility of commercializing predictive maintenance as a standalone service level offering was noted, suggesting new avenues for revenue generation and underscoring the broader business value of intelligent system features.

The architecture of the system was consistently identified as a key enabler of international scalability, particularly through its remote diagnostic capabilities. By minimizing the need for on-site presence across geographically dispersed operations, the system supports efficient deployment in global contexts while simultaneously reducing service costs. This functionality exemplifies how operational efficiency and strategic expansion can be mutually reinforcing, as remote diagnostics not only streamline maintenance processes but also facilitate broader market reach without proportional increases in resource demands.

### 5.5.2 Customer value

According to Yi [119, p. 6], creating customer value is a key factor in improving a company's performance, as it increases sales and profitability while also promotes efficiency and innovation. The concept of customer value creation is understood as a series of behavioral entities, originally conceptualized by Etgar [120], each of which contributes to the creation of value. Because services are performance-based, customer value creation is closely linked to customer behavior during service delivery. The more actively customers participate in service-related activities, the greater the value created. [119] Furthermore Yi [119, p. 18] reported that customer-driven value creation is positively associated with improved business performance.

Liang [121] defined customer value as the balance between the benefits an enterprise receives from its customers and the costs associated with acquiring and serving those customers. In customer relationship management, assessing customer value is essential, as it forms the basis for identifying the long-term contribution of individual customers [122]. When enterprises succeed in increasing customer lifetime value, they typically achieve higher returns on investment, enhance customer loyalty and increase profitability

from existing customers [121].

According to Liang [121], the ability to generate superior customer value is closely tied to a company's competitive advantage. When a company can create value more efficiently and effectively than its competitors, it achieves a comparative advantage that supports long-term financial gains from customer relationships [121].

The interviews revealed clear expectations from external stakeholders regarding the structure and content of reporting. Reports are expected to include fault descriptions, root cause analyses, and details of corrective actions or maintenance performed. The format and presentation of reports were emphasized as essential, not only for effective communication but also for ensuring contractual compliance. A clear and professionally formatted report was seen to enhance credibility and customer satisfaction, reinforcing the role of the system in long-term relationship management. Additionally, transparency emerged as a critical theme. External stakeholders place high value on clear access to operational information, while demanding consistent and comprehensive visibility across systems and reporting periods.

Interview insights revealed several dimensions of customer value associated with the monitoring system. Through these factors, the system generates customer value in concrete ways. A frequently emphasized benefit was the potential for extended system uptime, enabled by the early detection of emerging issues. Participants consistently noted that the system facilitates timely identification of faults or abnormal behavior, enabling quicker identification of root causes and reducing downtime and allowing for proactive interventions before problems escalate.

Customer trust emerged as another central theme, closely linked to the ability of the system to provide transparent access to operational data. By offering visibility into key parameters and historical trends, the system fosters a sense of control and confidence among external stakeholders, particularly valuable in long-term partnerships and projects involving external stakeholders.

The system supports service level agreement monitoring, which is critical because availability metrics directly impact business operations. Clear and verifiable service level agreement monitoring ensures reliable reporting both internally and externally. Furthermore, customer satisfaction was found to benefit from the clarity and structure of the monitoring outputs. Well-organized reports and visual representations of system status enhance the perceived quality of service.

## 5.6 Proposal for new performance reporting framework

This section proposes the development of a performance reporting framework that could be automated and integrated into the company's broader operations, maintenance, and after-sales services in the future, which would support more systematic and data-driven life cycle management. The reporting framework is intended to provide a clear and comparable view of key BESS performance indicators so that both technical maintenance personnel and other stakeholders, such as customers, have an up-to-date view of the systems operation, availability and performance.

In this thesis, the detailed structure and contents of the proposed performance reporting framework are not disclosed, as these elements are closely linked to confidential business

information. Consequently, the analysis excludes the full report template and the precise performance metrics utilized in the present framework. Instead, this section identifies and discusses the additional requirements and development needs that emerged from the empirical findings and the literature review. The proposed improvements focus on data availability, usability, asset reliability and life cycle management, and value delivered to the customer.

