Digital Twinning of the Battery Systems—A Review

H. C. Gururaj and Vasudha Hegde

1 Introduction

Battery is an electrochemical device used to store electrical energy. Battery undergoes numerous charging and discharging cycles during the lifetime affecting its parameters [1]. Among various types of batteries, lithium ion batteries (LIB) have carved out a niche for themselves, thanks to their high energy density, allowing them last longer in between charges while providing high output current. Having a low self-discharge rate allows them to retain the charge when not in use. They demand very little maintenance. For the same size, LIBs are much lighter than their counterparts. The most valuable attribute of a LIB is the versatility with shapes and sizes offering users a plethora of options to suit their needs [2]. Since the battery is a major chunk in the entire product cost [3], it is imperative to accurately estimate the battery parameters employing battery management system (BMS) to cut down the design costs and to extract maximum energy.

NASA pioneered the concept of pairing technology, the predecessor of the present-day digital twin technology. Digital twin technology is so vital to the business today that in the year 2017 it was declared as one of the Gartner's Top 10 Strategic Technology Trends [4]. Digital twin is much more than just a simulation. Simulation is static, whereas a digital twin is active as it receives real-time data from its physical counterpart. Simulation focuses just on the product, whereas a digital twin focuses on the entire business, helps improve the process and make better decisions [5].

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Endeavour of this paper is to emphasize the importance of digital twin for the battery systems. Organization of this paper is as follows: Section 2 introduces contemporary publications on digital twins for batteries, and Sect. 3 has the summary.

2 Digital Twin

The digital twin platform from some of the most recent publications is discussed in this section.

2.1 *Digital Twin for Assessment of Battery Pack Degradation*

In [6], an economical platform for the digital twin for lithium ion battery pack employed in the spacecraft was developed to assess its degradation. Figure 1 shows the architecture for the digital twin platform comprising the assessment unit and the visual software unit. Remote sensing link transmits real-time data to ground station, which is then processed by the assessment unit to provide the degradation result. As shown in Fig. 2, visual software unit displays both the real-time data and the results from the assessment unit. Temperatures, voltage, current, etc., of the battery are the state parameters for real-time data transmission that are stored first and later used for the analysis.

The output of the unit for assessment can be the prediction of state of charge (SoC) [7], remaining useful life (RUL)/state of health (SoH) [8]. SoC associates with cells of the battery, while RUL is pertaining to entire battery pack.

Testing and verification of accurate mirroring of the battery state in real-time is the basic function of digital twin. Visual software will present effects after assessment of real-time data which can be correlated to test data for verifying the functioning of

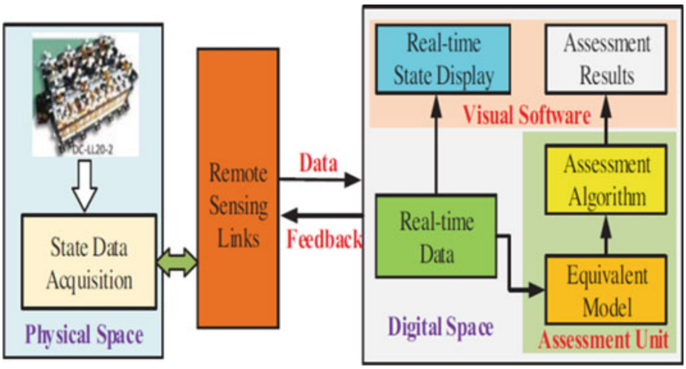


Fig. 1 Architecture of the digital twin platform [6]

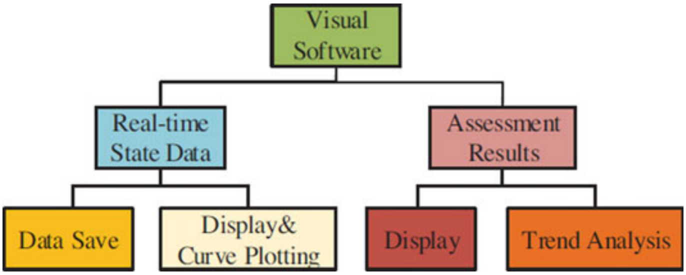


Fig. 2 Function framework of visual software [6]

digital twin. The assessment of degradation of the battery pack (SoC prediction and RUL estimation) is the core function of digital twin platform.

