Digital Twin Framework for Enhancing BESS Performance, Safety and Reliability

Vishnu Nair **Vikas Yadav** **Sweekruti** **Sarthak Chopra** **Tripti Gangwar**
Sarnaduti Brahma **Pragya Tripathi** **Lalit Kumar** **Rishi Relan** *
BESS Digital Solutions, Siemens Energy, India

Abstract

This paper presents a novel approach to developing a Digital Twin (DT) framework for Battery Energy Storage Systems (BESS), signifying a substantial advancement in energy storage technology. The DT encompasses multiple strata, from intricate multiphysics simulations at the cell level to modules, packs, racks, and banks, ensuring precise virtual representations. Seamless data acquisition from physical assets, rigorous quality assurance, and robust cybersecurity measures facilitate safe, real-time decision-making through advanced models and algorithms. Advanced control and optimisation methods, driven by energy market dynamics, enhance operational efficacy. Descriptive, predictive, and prescriptive analytics interpret BESS signals to evaluate key performance indicators (KPIs) related to safety and performance. By integrating MLOps and DevOps principles, the DT ensures continuous integration, deployment, and scalability. This framework positions BESS as a pivotal asset in the dynamic energy landscape, augmenting operational efficiency, safety, and reliability.

1 Introduction

BESS is pivotal in modern energy management, providing critical support for grid stability, renewable energy integration, and peak load management. In Figure 1, the overall DT concept is illustrated, including the physical space, the virtual world and the interface layer between the two. However, their

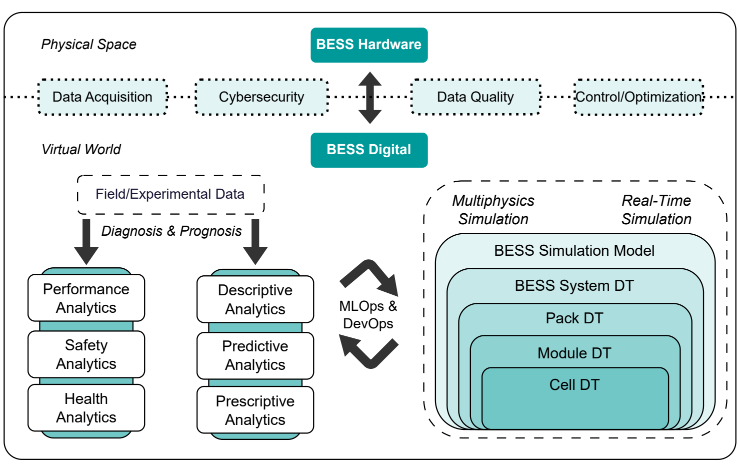


Figure 1: BESS Digital Twin Concept

*Corresponding author: Dr.ir. Rishi Relan (`rishi.relan.ext@siemens-energy.com`).
All authors are equal contributors to the paper.

performance and lifetime depend on factors such as battery chemistry, design and arrangement of other assets such as inverters, auxiliary systems etc. and operating conditions (Dubarry et al. [2023]). This coupled system adds to uncertainty that can be mitigated by developing DT. Potential BESS DT and its applications are highlighted in (Kharlamova et al. [2022]) and (Kharlamova and Hashemi [2023]). This paper outlines a framework of BESS DT design, detailing the data acquisition, models, and advanced algorithms that collectively elevate BESS performance. The goal is to demonstrate how DT can lead to more efficient, reliable, and economically viable energy storage solutions.

2 Physical Space

BESS comprises of various components, including battery modules, converters, control systems, and thermal management units. These components are intricately interconnected and must communicate seamlessly to function as a cohesive system. The communication and coordination among these components elevate BESS to a System-of-Systems (SoS) architecture. This optimises energy storage and dispatch, enhances grid stability, and contributes to a more sustainable and resilient energy landscape. To create DT for monitoring, control, and optimisation, real-time data extracted from the BESS components through sensors is transferred using communication protocols such as MODBUS/Profibus/OPC-UA etc., for processing on edge, on-premise and in the cloud.