The analysis revealed several areas in which the current reporting practices could be strengthened to better support operational decision-making, maintenance planning, and customer-facing transparency. Although the existing reports provide a general overview of system status and selected energy-related metrics, they do not yet encompass the extent or depth of information required for systematic and data-driven life cycle management of BESSs. The interviews conducted for this study highlighted a consistent expectation for reporting that is more diagnostic, more predictive, and more closely aligned with real operational behavior. Stakeholders emphasized the need for indicators that not only describe current system conditions but also assist in interpreting trends, anticipating degradation, and justifying maintenance actions.

The reporting framework could benefit from a modular structure. Rather than treating reporting as a single static document, the framework should consist of reporting layers that serve distinct audiences and decision contexts. At minimum, the framework should support a technical layer for service and engineering teams, and a customer layer that communicates performance and availability in a controlled, contract-aligned manner. This addresses a recurring empirical finding: different teams access the monitoring system for different purposes, and the same data must be interpreted differently depending on whether the goal is root cause analysis, preventive planning, or customer communication. A modular approach also reduces the need for manual tailoring and enables automation without forcing all stakeholders to consume the same level of technical detail.

For technical maintenance personnel, reporting should function as a near real-time operational view that enables simultaneous monitoring of multiple sites. A unified, fleet-level overview would allow technicians to track key performance indicators across installed BESSs and receive clear anomaly notifications when deviations from expected operating behavior occur. This approach reduces the need to assess sites individually, improves situational awareness, supports faster prioritization of service cases, and enables proactive maintenance by directing attention to installations where operational risk is increasing.

In contrast, customer-facing reporting is intended to be periodic rather than real time, typically delivered on a monthly or annual basis. These reports would provide a structured summary of system performance, availability, efficiency, and significant events over the reporting period. By aggregating and contextualizing operational data, periodic reports offer customers a clear and comprehensible overview of how the system has performed relative to expectations and contractual commitments, without exposing unnecessary operational complexity.

The reporting framework is intended to provide a coherent overview of key BESS performance indicators, so that system operation and performance can be assessed consistently across installations and reporting periods. By presenting these indicators in a standardized manner, the framework aims to support condition monitoring, maintenance planning, and performance assurance, while also improving transparency toward external stakeholders, including customers. In agreement with Patton [123], reporting in maintain-

ability and maintenance should prioritize clear communication. Visual tools such as pie charts, bar charts, and control charts should be used to effectively convey trends, magnitudes, and performance status. Effective reports compare results against defined goals, using either absolute or relative measures. Emphasis should be placed on identifying and highlighting variances or exceptions rather than presenting extensive raw data. Establishing targets and control limits helps prioritize critical issues and support focused decision-making. [123]

A central gap concerns the limited set of performance metrics currently available. Several key indicators commonly used in BESS monitoring, such as the cycle count and energy throughput, are not included in the present reporting framework. These metrics are essential for quantifying usage intensity, evaluating aging processes, and supporting warranty or service-contract considerations. In addition, a range of advanced state indicators that form the foundation of modern battery diagnostics are not calculated or presented. These include the SOB, SOE, SOF, SOH, SOP, SOS, and SOT. Together, these parameters provide a holistic description of the condition of the battery system, performance capability, and safety status. Their absence limits both the granularity of system understanding and the ability to conduct longitudinal assessments of asset degradation.

The current reporting also lacks several system-level operational metrics that would provide meaningful context for evaluating performance variations across installations. Such metrics include operating modes (e.g., charge, discharge, idle, fault states), RTE, and relevant environmental parameters such as ambient temperature. Inclusion of these indicators would facilitate more accurate interpretation of operational patterns, identify conditions contributing to reduced efficiency or accelerated degradation, and support benchmarking across sites. Furthermore, the current approach does not provide systematic, data-driven safety or reliability indicators, such as RUL or quantified safety metrics, despite their relevance for predictive maintenance and risk evaluation.

In addition to the aforementioned data gaps, period-to-period comparisons, such as month-to-month or year-on-year views, could be a valuable addition to reports. Temporal comparisons help to place individual performance indicators in context by revealing longer-term trends that may not be apparent from single reporting periods. These comparisons would help maintenance personnel recognize gradual changes in system behavior and help customers understand how system performance evolves over time.

