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Digital twin of electric vehicle battery systems: Comprehensive review of the use cases, requirements, and platforms

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ABSTRACT

Transportation electrification has been fueled by recent advancements in the technology and manufacturing of battery systems, but the industry yet is facing serious challenges that could be addressed using cutting-edge digital technologies. One such novel technology is based on the digital twining of battery systems. Digital twins (DTs) of batteries utilize advanced multi-layer models, artificial intelligence, advanced sensing units, Internet-of-Things technologies, and cloud computing techniques to provide a virtual live representation of the real battery system (the physical twin) to improve the performance, safety, and cost-effectiveness. Furthermore, they orchestrate the operation of the entire battery value chain offering great advantages, such as improving the economy of manufacturing, re-purposing, and recycling processes. In this context, various studies have been carried out discussing the DT applications and use cases from cloud-enabled battery management systems to the digitalization of battery testing. This work provides a comprehensive review of different possible use cases, key enabling technologies, and requirements for battery DTs. The review inclusively discusses the use cases, development/integration platforms, as well as hardware and software requirements for implementation of the battery DTs, including electrical topics related to the modeling and algorithmic approaches, software architectures, and digital platforms for DT development and integration. The existing challenges are identified and circumstances that will create enough value to justify these challenges, such as the added costs, are discussed.

1. Introduction

Transportation electrification is an essential pathway to limiting global warming below 1.5 $^{\circ}C$ as set out in the Paris Agreement [1]. Electric vehicles (EVs) crucially rely on lithium-ion batteries to store the required energy for propulsion. Due to their significance, batteries have been an active field in academia, industry, and among policymakers, and large investments have been secured to improve them. The advancements in battery technology cannot be underestimated. However, there are still unresolved challenges in the field that have slowed down the electric transportation paradigm, for example, long charging times and quick degradation, especially under fast charging conditions [2,3]. The lithium-ion cells are sensitive to abusive operating conditions such as over-charging and elevated operating temperatures. Such conditions may on rare occasions initiate unstable chain reactions which could cause a thermal runaway leading to the fire or explosion of the battery [4,5]. Batteries face challenges not only when they are in use, but also across their whole value chain from raw material and supply chain to the repurposing and recycling of batteries. Despite the decreasing trend in their cost, EVs are still deemed expensive and unaffordable.

A battery management system (BMS) is usually used to ensure that the EV battery is operated within safe limits [6]. However, BMSs often use a low-cost microprocessor that hinders the use of best-in-class algorithms for the optimum operation of the batteries. Novel digitalization techniques can address the challenges in the battery processes including manufacturing, assembling, operating, repurposing, and recycling [7]. One such technology is based on the digital twin (DT) concept. The DT of a battery is its live digital equivalent with prediction capabilities, which is formed by employing multi-scale models, advanced data processing techniques based on artificial intelligence, machine learning (ML), and internet-of-things (IoT) driven two-way data connectivity between the

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Abbreviations

AAS	Asset Administration Shell
AWS	Amazon Web Services
BMS	Battery Management System
CAD	Computer-Aided Design
CAN	Controller Area Network
DT	Digital Twin
DTI	Digital Twin Instance
DTP	Digital Twin Prototype
EMS	Energy Management System
EV	Electric Vehicle
IoT	Internet-of-Things
KF	Kalman Filter
LCC	Life Cycle Cost
MAE	Mean Absolute Error
ML	Machine Learning
NN	Neural Network
PDT	Performance Digital Twin
PF	Particle Filter
PT	Physical Twin
RDF	Resource Description Framework
RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition
SoC	State-of-Charge
SoH	State-of-Health
SoP	State-of-Power
SotA	State-of-the-Art
SoX	State-of-X
TMS	Thermal Management System
VIT	Voltage, Current, and Temperature

physical twin (PT) and DT, to allow an accurate replication/prediction of the battery behavior [8]. The battery DT technology is advantageous in different terms as outlined in the following:

- **Application**: It facilitates battery design optimization, improves battery operation and maintenance, and makes batteries more efficient and cost-effective.
- **Emissions/Environment**: It contributes to mitigating the effects of climate change by enabling more widespread use of clean energy and reducing emissions from transportation. It also supports the fulfillment of environmental, social, and governance and United Nations (UN) sustainable development goals by promoting sustainable energy systems and reducing greenhouse gas emissions.
- **Policy targets**: It supports the fulfillment of policy targets related to the energy storage, reduction in emissions, and sustainability, by providing a comprehensive understanding of battery behavior and performance over the entire lifetime.
- **Regulation/Standards**: It catalyzes the process of battery standardization and regulation in terms of safety and performance.
- **Cost**: It improves the life cycle cost (LCC) by improving the economy of manufacturing, reducing maintenance costs, helping batteries last longer, etc.

Despite being an active research topic in recent years, the battery DT requirements and use cases are still unclear in an industrial setting. In addition, the simulation and software platforms that can be used for the development and integration of the DTs have not been surveyed before. The works on battery DTs have been mostly focused on developing advanced BMS functionalities such as advanced modeling and state estimation functions for batteries in addition to the works which have described some of the DT requirements and frameworks. Several review/survey works have also been published on this topic. Table 1 lists these papers, the related publication year, as well as the focus area of each paper.

Table 1
Review/survey papers published on the topic of battery DTs.

Ref.	Year published	Topics covered
[9]	2022	• Brief review of DT use cases • Review of the DT architecture
[10]	2021	• Review of DTs in EV context including batteries, power electronics, advanced driving assistance systems, etc • DT use cases focused on BMS algorithms
[11]	2021	• Review of use cases of battery DTs in EVs
[12]	2021	• Review of DTs applications in the design, manufacturing, operation, and post-operation phases • Brief overview of the DT framework
[13]	2021	• Brief review of the use cases focused on EV operation
[14]	2020	• Battery models and data processing for digital twining • Battery state estimation

The existing review/survey works have mostly focused on the possible DT applications and the DT conceptualization while some of them have referred to existing possible frameworks. These papers have addressed DTs only from the electrical perspective. However, battery DT requires knowledge of multiple disciplines due to the interdependence of the electrical, software, and digital systems. Except in Ref. [12], all review works have addressed battery DTs merely within the EV context without reviewing DT opportunities across the whole battery value chain such as the repurposing and 2nd life applications.

Unlike other works, this review addresses the battery DT use cases across the whole value chain. In addition to discussing the electrical and software requirements together, the review provides insight into the commercial and open-source DT design, development, and integration platforms, as well as their pros and cons. Furthermore, the results of an industry questionnaire are interpreted to identify the gaps and reveal circumstances where the DT can create real value from a business standpoint to justify its costs. The audience of this review is very broad including industry and academic experts working across the whole battery value chain from EV users, fleet operators, and component integrators to battery recyclers, as fully depicted in Fig. 1.

The main objective of this review is to provide a useful indication of the scope of the existing research literature including the ongoing trends on different aspects of battery DTs including their use cases, requirements, and platforms. The literature search is limited to the English language, in Scopus, Science Direct, and IEEE Xplore for publications between 2003 to January 2023. Any peer-reviewed article containing information about battery DT use cases, requirements, and DT development/integration platforms is included in the review. Additionally, the DT platforms that are commercially available were found and reviewed through an internet search. Some articles in which a review of their title and/or abstract disclosed little pertinent to the batteries were excluded without further review. Reviewers with a relevant discipline were assigned to abstract the information from different articles in the reviewed database. Information was collected on the type of DT use cases considered and the achieved performance indicators, electrical, mechanical, and software requirements, as well as the existing platforms used for the design, development, and integration of the DTs and their potential in terms of data storage, security, processing power, visualization, etc. The analysis is fulfilled to provide an adequate level of detail about the battery DT potential, trends, and gaps while it also determines the value of undertaking a full systematic review of individual use cases, technologies, and platforms.

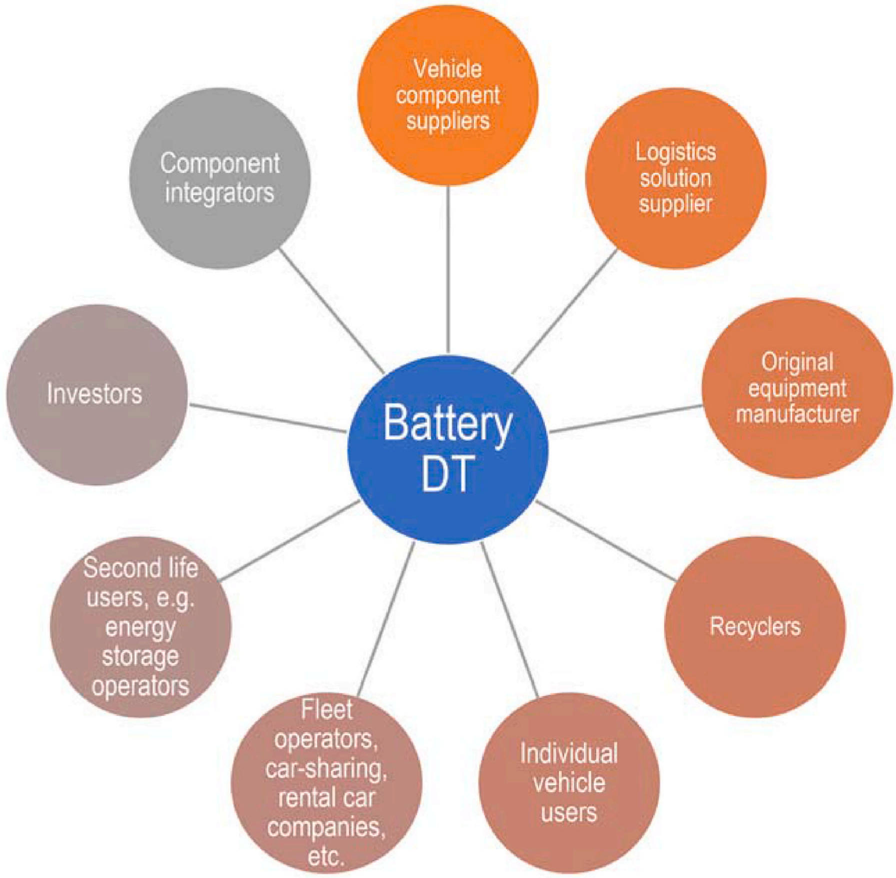


Fig. 1. Potential stakeholders of the battery DT concept and audience of this review.