3 Interface

The interface layer facilitates the secure acquisition and movement of BESS data from the physical/hardware world to the virtual/digital world. This requires a reliable data acquisition system that can handle the volume, velocity, and variety of data generated by BESS. Detailed checks must be in place to ensure that the quality of the acquired data adheres to the requirements for the DT to work effectively. Control and optimisation algorithms ensure the system meets technical and economic business requirements, facilitated by the Energy Management System (EMS). Additionally, robust cybersecurity measures are essential to protect data and safeguard sensitive information against unauthorised access, breaches, and potential cyber threats. The data flow from the physical space to the virtual space is illustrated in Figure 2.

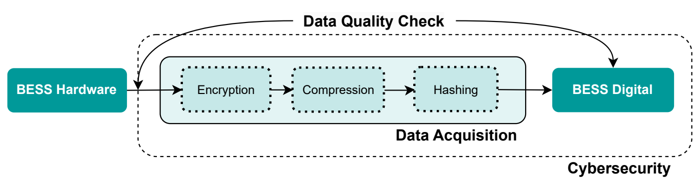


Figure 2: Data Acquisition, Data Quality Check, and Cybersecurity for BESS data

3.1 Data Acquisition

Efficient data acquisition in BESS is essential for optimal performance, ensuring safety, and achieving economic benefits. Continuous data collection aids in predictive maintenance, early fault detection, and lifecycle management, reducing downtime and maintenance costs. Additionally, accurate data ensures regulatory compliance and transparency, providing stakeholders with reliable performance insights. Data compression, encryption, and hashing reduce storage and transmission costs, ensure data security and privacy, and provide data integrity, ensuring that the information remains unaltered.

3.2 Cybersecurity

Various cybersecurity measures need to be taken into account to ensure the safety and reliability of the BESS DT Trevizan et al. [2022]. Data integrity and confidentiality is ensured using robust access controls and encryption to protect operational data. Communication channels are secured using network security features, while intrusion detection and prevention systems monitor for threats. Regular software updates and evolving security protocols are essential to counter vulnerabilities. Designing resilient and redundant infrastructure ensures continuous operation during cyber-attacks.

Addressing these considerations secures the integration of DTs with BESS, ensuring reliable and efficient energy storage while safeguarding against cyber threats.

3.3 Data Quality

Model development relies on high-quality data, making data quality control and assurance essential (ISO 8000-1:2022, ISO 8000-8:2015) for DTs. Poor data quality can lead to flawed simulations, incorrect predictions, and suboptimal decision-making. Ensuring data quality may also be a regulatory requirement. Data quality must be verified at every stage of the pipeline—generation, collection, processing, and usage (Byabazaire et al. [2022]). This is an ongoing process. Context-specific metrics should be defined to assess data quality at each stage, both qualitatively and quantitatively (ISO/IEC 25012:2008, Bayram et al. [2023]).

3.4 Control and Optimisation

Control and optimisation decisions play a pivotal role in the operation and maintenance of BESS. With the help of a DT, these decisions are based not only on the monitored signals but also on the dynamic models and algorithms. A typical EMS structure is given in Figure 3. The EMS will continually

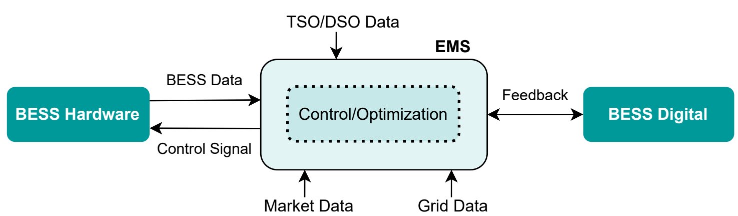
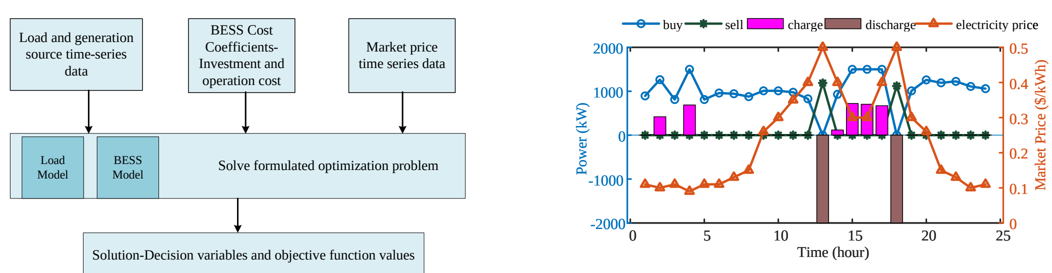