Underlying many of these gaps is a technical constraint related to data availability and data granularity. Several of the missing indicators require high-frequency and long-term measurements or subsystem-level monitoring that exceeds the temporal resolution currently transmitted to the cloud platform. Examples of these more advanced metrics include cycle counting, state estimations, and predictions of the RUL. To address this limitation, the integration of edge computing is essential. By enabling local preprocessing, aggregation, and estimation of derived metrics, edge devices could compute key performance indicators close to the source while transmitting only the relevant results to the cloud. This reduces bandwidth requirements and allows for the inclusion of advanced diagnostics that would otherwise be infeasible. Establishing such capabilities would significantly enhance the accuracy, completeness, and interpretability of the reporting framework.

Lastly, the reporting framework should be designed so that it can incorporate progressively more advanced analytics as data quality and model maturity improve. Importantly,

the empirical analysis shows that predictive and ML–based recommendations remain conceptual in this study. It is therefore essential that the framework clearly differentiates between "measured and verified" indicators and "estimated and model-based" indicators. This distinction supports trust and avoids over-claiming predictive capability before technical readiness is demonstrated.

# 6. CONCLUSION

In this thesis, the company's cloud-based IoT service was examined with the aim of improving the monitoring, maintenance, and performance reporting of battery energy storage systems. The study focused on analyzing the availability and quality of collected data, current monitoring and reporting practices, and the identified development needs related to data-driven maintenance and customer value. Based on these findings, a proposal for enhancing the performance reporting framework was presented.

The work was divided into two main phases: a literature review and an empirical analysis. The literature review established a theoretical foundation by defining battery energy storage systems, presenting monitoring and maintenance principles, and identifying current practices and emerging trends in the field. This framework provided a conceptual basis for analyzing the company's cloud-based IoT service. In the empirical phase, the cloud-based IoT service was examined in practice through system observations, technical documentation, and interviews, enabling a comprehensive assessment of its features, limitations, and development needs.

The results of this study show that the company's cloud-based IoT service provides a solid foundation for remote monitoring of battery energy storage systems, yet its current functionality remains primarily descriptive and diagnostic rather than predictive. While the system supports day-to-day supervision, alarm handling, and basic fault analysis, its usability and analytical depth are limited by missing data signals, short retention times, and interface constraints. The findings also indicate that the platform is used inconsistently across teams, often supplemented with SCADA or EMS tools due to clearer visualizations and more granular data. Significant development needs were identified, including enhanced data granularity, automated reporting, improved dashboards, mobile accessibility, and better integration with maintenance tools and organizational feedback processes. Despite these limitations, the monitoring system already creates tangible value by improving up-time, supporting service level agreement verification, and offering transparency to customers. Moreover, the results highlight clear business potential in expanding the system toward predictive maintenance, automated performance reporting and enhanced remote diagnostics. Together, these findings indicate that the platform is valuable in its current form but requires targeted technical and organizational improvements to fully support data-driven BESS life cycle management and customer value creation.

The identified reporting needs indicate that a more comprehensive, analytics-oriented, and multi-layered framework is required to support both operational and strategic decision-making. Expanding the reporting content to include usage metrics, state indicators, environmental conditions, and predictive maintenance parameters would provide a clearer picture of system performance and asset condition. Moreover, integrating edge-based computation would create the technical foundation needed to incorporate these metrics in

a reliable and scalable manner. Addressing these development needs would strengthen the role of the reporting framework as a tool for system optimization, life cycle management, and customer value creation.

Although the study identifies predictive maintenance as a key development direction, it does not empirically test whether existing system data could support such methods. No prototype models, feasibility analyses, or experimental evaluations were conducted to assess the suitability of current signals for tasks such as anomaly detection or RUL estimation. Consequently, recommendations for machine learning–based diagnostics remain conceptual rather than evidence-based, and further research is needed to evaluate technical readiness. Additionally, while interviews provide valuable qualitative insights, the small sample size and exclusion of external customers or field operators limit the diversity of perspectives and may bias findings toward internal viewpoints. The cross-sectional design further restricts understanding of system evolution, reducing the ability to assess long-term maintainability and scalability.