The presentation of the work is organized as follows: In Section 2, the definitions of the DTs are reviewed and the existing challenges in the EV battery value chain are outlined. Section 3 provides a review of the state-of-the-art (SotA) battery DTs and the relevant use cases to address the challenges of the batteries throughout the value chain. Then, in Section 4, the requirements of the battery DTs from electrical and software perspectives are reviewed. Section 5 provides a review of the existing commercial and open-source battery DT development and integration platforms. The existing gaps, challenges, and opportunities, are discussed in Section 6, and finally, conclusions are provided in Section 7.

2. Background on DTs and battery challenges

Based on the field of application, the DT is defined and understood in different ways. The DT has been referred to as a mega-model, avatar, mirrored system, digital shadow, or synchronized virtual prototype

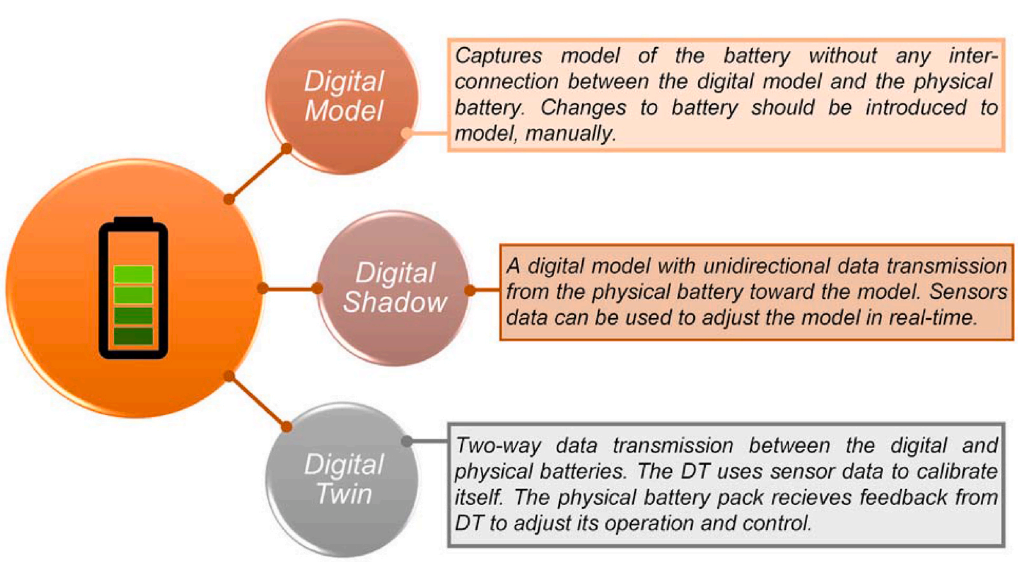


Fig. 2. Difference between battery model, digital shadow, and DT [17].

[15]. Therefore, a generally accepted term and definition for DT is still lacking. Fig. 2 illustrates how a battery DT can be distinguished from a battery digital model and a battery digital shadow [16]. Benchmark definitions of the DT are also reviewed in Table 2.

Depending on the application area and use case, this research proposes the following three kinds of DTs, as illustrated in Fig. 3(a). Each DT type addresses specific needs in different life stages of the battery, i.e., the digital twin prototype (DTP) addresses the manufacturing of batteries while the performance digital twin (PDT) deals with the operation of batteries in 1st life and 2nd life. The digital twin instance (DTI) is the most complicated type of DT covering the whole lifecycle of the batteries from manufacturing to material recycling. Stakeholders' interests in different DT types are shown in Fig. 3(b).

Generally, the DT has found several applications in the EV context including autonomous driving, converters and inverters, digital design and manufacturing, health monitoring, advanced driving assistant systems, and battery systems. The applications cover various EV components and subsystems to improve performance and safety. Detailed descriptions of the DT use cases in the EV context can be found in Ref. [11]. However, this review focuses on the use cases related to battery systems only. The use cases are driven by the challenges across the whole battery value chain including battery raw material, manufacturing of cells, pack assembly, operation phases (EV and second-life), and recycling of batteries. Fig. 4 depicts the challenges in different stages of cycle life. At the material stage, the challenge is to find and use effective and abundant battery materials to ensure sustainability. An important challenge in the manufacturing phases (cell and pack) is the production quality and quality assurance, which involves extensive design effort, and long and expensive certification processes. In addition, the evolving battery materials mean that until the search for an ultimate battery is not concluded, new designs and technologies at cell and pack levels should be brought forward, which is expensive and time-consuming. In EVs, the key challenge is battery durability and safety. Batteries require many algorithms to operate them, safely, and expensive electronics are needed to achieve this. Likewise, batteries tend to degrade fast under harsh operating conditions such as elevated temperatures or high discharge rates. Design of a high-performance yet cost-effective BMS to maximize safety and durability is challenging. Battery repurposing and recycling phases are challenged mainly by the complexity of processes and lack of regulations. A challenge that can be attributed to the whole value chain is the lack of interoperability to interconnect stakeholders who play roles in different life cycle stages and to facilitate harmonization, legislation, and standardization of different battery technologies. A universal and transparent framework to benchmark battery technologies and validate/track progress toward sustainable and resource-efficient battery designs is still missing. In the next Section, the DT's potential to address some of these challenges is reviewed.

Table 2
Benchmark definitions of the DT.

Author/institution	Year	DT concept/definition
Michael Grieves [18]	2003	A "virtual digital expression equivalent to physical products."
NASA [19]	2010	An "integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin."
Roland Rosen [20]	2015	A "new wave in modeling, simulation, and optimization technology, which provides a big set of all digital artifacts."
Michael Schluse [21]	2016	A "virtual representation of a real-world subject" or a "real-world object."
Edward M. Kraft (U.S. Air Force) [22]	2016	A "multidiscipline simulation of a real-world product, which uses data and sensor information as input to model that mirror and predict the states and behavior over the lifespan of the physical system."
Rikard Soderberg [23]	2017	It "contains geometry representation of the assembly, kinematic relations, Finite Element Analysis functionality, Monte Carlo simulation, material properties and link to inspection database."
Billy Wu [14]	2020	A "digital replica of a physical entity with a close connection between the two."

3. Review of the use cases and functionalities of the battery DT

The research on battery DT has sped up in recent years. New features and functionalities are being introduced for the battery DT as the technologies related to IoT, artificial intelligence, big data, and cloud computing are evolving. The DT can be used not only to address the challenges in each stage of battery life but also to interconnect different life cycle phases of the battery orchestrating its performance and resulting in reduced LCC. The following subsections review the existing and potential use cases of battery DTs.

3.1. SoX estimation and cell balancing

The state-of-X (SoX) variables, i.e., state-of-charge (SoC), state-of-health (SoH), and state-of-power (SoP) are very important in the BMS context since they are input to many algorithms that are responsible for monitoring, controlling, and protecting the battery pack. The SoC is equivalent to the fuel gauge in non-electric cars. SoH indicates battery health which is commonly characterized by the battery capacity or internal resistance. The SoP determines the safe battery power boundaries during normal EV operation or regenerative braking. Traditionally, these algorithms are implemented in the onboard BMS which runs on a microprocessor with a capacity of a few hundred Mbytes [24]. Because of the CPU and memory limits in the BMS, best-in-class SoX estimation algorithms cannot be implemented due to the infeasibility of the embedded platforms. This leaves an undesired state estimation error leading to potentially poorer battery performance and safety. On the other hand, the DT sits on the cloud which offers considerably higher computational resources compared to the BMS allowing higher achievable accuracy.