Figure 3: Interaction of EMS with the BESS hardware and its DT

gather data from the physical BESS and its other components. This real-time data monitoring will enable EMS to make decisions for a profitable and efficient operation. For example, the DT can predict the load demand, energy price and ensure energy availability from the BESS. Further, the EMS integrates with the DT to execute optimisation algorithms and the results are refined based on the feedback from the DT. The typical applications of the BESS for the EMS algorithms are: 1. **Energy Market Participation**: DT can optimise the participation of BESS in energy markets by maximising economic returns. A trade-off between the market data and performance can be made to schedule the dispatch of BESS. 2. **Grid Services**: The EMS provides ancillary services like frequency regulation, and voltage support by adjusting the BESS dispatch through the DT enhancing the grid stability. 3. **Demand Response**: The EMS can participate in demand response by using the DT to predict and respond to grid signals.



(a) Workflow for BESS dispatch optimisation.

(b) Example of BESS dispatch with the variation in market price.

Figure 4: Demonstrating the energy arbitrage application using BESS

3.4.1 Case Study on Energy Arbitrage Application

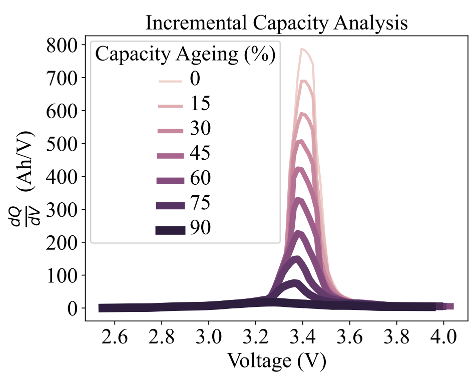
Energy arbitrage involves buying energy when the prices are low and selling when the prices are high. Therefore, significant revenue can be generated by charging the BESS during off-peak hours (low price) and discharging during peak hours (high price). A general methodology is given in Figure 4a for the optimisation algorithm execution. Further, Figure 4b represents a 24-hour BESS dispatch for a general optimisation algorithm with the variation in market price.

4 Virtual World

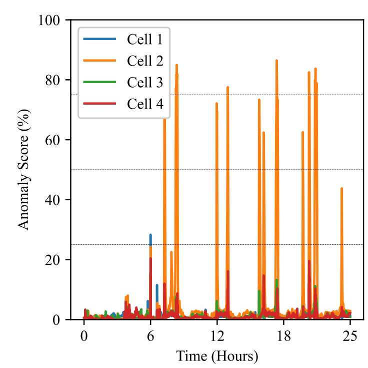
After the data has been transferred to the virtual world, it can be used for developing models and performing analytics by calculating KPIs and running algorithms. All analytics and models need to be validated using experimental data and continuously calibrated using field data.

4.1 Diagnosis and Prognosis

Using an ensemble of techniques, BESS data can be analysed to identify abnormalities. Pinpointing system issues enhances performance, health, and safety. Data-driven models and algorithms can be descriptive (analysing present and historical data), predictive (forecasting future states), and/or prescriptive (recommending preventive measures). As an example of descriptive analytics for the State of Health (SoH), Figure 5 shows the results of a capacity fade estimation algorithm developed and tested using a validated cell model involving peaks of Incremental Capacity Analysis (ICA) curves and Gaussian Process Regression (GPR) (Brahma and Relan [2024b]). A data-driven algorithm for estimating power fade has been developed by applying control and system-theoretic concepts and GPR to multisine-based electrochemical impedance spectroscopy data (Brahma and Relan [2024a]). Similarly, in Chopra et al. [2024] various statistical metrics are used to compute an anomaly score for each cell in the module.