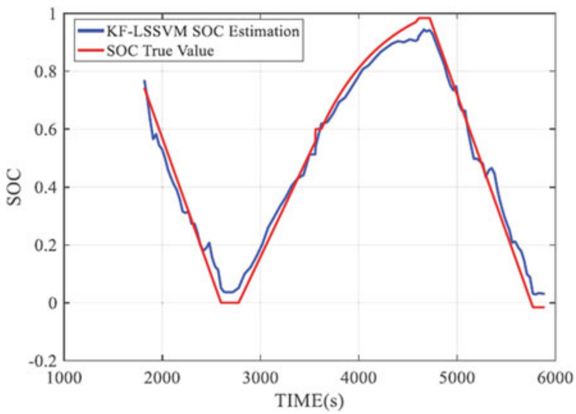
Status of the LIB pack is assessed by the assessment unit based on algorithms and models. SoC of the cells is estimated using the algorithm of Kalman filter–least squares support vector machine (KF-LSSVM). Electric current, terminal voltage (real-time data), and historical test data (training data) are the inputs to the algorithm. Output of the algorithm and current value are fed as the input to the Kalman filter, whose yield is SoC estimation.

SoH is evaluated using the algorithm of auto regression model-particle filter (AR-PF). Historical test data (training data), real-time data are the input for auto regression (AR) model. Yield of the model is the Health Index (HI). HI along with real-time data are inputs to particle filter, whose yield is SoH/RUL prediction.

Figure 3 shows the plots for true value obtained from test data and SoC estimation using KF-LSSVM [9], both being consistent with one other proving accurate prediction of SoC can be carried using the specified model.

Figure 4 shows the plots for true value obtained from test data and RUL estimation using AR-PF algorithm. As seen from the plots estimation of RUL, test data's true values are in close agreement.

Fig. 3 Results of KF-ALSSM algorithm [6]



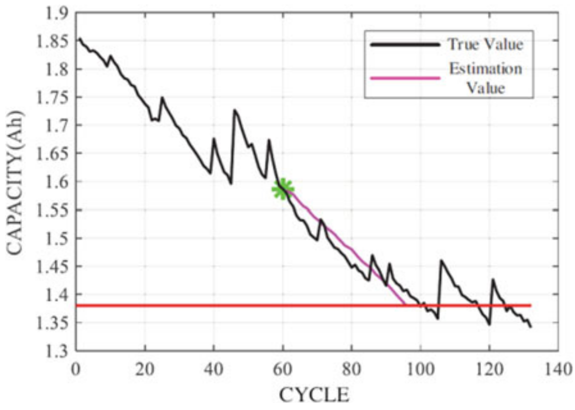


Fig. 4 Results of AR-PF algorithm [6]

The proposed platform needs improvement as it is incompatible with different algorithms and types of batteries.

2.2 Digital Twin For Digital Services of Battery System

In [10], a digital twin model was presented to cover the complete life cycle of the battery. Figure 5 shows the proposed architecture comprising three levels: service level, twin level, and hardware + connectivity level. Hardware + connectivity level serves the purpose of data accumulation. In a modern industry, the relevant data may be obtained through manufacturing execution system (MES)/enterprise resource planning (ERP) [11]. Supplementary data loggers and sensors are used to supervise the ambient conditions during production and logistics. Data loggers amass measured data which can be automatically/manually read out or transmitted live data through Internet of Things (IoT) networks [12].