DT-based SoX estimation has been the subject of several publications. In Ref. [25], SoC and SoH estimation is fulfilled on the cloud-based DT using the adaptive H-infinity filter and particle swarm optimization, respectively. As illustrated in Fig. 5, taken from Ref. [25], the VIT data (voltage, current, and temperature) are sent from the slave BMS to a Raspberry Pi by the controller area network (CAN) protocol. The data is then transmitted to the DT using the MQTT protocol. The SoX algorithms are validated on a real uninterruptable power supply set-up resulting in an SoC estimation mean absolute error (MAE) of 0.49%. Likewise, DT-based SoH estimation was reported to achieve MAE of 0.74% and 1.7% for capacity and resistance estimation, respectively. In Ref. [26], a joint H-infinity filter and particle filter (PF) online algorithm has been proposed for cloud-based SoC estimation resulting in an MAE of 0.14%. An effective approach for SoH estimation has been proposed in Ref. [27], where a battery DT based on the long short-term memory is developed and used to virtually discharge the battery to estimate its capacity. The MAE of SoH estimation is obtained at 2.86%. The DT-based SoC and SoH estimation has also been fulfilled in Ref. [28], in which different ML techniques based on random forest, light gradient boosting, and deep NN were applied resulting in the MAE of 0.549% and 0.603% for SoC and SoH estimation, respectively. The DT is structured to fulfill regular estimation of the battery degradation while retraining the SoC mechanisms to reflect the battery aging effect. In Ref. [29], the battery DT has been used for SoX estimation and cell balancing control. The PF algorithm was used for SoX estimation, which yielded MAE of 0.3% and 0.5% for SoC and SoH estimations, respectively. Based on the predictions of the actual capacity, the DT predicts the time that each cell requires to be balanced and accordingly formulates a fast and accurate

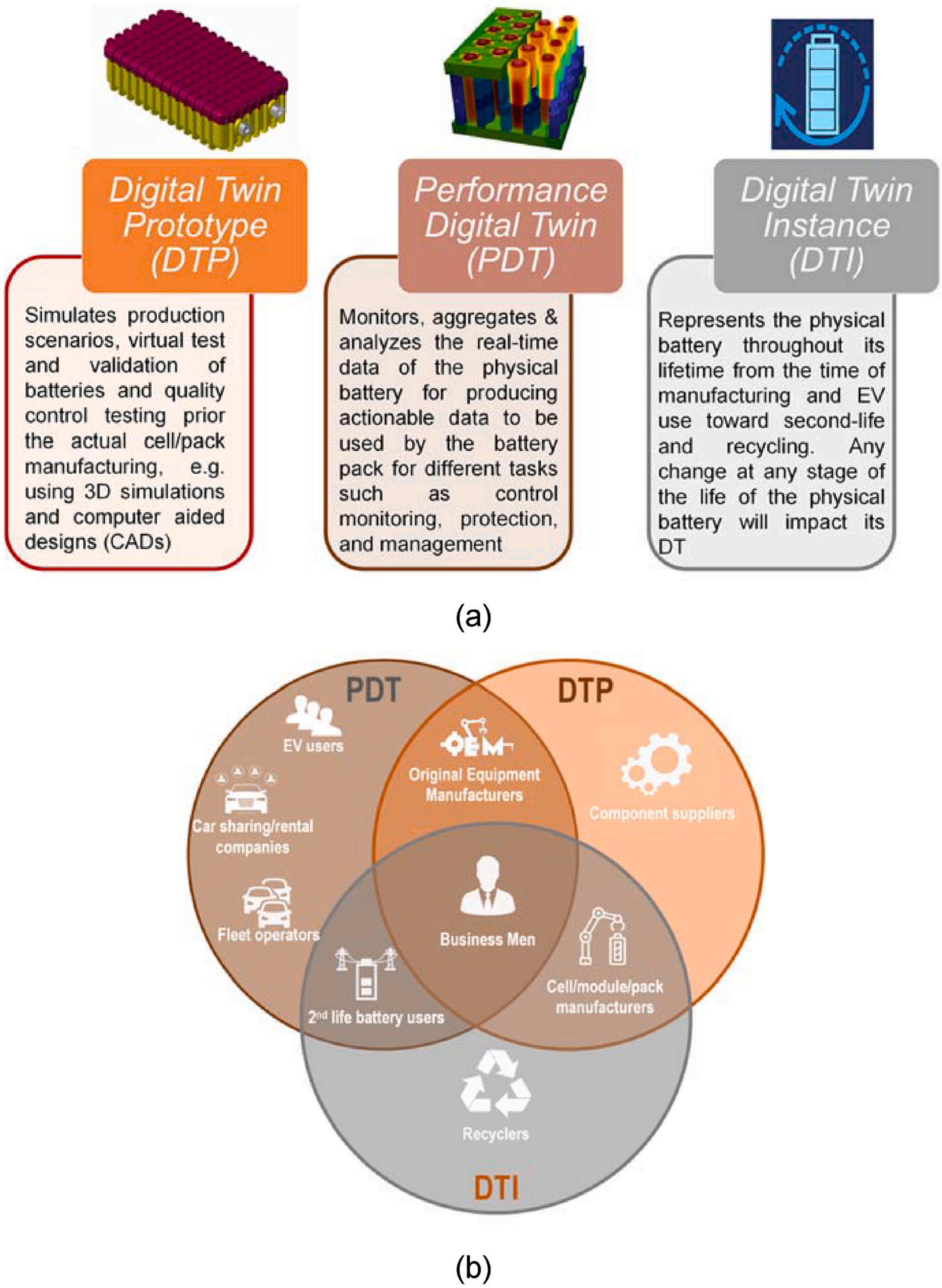


Fig. 3. (a) Different types of battery DTs (b) Relevance of the DT type to stakeholders.

balancing strategy. The concept of the DT-assisted equalization strategy is shown in Fig. 6 [29]. As seen, the BMS boards measure the key variables of different batteries and this data will be sent to the DT on the cloud, where balancing algorithms are placed. The necessary commands to control the balancing actuators will be generated by the DT and will be sent back to the batteries. Other works have used DT for SoC and SoH estimation based on extended Kalman filter-particle swarm optimization [30], Kalman filter (KF) combined with least-squares support vector machine and PF[31], ML [32,33], etc.

The battery algorithms can also be implemented within the cloud BMS concept proposed in Ref. [34]. The differences between the battery DT and the cloud BMS depend on the implementation philosophy and the DT definition. In cases where the cloud BMS is defined as a PDT of the battery, the terms can be used, interchangeably.

3.2. Fault diagnosis and prognosis

Onboard BMS uses classic fault detection and protection methods against the battery faults such as over-discharge, over-charge, short-circuit, etc. The fault diagnosis is usually fulfilled using single-variate

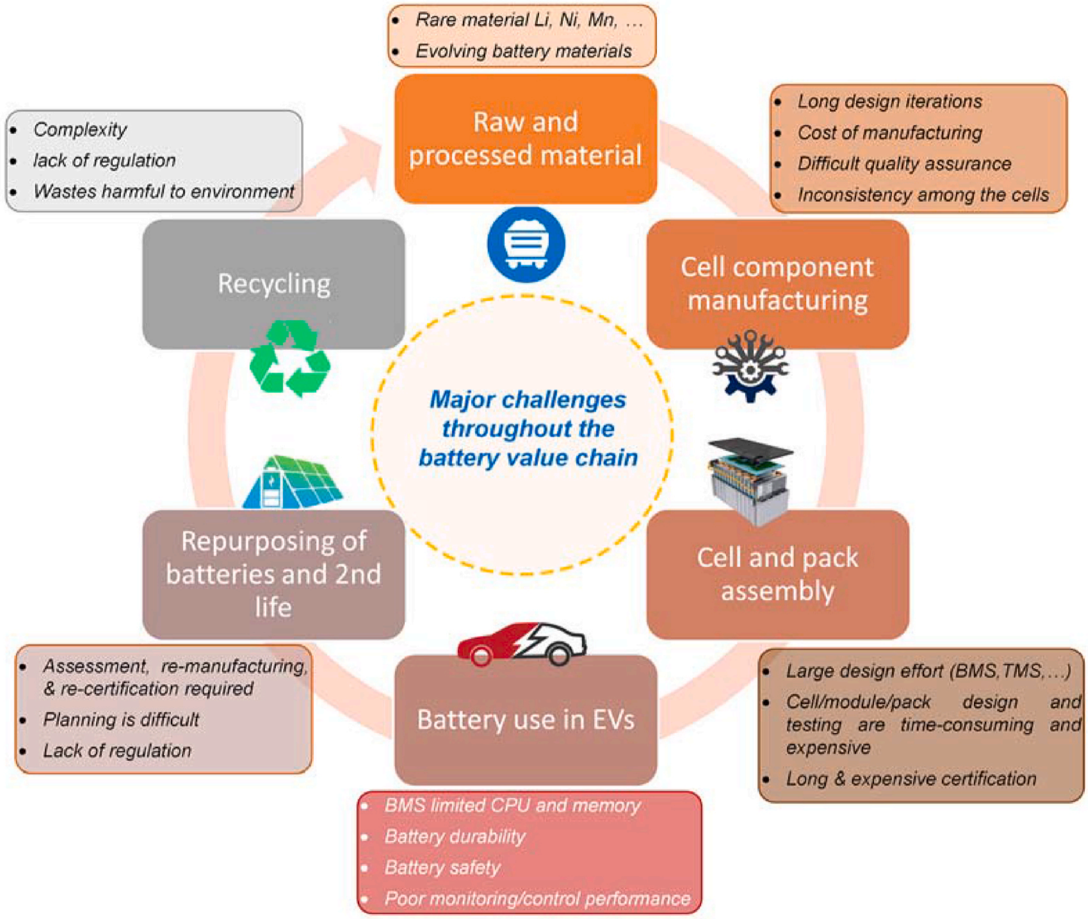


Fig. 4. Battery challenges throughout the value chain.