(a) ICA vs Cell SOH Brahma and Relan [2024b]

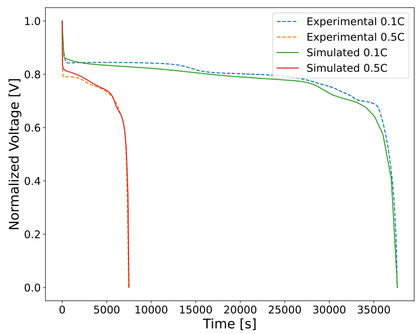


(b) Short-circuit anomaly detection in a battery module Chopra et al. [2024]

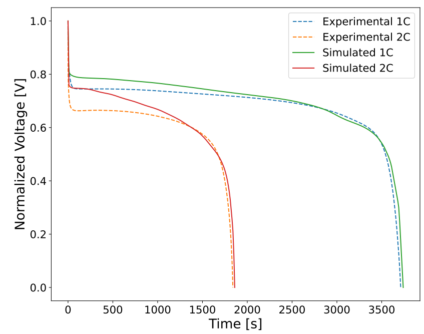
Figure 5: Algorithms for cell SOH Estimation and anomaly detection in a battery module

4.2 Battery Digital Twin

A BESS DT is an advanced virtual model that generates a dynamic and accurate representation of the real system by imitating the physical BESS in real-time. The smallest entity in a BESS is a Lithium-ion battery cell. In the manuscript Tripathi and Relan [2024] (under review), a sensitivity-assisted optimisation framework utilizing the Newman Pseudo two-dimensional (P2D) model was used to develop a Multi-length Scale Multi-Physics Model of a battery cell-level digital twin. Figure 6 compares normalised modelled voltage and experimental results, that shows a good agreement across various C-rates. At lower rates of 0.1C and 0.5C, the root mean squared error (RMSE) is around 18mV and 27mV, respectively. However, at a higher C rate of 2C, the RMSE value of 40 mV was observed, indicating model limitations at higher C-rates. The proposed DT of the cell can be scaled up to develop a module-level DT, which can then be utilised by the battery management systems for its efficient operation. The transition from a cell-level DT to a BESS-level requires



(a) Voltage Validation at 0.1C and 0.5C rates



(b) Voltage Validation at 1C and 2C rates

Figure 6: Voltage validation at 25 °C and C-rates: 0.1C, 0.5C, 1C, 2C

scaling up of the model through aggregation of high-fidelity simulation data of individual cells to above hierarchical levels, and integrating with other assets like inverters, transformers, etc. in the overall system reflecting overall BESS-level characteristics.

4.3 Software Architecture, MLOps and DevOps

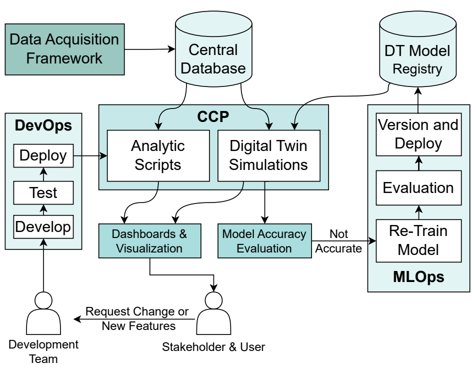


Figure 7: Data flow from database to dashboard with MLOps and DevOps

Figure 8: Example User Interface

The BESS DT software architecture is designed for analytics and DT model execution, leveraging data from physical systems stored in a suitable database. Operating in a cloud-native environment with optional on-premise replication via containerisation, a central control program (CCP) manages both continuous and event-driven analytics processing. The CCP orchestrates computational scripts, including analytics and DT models, dynamically managing data access, resource allocation, and result storage for visualisation.