The twin level is placed in the environment of cloud computing [13]. Twin level offers micro-services [14], each performing one task and corresponding through numerous interfaces. Figure 6 shows outline of the architecture's data types. Master

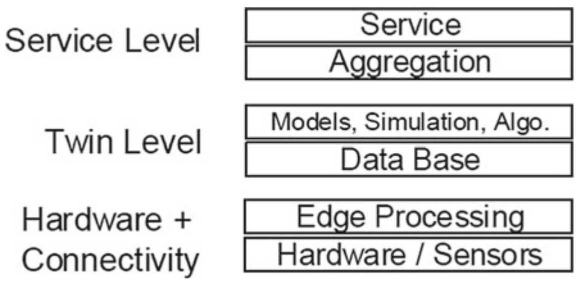


Fig. 5 Reference architecture of a digital twin [10]

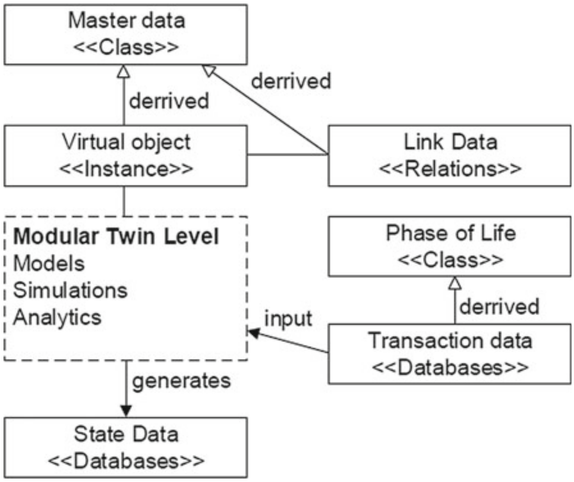


Fig. 6 Outline of datatypes pertaining to architecture of digital twin [10]

data is the technical description of the physical objects, represented in the virtual world. Transaction data is used to acquire the continued experience concerning the physical component. Simulations or models are fed with transaction data to obtain insight regarding state of real system. Results are composed as state data. Parent–child relationship among the components is monitored using the link data. Knowledge created in twin level can be utilized to cater to particular user's needs in service level. Service level contains aggregation layer. The collected information is first conditioned and later formatted during aggregation. The output layer acts as a link to the service layer. Output layer can be an application programming interface (API) or graphical interface.

The proposed metamodel has subset high voltage battery system (HVBS), logistics subset, production subset, monitoring, and testing. Subset HVBS is prevalent in every life phase. The life cycle begins with bringing together of relevant components of the system. During the onset of the manufacturing process, every single component is the subject of twin architecture, and once assembled, the entire battery system will be the physical subject. In order to mimic the process of manufacturing, a virtual assembly is implemented. Vehicle life cycle temperature, voltage, current, etc., are the transaction data. During the second life, criterion for transaction data remains the same, but only the ambient system changes.

The logistics subset has logistic entity, transport, and storage as the sub-modules. Shock, vibrations, temperature, and humidity during the transport form the transaction data. The production subset is comprised of various states pertaining to production. The focus is on system assembly. Transaction data is the measurement of the effect of vibration, shock on the battery components. Data in every subset is logged in a uniform way in the monitoring subset. Standardized classes are used for logging different parameters. Testing subset provides analysis on the documented transaction data and generates the state data specific to each test carried out. Further research is suggested with regard to use-cases, stakeholders, and implementation.