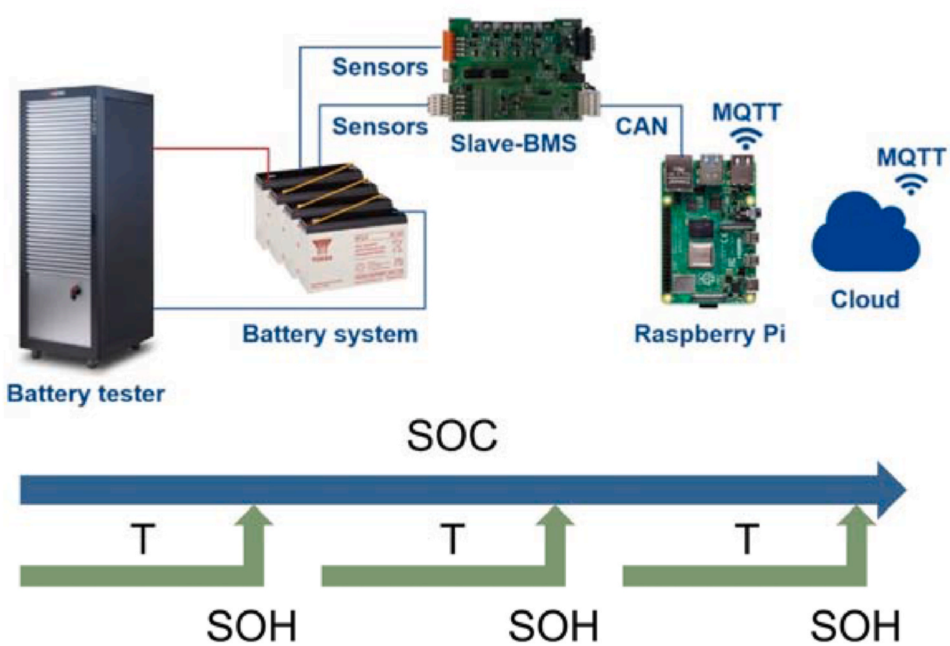


Fig. 5. Cloud-based DT is used for SoX estimation. SoC is estimated continuously while SoH is updated from time to time and is provided as input to the SoC estimation algorithm [25].

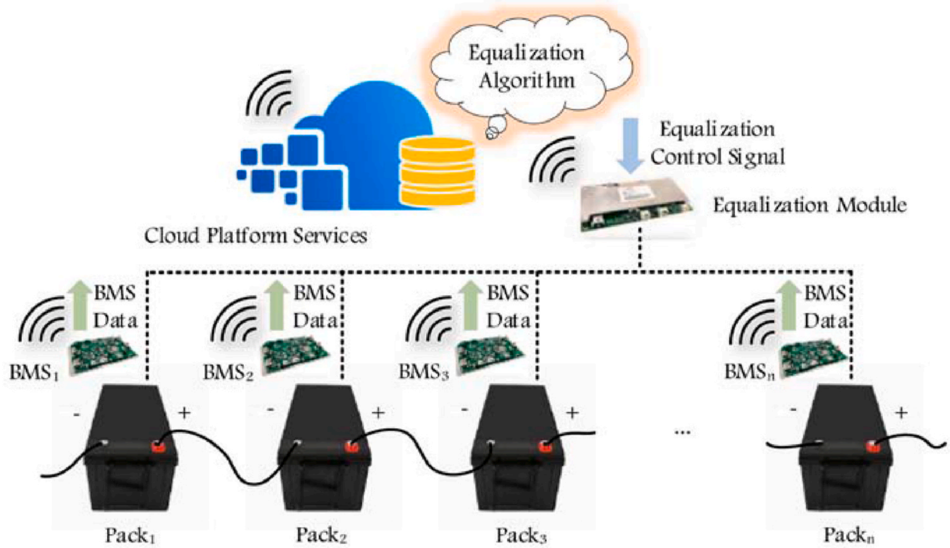


Fig. 6. DT-based equalization of the batteries [29].

techniques by comparing VIT variables to fixed threshold values disregarding the historical usage data. In the battery DT, the availability of large computational resources and historical battery usage data offer the possibility to explore more advanced fault diagnosis techniques. The abundance of sensory data enables the use of advanced multi-variate condition monitoring techniques to improve accuracy in detecting and locating faults. Fault prognosis is another interesting topic that can be explored in a DT context. Thanks to DT computation, advanced multi-scale and physics-based models can be run online to detect or predict faults, an option that is conventionally beyond the BMS capability due to the lack of resources. DT-enabled physics-based battery models can monitor the mechanisms and processes that eventually may trigger the faults. Examples of such model-based methods are presented in Refs. [35,36], wherein the DT is created by combining the electrical, thermal, and degradation models of the battery, reduced order models, or using the dynamic mode decomposition-based data-driven model. Intelligent monitoring of batteries using DT has been discussed in Ref. [37]. This use case of the DT has also been studied in other fields, e.g. monitoring of steam turbines [8]. This type of DT falls under the category of PDTs.

3.3. RUL estimation

RUL gives information about the durability of the battery pack before it reaches its end-of-life. Unlike the SoH which shows the battery status at present time, the RUL is an indicator that predicts future battery degradation trends. Normally, the RUL is estimated in terms of the number of cycles that have remained before reaching the end-of-life. Despite significant work that has been fulfilled in academia to perform battery RUL estimation, none of the existing commercial BMSs have the RUL estimation function up to now. However, RUL estimation on the DT and cloud offer several advantages as listed in Fig. 7.

A large number of algorithms have been proposed to estimate the RUL which rely on the model of the battery, data, or a combination of both. A detailed review of RUL estimation algorithms can be found in Ref. [38].

3.4. Predictive maintenance

EVs need regular service and maintenance. The conventional maintenance schemes are inefficient and economically inviable since they are normally applied either too soon, e.g. when the battery pack does not need maintenance, or too late when a defect or expensive damage shows up. With the battery DT, the RUL can be monitored in real-time, and thus, the maintenance can be scheduled only in case a repair or service is deemed necessary resulting in cost savings, improved battery lifetime and durability, and avoiding unwanted shut-downs [39]. Likewise, the manual battery check-up can be automated which saves time and money for EV owners. The predictive maintenance use case for the battery DT using the Bayesian-based adaptive evolution method has been studied in Ref. [40] wherein the lifetime prediction and reliability evaluation algorithms have been developed to estimate the RUL. It was concluded that the battery maintenance costs can be reduced by up to 62% when

Performance optimization	Awareness about future health allows optimization of operations, e.g. by changing the operating limits to de-risk failures.
Predictive maintenance	Optimized maintenance reduces downtimes and improves safety and reliability.
Second-life planning	Helps to know when the batteries should be retired and this information can be useful for planning re-use or replacement.
Guaranty/Warranty	Support of warranty claims against cell/module/pack providers.
Fleet management	Enabling informed decision systems for maintenance, management, and replacement of the EV fleet.

Fig. 7. Use cases of the RUL estimation on the cloud-located DT.

the predictive maintenance strategy was used.

3.5. Battery repurposing, second-life, and recycling

The repurposing process from an EV battery to a second-use application (e.g., stationary energy storage systems) is costly and time-consuming due to the need for disassembly and manual lifetime testing at the module or cell levels. With the DT concept, the SoH of the batteries can be continuously estimated, stored in the DT database, and interpreted when needed, while this data can also be shared with second-life stakeholders such as battery manufacturers for operational planning, e.g., to forecast the availability of batteries exiting from first life. Likewise, the economic value for different second-use applications can be assessed, e.g., the energy and power capabilities of the batteries can be accurately mapped to obtain the most viable application for the second-life. Batteries with more power capability can be used for grid ancillary services (power conditioning, frequency support, etc.) while batteries with more energy potential can be used in uninterruptable power supply systems. This use case has been considered in Ref. [41], wherein DT was used for battery residual value estimation as depicted in Fig. 8.

3.6. Sharing (swapping) services

Battery sharing use case has been studied in Ref. [42], where a DT was used to grasp the status of the shared batteries to facilitate their replacement. This allows swapping stations to understand the status of the battery, how it was operated, and to what extent it was degraded when it was being used by a distinct EV. Likewise, EV owners can swap batteries without being worried about the true health state of the battery. Battery DT also creates opportunities for financial services and insurance companies since they know the reliability and degradation of batteries and they can adjust fees and financial strategies, accordingly. Stakeholders can develop more viable guarantee/warrantee plans when detailed conditions of the EV batteries are available online. The same DT-based concept can be used in the case of EV rental and leasing companies. An example of this use case is presented in Ref. [42], wherein the SoC, SoH, and running distance of the EVs are estimated and stored on the DT to facilitate the sharing services.

3.7. Design and production optimization

The battery DT (DTP type) can be used to improve the manufacturing processes of batteries. Conventional methods for quality assurance, such as those based on the house-of-quality or Pareto chart require significant resources by multi-disciplined teams to address a specific problem or defect related to the product, which can take several weeks to months. However, with a DT, it is easier to find the root cause of the defects in the manufacturing process and the quality assurance can be fulfilled within a few days [23]. Likewise, with the battery DT, the information from the manufacturing level can be supplied to the EV operational stage, for instance, to calibrate some models and algorithms. Vice versa, the operational data of the battery can be used as feedback to adjust the design and optimization processes. Through providing this cross-stage exchange of data and information, the DT will create flexibility to improve performance in different state-of-life of the battery. This application falls under the DTI category.