MLOps and DevOps are pivotal to the BESS DT platform's evolution. MLOps automates model retraining to adapt DT models to changing system conditions, ensuring accurate simulations. Model versioning, validation, and testing maintain robustness and alignment with current asset conditions, enhancing predictive capabilities. DevOps supports continuous integration and deployment, enabling rapid analytics updates without operational disruption. It ensures consistent deployments across environments through infrastructure as code, facilitating scalable and reliable deployments. The complete workflow, from data acquisition to user interface with integrated MLOps and DevOps, is illustrated in Figure 7, with an example user interface in Figure 8.

5 Conclusion

This concept paper delineates the essential components for developing a DT for BESS, integrating diverse fields such as computer science, data and cybersecurity, control theory, electrical engineering, and electrochemistry. This interdisciplinary approach necessitates comprehensive input from various domains. While this paper concentrates on BESS, the DT concept is equally applicable to a multitude of systems across different sectors.

References

Firas Bayram, Bestoun S. Ahmed, Erik Hallin, and Anton Engman. Dqsops: Data quality scoring operations framework for data-driven applications. In *Proceedings of the 27th International Conference on Evaluation and Assessment in Software Engineering*, EASE '23, page 32–41, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 9798400700446. doi: 10.1145/3593434.3593445.

Sarnaduti Brahma and Rishi Relan. System-theoretic insights into battery power fade prediction: A probabilistic framework. In *2024 IEEE Tenth Indian Control Conference (ICC) (accepted)*, 2024a.

Sarnaduti Brahma and Rishi Relan. Online conformal prediction of battery capacity ageing from partial charging/discharging profiles. In *2024 23rd IEEE National Power Systems Conference (NPSC) (accepted)*, 2024b.

John Byabazaire, Gregory M.P. O'Hare, and Declan T. Delaney. End-to-end data quality assessment using trust for data shared iot deployments. *IEEE Sensors Journal*, 22(20):19995–20009, 2022. doi: 10.1109/JSEN.2022.3203853.

Sarthak Chopra, Sarnaduti Brahma, and Rishi Relan. Securing Bess Modules: Anomaly Detection in Cell Voltages through Statistical Analysis. In *2024 11th IEEE International Conference on Power Electronics Drives and Energy Systems (PEDES) (accepted)*, 2024.

Matthieu Dubarry, David Howey, and Billy Wu. Enabling battery digital twins at the industrial scale. *Joule*, 7: 1134 – 1144, 2023. doi: 10.1016/j.joule.2023.05.005.

ISO 8000-1:2022. Data quality - Part 1: Overview. Standard, International Organization for Standardization, Geneva, CH, April 2022.

ISO 8000-8:2015. Data quality - Part 8: Information and data quality: Concepts and measuring. Standard, International Organization for Standardization, Geneva, CH, November 2015.

ISO/IEC 25012:2008. Software engineering — Software product Quality Requirements and Evaluation (SQuaRE) — Data quality model. Standard, International Organization for Standardization, Geneva, CH, November 2008.

Nina Kharlamova and Seyedmostafa Hashemi. Evaluating machine-learning-based methods for modeling a digital twin of battery systems providing frequency regulation. *IEEE Systems Journal*, 17(2):2698–2708, 2023. doi: 10.1109/JSYST.2023.3238287.

Nina Kharlamova, Chresten Træholt, and Seyedmostafa Hashemi. A digital twin of battery energy storage systems providing frequency regulation. In *2022 IEEE International Systems Conference (SysCon)*, pages 1–7, 2022. doi: 10.1109/SysCon53536.2022.9773919.

Rodrigo D Trevizan, James Obert, Valerio De Angelis, Tu A Nguyen, Vittal S Rao, and Babu R Chalamala. Cyberphysical security of grid battery energy storage systems. *IEEE Access*, 10:59675–59722, 2022.

Pragya Tripathi and Rishi Relan. Navigating the unknown and uncertain: A sensitivity-driven optimisation framework for high-fidelity battery modelling. In *1st International and 7th National Conference on Multidisciplinary Design, Analysis and Optimization (iNCMDAO 2024) (accepted)*, 2024.