Looking ahead, the future outlook for the system is promising. The current architecture provides a solid technological foundation for implementing predictive, automated, and analytics-driven functionalities. With targeted enhancements in data granularity, analytics, usability, and integration, the platform could evolve into a comprehensive life cycle management tool capable of supporting asset optimization, remote diagnostics at scale, and advanced performance guarantee management. Such developments would not only strengthen the company's competitive position but also open avenues for new service concepts, including predictive maintenance as a product offering and enhanced customer-value delivery through transparent, automated reporting. The power industry must continue to evolve by integrating advanced maintenance strategies and sustainable practices to address the challenges posed by new energy sources, climate changes, and ecological factors. Embracing technologies like AI, ML and IoT, along with robust preventive and predictive maintenance programs, will be essential for maintaining equipment functionality, preventing environmental pollution, and ensuring the reliability and efficiency of power generation systems.

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# APPENDIX A: INTERVIEW FRAMEWORK FOR STAKEHOLDERS

**Section 1: Background and role**

1. Could you briefly describe your role and responsibilities in the company?
2. What is your involvement with battery energy storage systems (BESSs)?
3. How familiar are you with the current cloud-based IoT service?
4. What kind of experience do you have in using or maintaining BESSs?

**Section 2: Current monitoring and maintenance practices**

5. How do you or your team currently use the monitoring system in daily or weekly routines?
6. What are the key signals or data points (e.g., SOC, SOH, alarms, efficiency) you find most useful?
7. Which data signals do you rely on most when making decisions about BESS operation or service?
8. Difficult user interface?
9. Are there any limitations in the system's capabilities that you've encountered?
   (a) Limited features?
   (b) Lack of automation?
   (c) Other?
10. In your view, how well does the current system support predictive or preventive maintenance?
11. How well is the monitoring system integrated with other tools or platforms you use (e.g., maintenance ticketing systems, ERP)

**Section 3: Data quality and usefulness**

12. Are there any signals you wish were available but are currently missing?
13. How would you evaluate the quality and reliability of the data collected (e.g., accuracy, resolution, frequency, completeness, timeliness)?
14. Have you encountered issues such as false alarms, delayed reporting, or inconsistent or low-accuracy measurements?

15. In your opinion, are there gaps in either data coverage or data quality that limit performance monitoring?
16. What kind of improvements in data collection, visualization or reporting would make your work easier?

**Section 4: Performance reporting**

17. Currently, how do you or others in the company report system performance to customers or internal teams?
18. What kinds of performance metrics (e.g., round-trip efficiency, availability, degradation rate, state estimations) are most valuable and should be standardized in reporting?
19. What kind of visualizations (e.g., trend graphs, color-coded dashboards, KPI gauges) would make reports easier to interpret and act upon?
20. How should reports be structured to best serve maintenance personnel (technical view) vs. customers (business/value view)?
21. How frequently should reports be generated (e.g., real-time, daily, monthly)?
22. What level of automation in reporting would improve efficiency?

**Section 5: Customer value and business integration**

23. In your view, how does (or could) better monitoring improve system reliability, maintenance planning, and cost-efficiency?
24. How do you see the role of cloud-based reporting in enhancing customer trust or transparency?
25. From your perspective, what kind of business value does improved monitoring and reporting provide to customers (e.g., reduced downtime, lower costs, longer lifetime)?
26. How could a better monitoring and reporting system be integrated into the company's after-sales and service offerings?
27. Are there business opportunities (e.g., upselling services, service level agreements, guarantees) that could be supported by better monitoring and reporting system?
28. Do you believe offering predictive maintenance and/or automated reporting would strengthen the company's competitive position? Why or why not?
29. Do customers ever give feedback about the monitoring or reporting system? If so, what kind of feedback have you received?

**Section 6: Future development and open feedback**

30. Looking forward, what features or capabilities would you like to see added to our cloud-based IoT service?
31. In your opinion, what organizational or technical challenges might arise if we implement more automated or predictive features?
32. Are there any industry benchmarks, tools, or methods you think we should follow?

33. Is there anything else about your experience with BESS monitoring and reporting that we have not covered but you see as important?