The application of DT in battery manufacturing has been considered in several publications. In Ref. [43], an efficient 3D discrete calendaring element model has been proposed for the DT of the battery electrode, which is the core of the battery manufacturing process. In Ref. [44], a 3D resolved electrochemical model of electrodes was established to evaluate the effect of manufacturing parameters such as slurry formulation on the electrode microstructure and battery performance. Other works include digital twining to consider 3D shapes of active material particles [45], the dying model of electrodes [46], and carbon-binder spatial location [47]. To accelerate and ramp up the manufacturing processes, in Refs. [48,49], DT has been used for fast and economic battery module assembly and for flexible pouch cell stack formation to enable virtual testing and evaluation of different solutions before real manufacturing. In Ref. [50], a DT environment has been developed to automate the test and evaluation of the batteries to speed up the manufacturing process. In Ref. [51], a DT has been developed for all-solid-state batteries to estimate experimentally inaccessible and difficult to obtain information such as dead particles, specific contact area, and charge distribution in 3D domain, which will help to map design and performance parameters

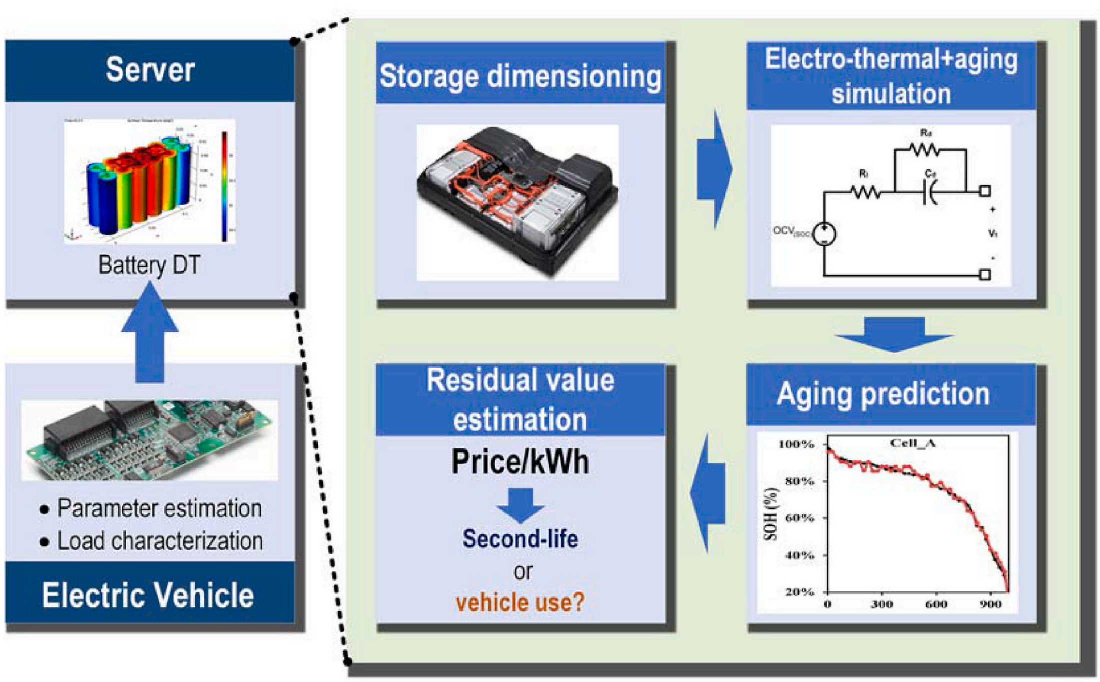


Fig. 8. Schematic of the cloud-based DT for battery repurposing and 2nd life decision-making [41].

for battery design optimization. The digitalization of battery testing will also reduce the time and cost associated with the experiments for battery characterization. Design optimization of the battery thermal management system (TMS) using the DT has also been considered in Ref. [52]. Most of the reviewed works fall under the category of DTPs targeting manufacturing processes.

3.8. Energy optimization

The performance of the energy management system (EMS) determines the EV driving range, lifetime of batteries, EV acceleration, etc. EMS is normally realized onboard the EVs and due to the limited processing power, embedding advanced EMS strategies which are based on sophisticated global and online optimization methods, stochastic algorithms, ML, etc. Is difficult. On the other hand, the DT offers sufficient computational power which can be used to run best-in-class EMS algorithms improving the EV performance under different driving conditions, e.g., to decide the optimum power limits during the acceleration and regenerative braking. Examples of such advanced EMS strategies can be found in Refs. [53,54]. Detailed analysis of these algorithms is beyond the scope of this review.

3.9. Thermal management system

The TMS is responsible to control the heating/cooling apparatus to maintain the battery temperature within a specific temperature range and reduce the temperature gradients and temperature inhomogeneous across the pack. Conventionally, the TMS is implemented onboard. However, the DT makes it possible to implement advanced predictive and intelligent control strategies to improve the overall TMS performance and battery lifetime. One such example has lately been proposed by Bosch™ Mobility Solutions. The so-called "Battery in the Cloud" concept receives data from the battery and fleet and takes predictive actions to improve the battery's performance. For example, the TMS starts to adjust the battery temperature a few minutes before the EV reaches a charge station that is already booked. This not only reduces the charging time (by preparing the battery to accept higher charge currents) but also results in less battery degradation under fast charging conditions.

3.10. Battery passport

A battery DT can be used to manage a so-called battery passport to monitor, collect, and integrate battery data and metadata starting at the cradle (manufacturing) toward the end-of-life gate (recycling) [55]. The battery passport is defined as a digital entity that conveys the social, governance, and environmental requirements to guarantee compliance with the regulations [56]. Through effective life cycle management with the battery passport concept, second-life services can save money and time by not testing batteries for a second time and recyclers can better set the requirements for the recycling processes as detailed in Ref. [55]. Fig. 9 shows the schematic of a Battery Identity Global Passport proposed in Ref. [55]. It is noteworthy that the Global Battery Alliance has recently called for prompt actions to exchange battery data through the battery passport concept [56].

The realization of the battery passport concept requires a framework that connects all operational phases. In this regard, an effective DT framework has been proposed in Ref. [12] to interconnect the research and design phase, manufacturing phase, after-sale phase, and post-operation phase based on the cloud space and 5G communication. Another DT framework for lifecycle management of the EV battery packs has been proposed in Ref. [57], wherein the design phase, manufacturing phase, and operations phase (including the second-life) are equipped with their battery DTs (research and development DT, manufacturing DT, battery DT, and DTs of other assets) while all DTs share information through centralized cloud storage in IT system. In Refs. [58,59], the importance of blockchain technology to empower sustainable manufacturing and lifecycle management in industry 4.0 is highlighted. Likewise, the challenges and future of DTs in the management of the product lifecycle are reviewed in Ref. [60].

3.11. Battery charging and vehicle-to-grid (V2G) operation

Different protocols can be used for battery charging including Constant Current (CC), Constant Voltage (CV), CC-CV, pulse charging, etc. The charging protocol affects the charging performance in terms of efficiency, battery degradation, charging time, and cost [61]. In this regard, an effective use case for DT is the health-aware charging of batteries [62]. In the DT, the charging problem can be formulated into a multi-objective optimization problem with a cost function that can consider degradation, charging cost, efficiency, and time, and decides the optimized protocol and charging parameters such as frequency and width of charging pulses during pulse charging. The cost function can be optimized, for example, to maximize the lifetime of the battery pack (by reducing the temperature gradients, preventing lithium plating, etc.) while reducing the charging time to the extent possible. In addition, constraints such as the maximum permissible charging power can be introduced to the charging optimization problem. An example of the use case is the convex multiperiod optimization strategy proposed in Ref. [63] to coordinate the battery charging while accounting for maximum charging power and voltage rise. Similarly, the application of artificial intelligence based on deep reinforcement learning for optimized fast charging of batteries has been reported in Ref. [64]. In this work, fast charging is realized through a multiphysics-constrained

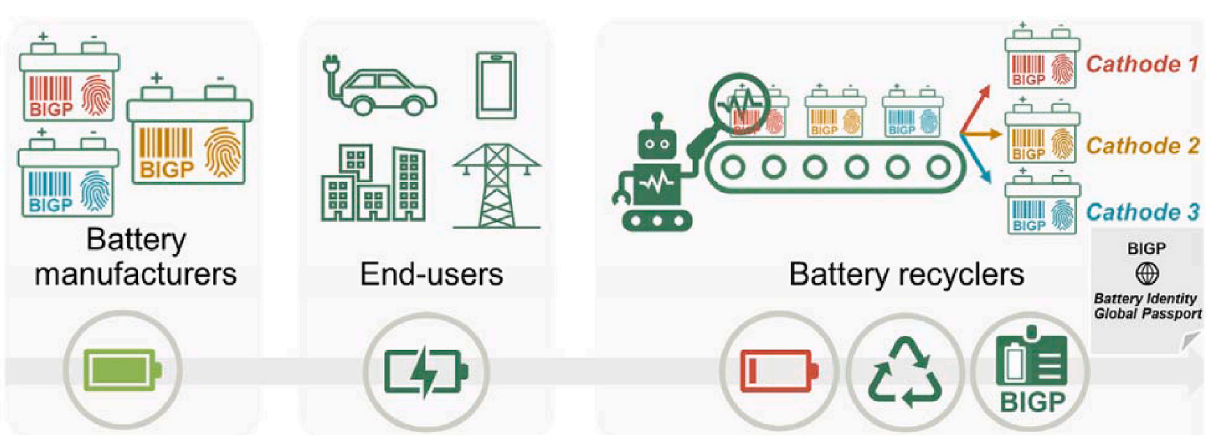


Fig. 9. Schematic of the Battery Identity Global Passport proposed in [55].

strategy with the consciousness of thermal safety and battery aging, and an extension of the battery life by about 15% at an equivalent charging speed is reported. Thanks to the large computational resource available on the cloud, the DT makes it possible to use advanced algorithms for solving large optimization problems like this.

Batteries also offer the possibility of V2G operation to support the electric grid when needed, e.g. to contribute to grid stabilization, peak-shaving, providing backup power, etc. [65,66]. Similar to battery charging, a cost function can be formulated to optimize the V2G operation using the DT, e.g. minimize the battery degradation when operating in V2G mode, increase the revenue, etc. Likewise, the usage profile and data of the EVs, batteries, charge stations, and grid can be stored on the DT and this data can be used for the optimization of charging stations.