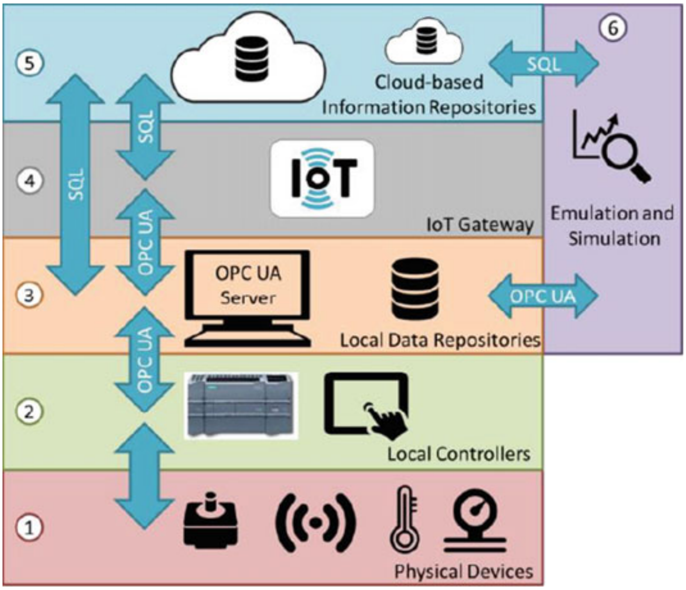


Fig. 7 Connection architecture for a digital twin [15]

2.3 6 Layer Digital Twin Architecture

In [15], a digital twin model with six layers for a manufacturing cell was presented. As shown in Fig. 7, layer 01 consists of numerous physical devices like sensors, actuators, etc., which feed to and receive signals from the next layer. Layer 02 comprises local controller such as a programmable logical controller (PLC) [16] in order to lend some additional capabilities to the digital twin. Layer 03 is the local data repository such as local database and Open Platform Communications United Architecture (OPCUA) [17]. This layer provides characteristics like global connectivity, reliability, real-time performance, and security. Layer 04 is the IoT gateway in the midst of connected world and the physical twin. This layer connects information from layer 05 to data in layer 03[18]. The layer 04 provides multi-dimensional data correlation/data intelligence [19], which modifies the data pertaining to different twin architectures into generic information, prevents bandwidth bottlenecks, avoids enormous database, makes sure that physical twin is in relevant state before passing any commands from layer 06 to layer 03, and resolves any arising conflict of data from repositories in layer 06. The layer 05 is the information repository for digital as well as physical twin. It has information regarding latest state of physical twin.

Layer 06 adds the intelligence to the digital twin. The layer can realize the following roles: Remote monitoring, predictive analytics, simulation of future behaviour, optimization along with validation, documentation along with communication, connection among disparate systems, and digital twin control. The effectiveness of the proposed architecture is tested through a case study where physical equipment's change of state is communicated from layer 01 to layer 06 and a command for data change was transmitted from layer 06 to layer 01 proving the operational capability of the architecture. However, this research raised concerns over incompatible versions and the complex installation procedure for drivers and the connection being slow to online cloud server.

3 Summary

A digital twin can not only perform the basic function of mirroring the present state of a physical object using the real-time data but also perform the core function like predicting the future state. LIBs are extensively used as power source in satellites, electric vehicles, and consumer electronics. The reliability and safety of the LIBs are directly linked to its degradation. Hence, the assessment of battery's degradation, estimation of SoH, SoC of the battery is critical. The SoH, SoC estimation can be achieved through suitable algorithm. A digital twin can provide digital services to different stakeholders like component and logistic suppliers, original equipment manufacturer, vehicle owner, fleet operator, and second life users covering the entire life cycle of the battery. In the reference architecture of a digital twin, hardware layer acquires the data, twin layer transforms data to knowledge, and service layer provides the access to this knowledge. Digital twin is defined by a metamodel comprising: Subset HVBS having various classes alongside attributes exhibiting master data of respective components in the physical world. The logistic subset provides the information on the logistic entity during storage and transportation. The production subset comprises all the states of the production pertaining to HVBS. Data in every subset is logged in a uniform way in the monitoring subset. Testing subset provides a digital platform for comprehensive testing under various conditions before the series production of the HVBS. Digital twin can be implemented using a multi-layer architecture comprising the physical twin, local controllers, local data repository, IoT gateway, data repository (cloud-based), and emulation and simulation layer. Data is collected at the physical twin level, processed by the local controllers and later stored in the local data repository employing an OPC-UA server. IoT provides the gateway between local data repository and the cloud storage. The brain of the digital twin is the sixth layer modelling both current and future behaviours. Going forward each product manufactured may possess its own digital twin generating the data for analysis, helping create real-time predictions relating to predictive maintenance, product life cycle, etc., and hence, revolutionizing product development and testing in almost every field.

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