Table 3
Review of the DT use cases.

Use case	Ref.	Description
SoX estimation	[25]	Cloud BMS with H-infinity filter-based SoC estimation algorithm and SoH estimation based on particle swarm optimization
	[26]	DT-based BMS with combined H-infinity and PF-based SoC estimation
	[27]	Battery DT was used to virtually apply a complete discharge cycle to measure SoH (discharge capacity)
	[29]	DT-assisted SoC, SoH, and SoP estimation using PF algorithm
	[30]	DT-based BMS for extended Kalman filter-based SoC estimation and particle swarm optimization-based SoH estimation
	[31]	DT-based BMS with KF-least-squares support vector machine SoC estimation and AR-PF SOH estimation
	[32]	Cloud-enabled DT for SoC and SoH estimation of batteries
	[28]	DT-based SoC and SoH estimation using data-driven methods based on random forest, light gradient boosting, and deep NN
	[33]	Cloud-enabled DT for SoC and SoH estimation using ML
Battery cell equalization	[29]	DT-assisted balancing control of the cells
Battery Monitoring	[35]	Module-level modeling of batteries based on cloud-enabled DT for monitoring of the batteries
	[37]	Intelligent monitoring based on battery DT
	[36]	Dynamic mode decomposition-based data-driven model for battery DT
Battery sharing services	[42]	Battery DT was developed to enable services that facilitate battery sharing, e.g., running distance calculation
Battery design and manufacturing	[43]	Battery DT model based on discrete element method for manufacturing optimization
	[48]	DT development for flexible cell stack formation of pouch battery cells
	[49]	DT was proposed to develop robotic workcells for fast and economic battery module assembly
	[51]	DT-driven battery model developed for design optimization and to reveal experimentally inaccessible information
	[50]	Battery DT was used to speed up development and manufacturing phases by eliminating actual system tests
	[52]	GPR-based battery virtual DT developed for design optimization of the TMS
Repurposing and second-life	[41]	Cloud-enabled battery DT to facilitate second-life decision-making process via DT-based aging prediction
Predictive Maintenance	[39]	Semi-analytical DT model of battery pack developed for real-time temperature monitoring and predictive maintenance
	[40]	DT was used to fulfill life prediction and reliability evaluation for predictive maintenance implementation

Table 3 summarizes the reported use cases of the battery DT. Fig. 10 shows that the battery digital twining is moving quickly and the number of applications and use cases reported has steadily increased in recent years.

4. Key enablers and requirements

The technologies, components, and requirements of the battery DTs depend on the DT type, application area, and the considered use cases. The elements are listed in Fig. 11 and key technologies are discussed in the following subsections.

4.1. Measurement of the key battery variables

Several sensors are usually integrated into the battery PT to measure the key variables including the VIT data. Voltage is normally measured for every cell while current is measured at pack level using current shunts or hall effect-based sensors. Temperature is normally measured for every other cell. Advanced battery packs also include multi-sensing units to measure additional variables such as gas, pressure, and strain to detect hazardous situations. The sensory measurements are the input to the DT models and algorithms. These data should thus be communicated to the cloud-located DT with proper sampling rates. Sample rates depend on the use cases. However, the common practice is 10HZ for voltage and current and 1 Hz for temperatures. The IoT gateway can listen to the vehicle CAN bus to read the data and pass them to the battery DT. Alternatively, the IoT gateway can directly listen to the BMS communication interfaces conditional on compatibility with the IoT gateway. The DT uses this data to update the models, perform data analysis, and operate algorithms for monitoring, optimization, SoX/RUL estimation, etc.

4.2. Battery models

Models serve several services and tasks related to battery operation [67]. Generally, the DT considers different modeling levels from material and cell components to the pack. Lithium-ion transport in the active material and between the electrodes takes place on the nanometer and micrometer scales whereas, at the cell level, behavior is described on the millimeter scale such as in heat transport [68]. Therefore, multi-scale modeling is required to involve different time scales. In this regard, 3D models are the most complicated type incorporating cell multi-physics to model the electrode porosity and inhomogeneous cell behavior along the 3D coordinates. The 3D models are very accurate and robust, but they contain nonlinear coupled partial differential equations that are too heavy to be solved in real-time. Thus, the key challenge has been about finding effective model order reduction techniques that can reduce the complexity of the models while maintaining fidelity. Various models have accordingly been developed. The electrochemical model based on the so-called Newman or P2D assumes homogeneous electrode particles of the same size and predicts the behavior in axial coordinates. Several model order reduction methods for discretizing and approximating the P2D model based on the finite-difference method, Pade approximation, etc. Have been proposed resulting in several electrochemical-thermal model combinations with different scales, e.g., P2D+0D, P2D+1D (also known as P3D), and P2D+2D/3D. In the simplest case, spatial lumping has been proposed to form the so-called single particle model wherein each electrode will be modeled only using one spherical particle and the electrolyte dynamics will be neglected. The model assumes a uniform temperature distribution within the cell. However, simplified models fall short in certain operating regimes such as C-rates typically higher than 3C. As shown in Ref. [69], the reduced version of the P2D model with thermal dynamics, also named P2D-T, can be extended to capture the degradation mechanisms such as the loss of lithium inventory. The model is then discretized and applied for the estimation of battery SoC using the singular

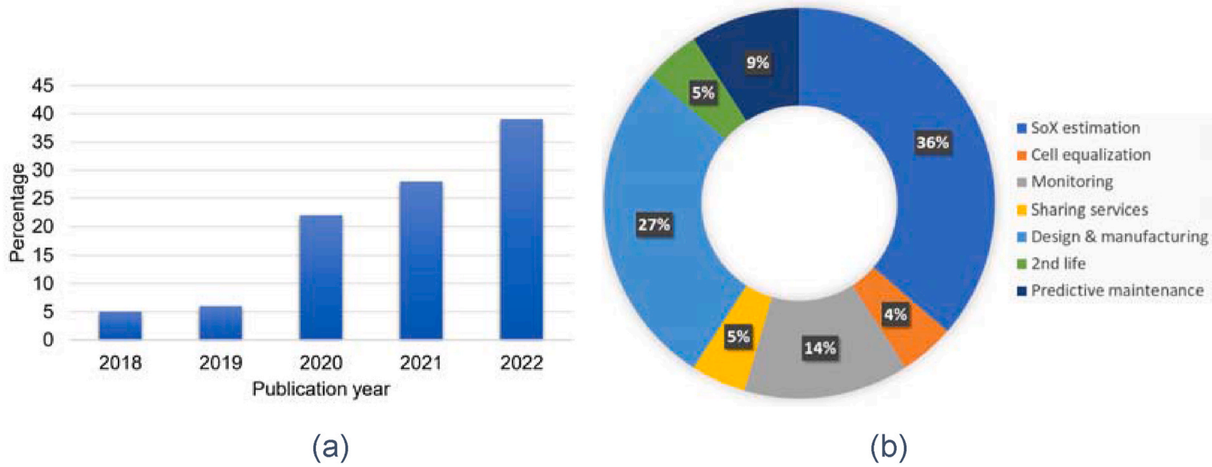


Fig. 10. (a) Publications per year on the battery DT concept (b) Share of battery DT use cases.

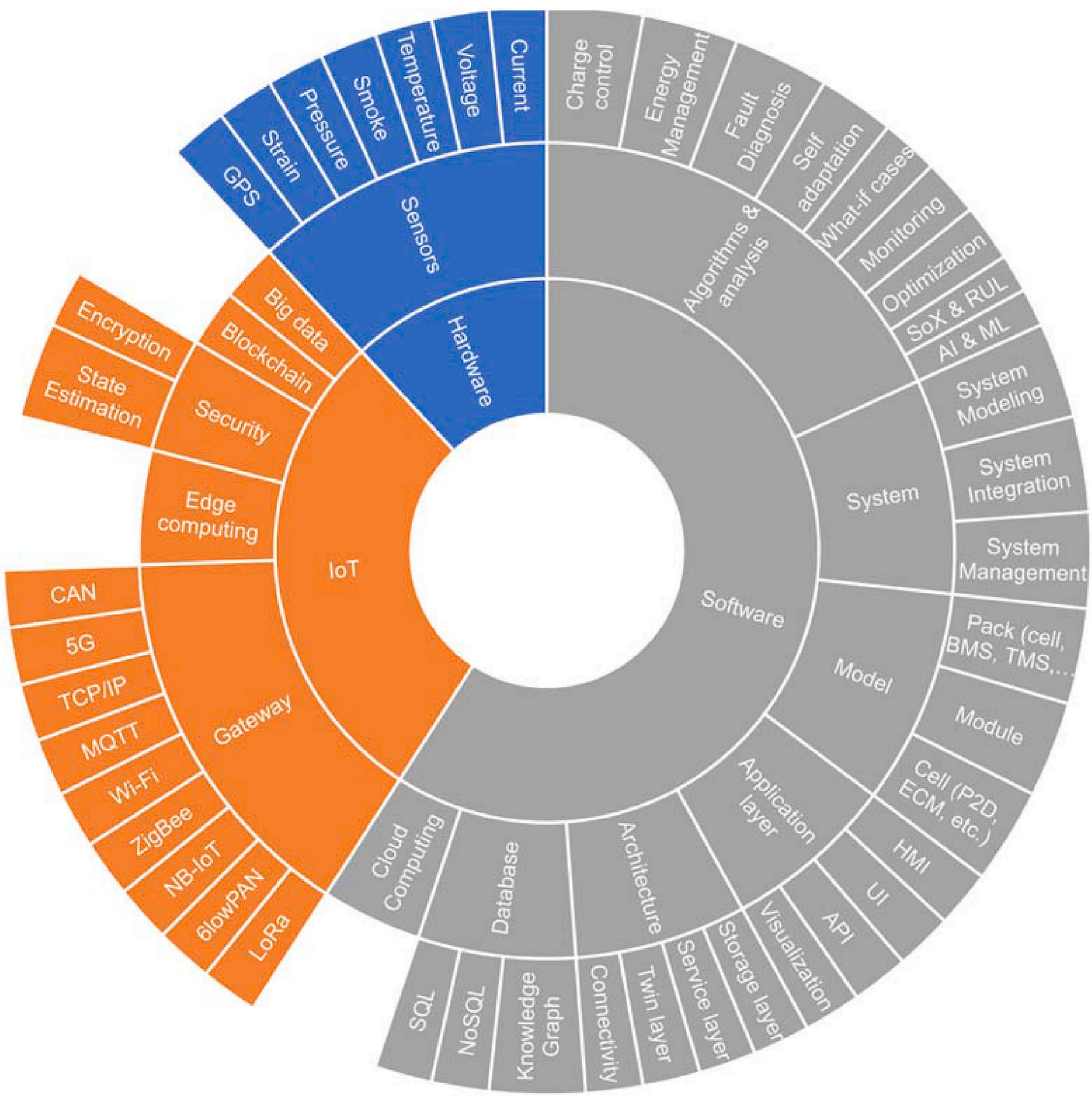


Fig. 11. Key elements of the battery DTs.

evolutive interpolated KF algorithm. In Ref. [70], distributed fiber optical sensors have been embedded in the battery and the data has been used to build a one-state thermal model for co-estimation of thermal parameters, heat generation rate, SoC, and maximum capacity. A more detailed review of thermal models can be found in Ref. [71]. Data-driven models such as those based on neural networks (NNs) or hybrid models (model-based combined with data-driven) can improve the DT generalization capability and overcome some of the limitations of reduced models. The availability of large quantities of data on the DT, user-friendly software frameworks [72,73], and specialized hardware [74] have made it simpler to apply NNs to the task of predicting the behavior of batteries. A good example of such data-driven modeling is the hybrid lumped-thermal-NN model proposed in Ref. [75], in which a mechanism-driven distributed lump thermal model is combined with an ML-based axial thermal gradient compensation segment. See Refs. [76–78] for an overview of NN architectures in use for the simulation of dynamical systems.

The model structures are designed such that some parameters affect the model behavior if certain inputs are given, i.e., it could be the case that some parameters are never found by calibration. In these cases, noise filtering techniques [79] and the design of experiments [80] have been demonstrated to be useful. Another challenge is the time-varying model behaviour which results in variations of the model parameters in different conditions such as different temperatures, SoC, C-rates, and degradation levels. Various real-time model parameterization algorithms have been proposed to address this challenge. Most popular methods are based on recursive filtering techniques such as the least-squares family [81] and more recently, the application of ML for battery model parametrization has also been explored [82].

The equivalent circuit models capture the battery behavior using the electrical circuit components. Despite relatively higher computational efficiency, the equivalent circuit models cannot represent the physiochemical attributes of the cells. However, they are found to be effective for specific tasks such as SoX estimation and fault diagnosis. As an example, in Ref. [83], an equivalent circuit model based on Thevenin's structure has been used to develop a model-based internal short-circuit detection technique, which features robustness against degradation and noise effects. Stochastic battery models have also been proposed to predict aging behavior due to the randomness of different operating conditions and aging mechanisms [84]. A detailed review of battery models is beyond the scope but some good review papers merely dedicated to the modeling topic have already been published [85–87]. Fig. 12 shows the advantages and disadvantages of each model type.

The cell model is the building block but in practice, the DT can be the union of different models related to other systems, subsystems, and processes. For example, the cell models can be combined to build module and pack models while the pack model could in addition contain the models of the BMS and TMS. This is conceptually shown in Fig. 13. In this regard, one should highlight the effective model development/improvement toolbox proposed in Ref. [88] wherein all DT modeling requirements such as cross-integration of multiple cell models, execution of models in "what-if" scenarios, and model update calculation are well considered.

4.3. DT architecture

The common feature of DT frameworks is the use of services that can be integrated into the platform [89,90]. Hao et al. argued in Ref. [91] that the most important services for DT are state estimation (also known as inverse modeling or sensor fusion), predictive maintenance, fault diagnosis, decision-making support, and self-adaptation. The architecture of the DT can therefore be represented by layers, where the lower layer enables connectivity and data exchange between the DT and the PT (effectively working as an IoT framework), and the upper layer provides more sophisticated services. To denote these layers [92], introduced the term 3D DT, to denote DTs that only have the lower layer.

The term 5D DT, introduced in Ref. [93], extends the 3D DT by the data and service dimensions. The 5D DT then provides a central storage location connected to the physical, virtual, and service space, and a service system for implementing data-driven services. The need for 5D DT appeared after applying the 3D DT in the industry, where the new services allow new functionality with a higher value.

Fig. 14 illustrates a basic architecture for a DT implemented in Ref. [94]. It uses a RabbitMQ server as a broker for communication between different services and InfluxDB as a database to store, access, and retrieve data. The middle three blocks in the DT represent the services.

All components communicate via the RabbitMQ message exchange, and the data is stored in a time series database (InfluxDB). In Ref. [95], a DT architecture has been proposed which consists of three different layers as shown in Fig. 15(a). The hardware and connectivity layer is responsible to collect all sensory data and fulfilling edge-processing to

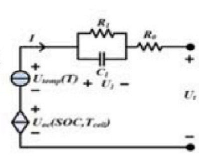
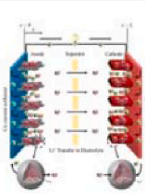
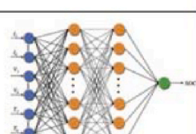
Model	Pros	Cons
Equivalent circuit models 	Widely used for SoX estimation, a nice trade-off between accuracy and complexity, error lower than 2% achievable	Parameterization requires special types of tests at different temperatures and SoC conditions Poor interpretation of battery physics
Electrochemical model 	High accuracy, Ability to track the aging of battery components, e.g., the thickness of the solid electrolyte interphase, Models the physics of battery	Prior knowledge of battery required, Manufacturing and construction data needed, Time-consuming training process, High computational burden
Data-driven 	Does not require prior knowledge about the cell, Strong mapping potential	Collecting the training datasets in the laboratory is very time-consuming and costly
Empirical $V_{battery} = f\,(SoC, I, T)$	Simple representation, Minimum complexity	Low accuracy

Figure 12. Potential of different battery models for use in the DT.

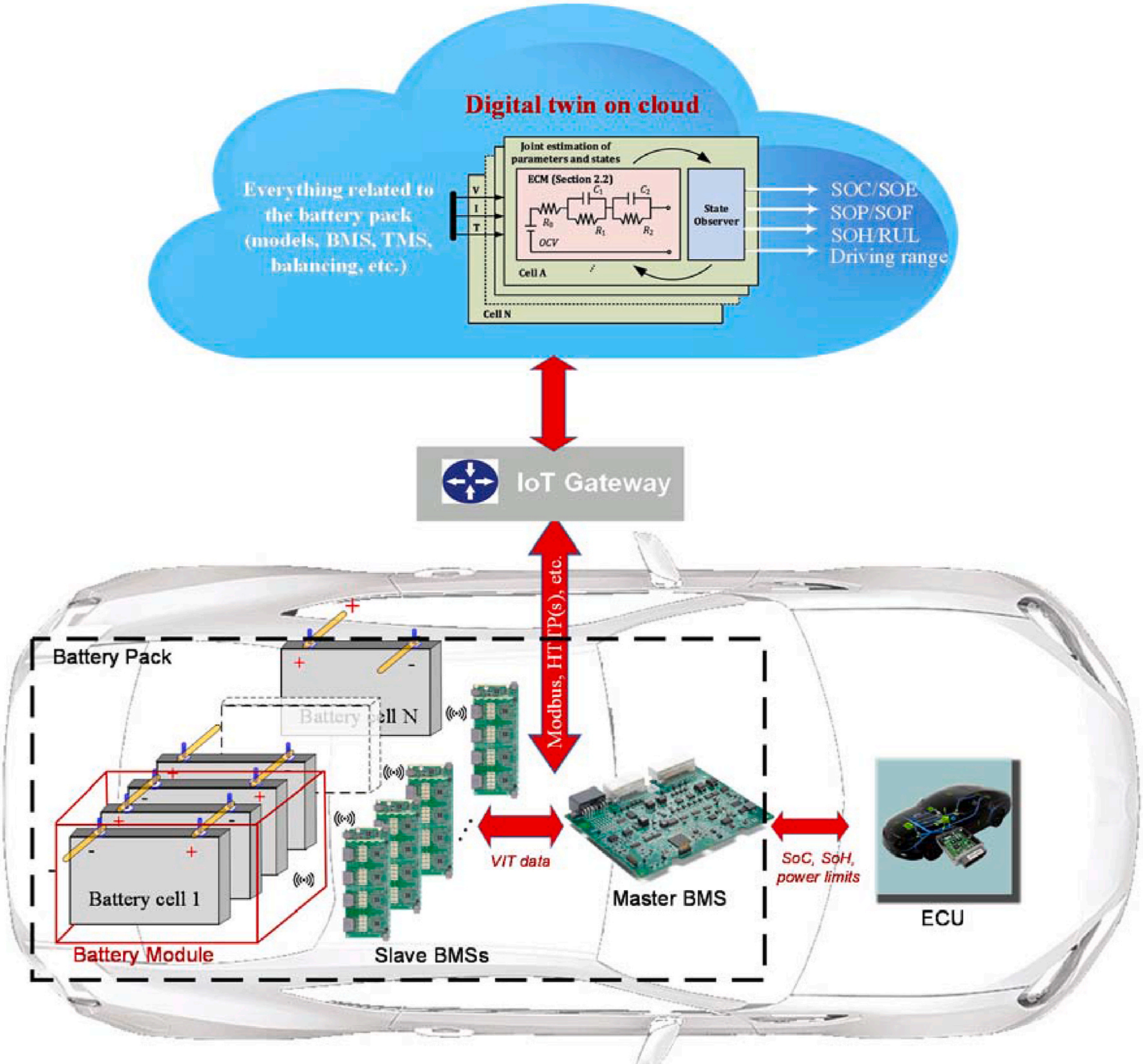


Fig. 13. Physical battery architecture and DT battery models for cell#1 to cell#N. All BMS/TMS algorithms are replicated on battery DT.

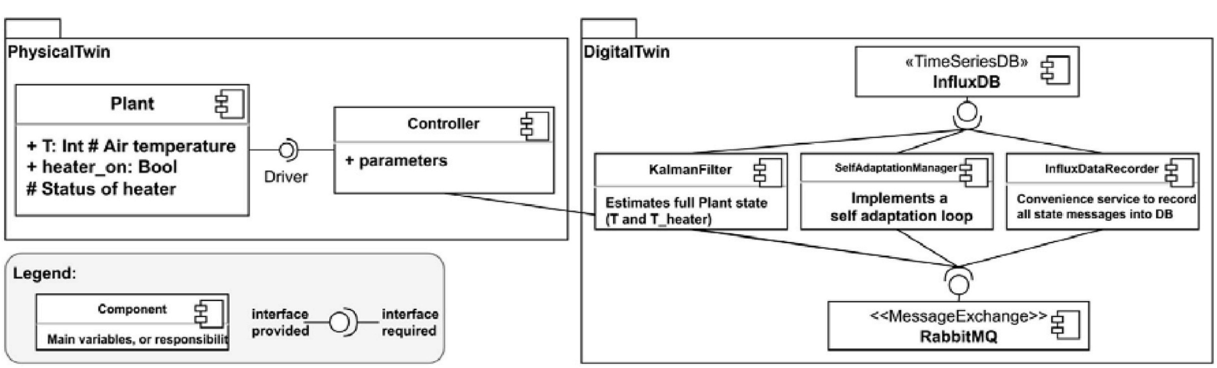


Fig. 14. Exemplary communication of incubator DT in relation to a self-adaptation service (from Ref. [94]).

remove the outliers. Battery simulations, models, and algorithms operate in the DT layer which also includes the databases. High-level services and aggregation operate in the service layer. The database in the twin layer considers four types of data, i.e., the master data (such as cell metadata), transaction data (such as VIT data), state data (processed data at the twin layer), and link data as illustrated in Fig. 15(b).

The DT functional architecture proposed in Ref. [96] consists of five different layers as shown in Fig. 16. The architecture is similar to Ref. [95] except that two additional layers are introduced for the database and connectivity. In Ref. [97], a new framework for DT-assisted enterprise resource planning of battery manufacturing systems has been proposed. The framework enables real-time access to

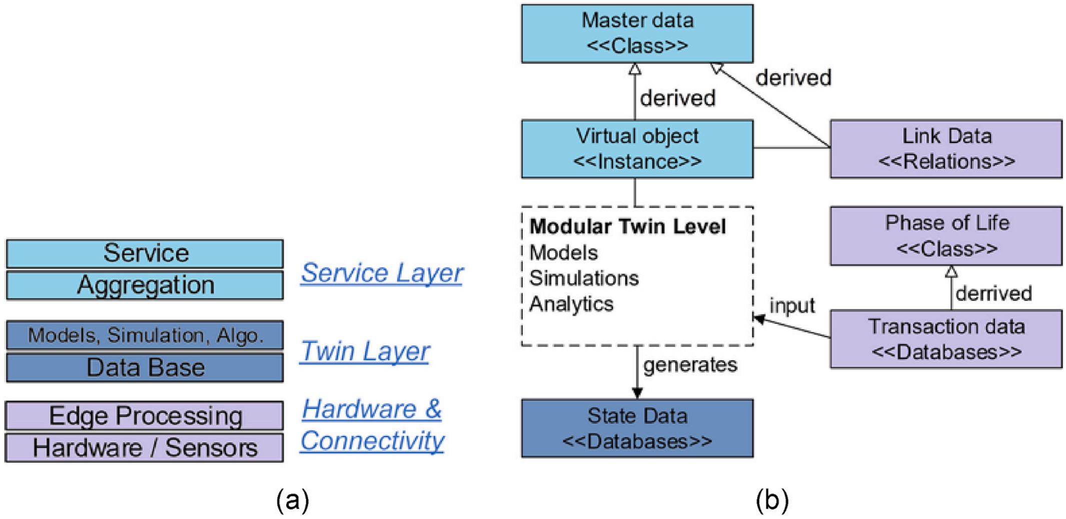


Fig. 15. (a) DT architecture proposed in Ref. [95] (b) Overview of data types in the DT architecture.

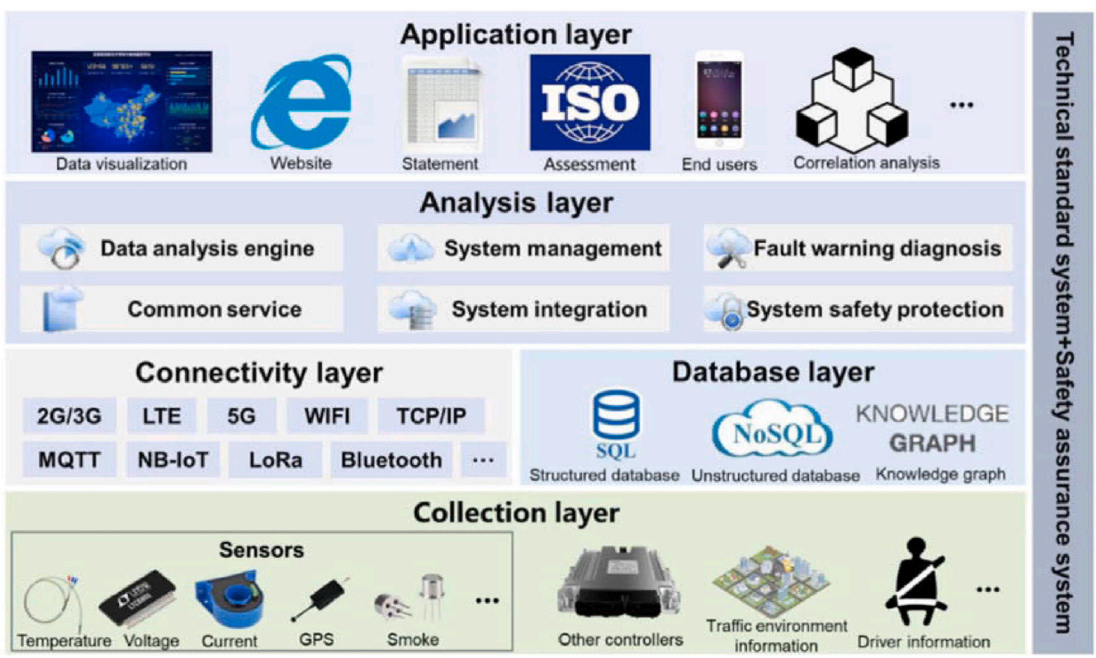


Fig. 16. The DT functional architecture proposed in [96].

multiple data types such as battery real-time operational data, production line data, and customer feedback data, which will help to optimize the production chain in manufacturing and to accelerate the decision-making processes.

A seven-layer DT architecture has also been proposed in Ref. [88] as shown in Fig. 17. The layered structure shown in Fig. 17 is similar to the one presented by Ref. [96] except that an additional layer for the security of the DT is foreseen.

As summarized, most DT architectures follow the layered architectural style combined with service-oriented architecture. The upcoming subsections detail the different steps and most common services required to form a DT.

4.4. IoT and connectivity

The communication framework is an integral part of the DT. It needs to support point-to-point communication, wildly different message sizes, message routing, handle packet dropout, and minimize communication delays while being resource efficient. Some communication technologies like RabbitMQ even enable load balancing and therefore increased resilience. Failures in communication typically can lead to disastrous consequences in a real-time battery monitoring scenario, such as overcharge, over-discharge, and thermal runaway.

Fortunately, there are many mature communication techniques in place: RabbitMQ and Apache Kafka, to name a few. On the research side, a wide review of IoT related to energy systems is carried out in Ref. [98], wherein the role, impact, challenges, and constraints in different scenarios and subdomains are described. They also listed some IoT protocols and technologies that can be used in different applications, including 6lowPAN, Power Line Carrier, ZigBee, among others. Reference [99] also highlights the capabilities of 5G-IoT and its comparison to other technologies, such as LoRa, Wi-Fi, ZigBee, and Bluetooth. NB-IoT and the 3 GPP low power wide area technologies offer a different promising alternative for IoT communication in smart grid and

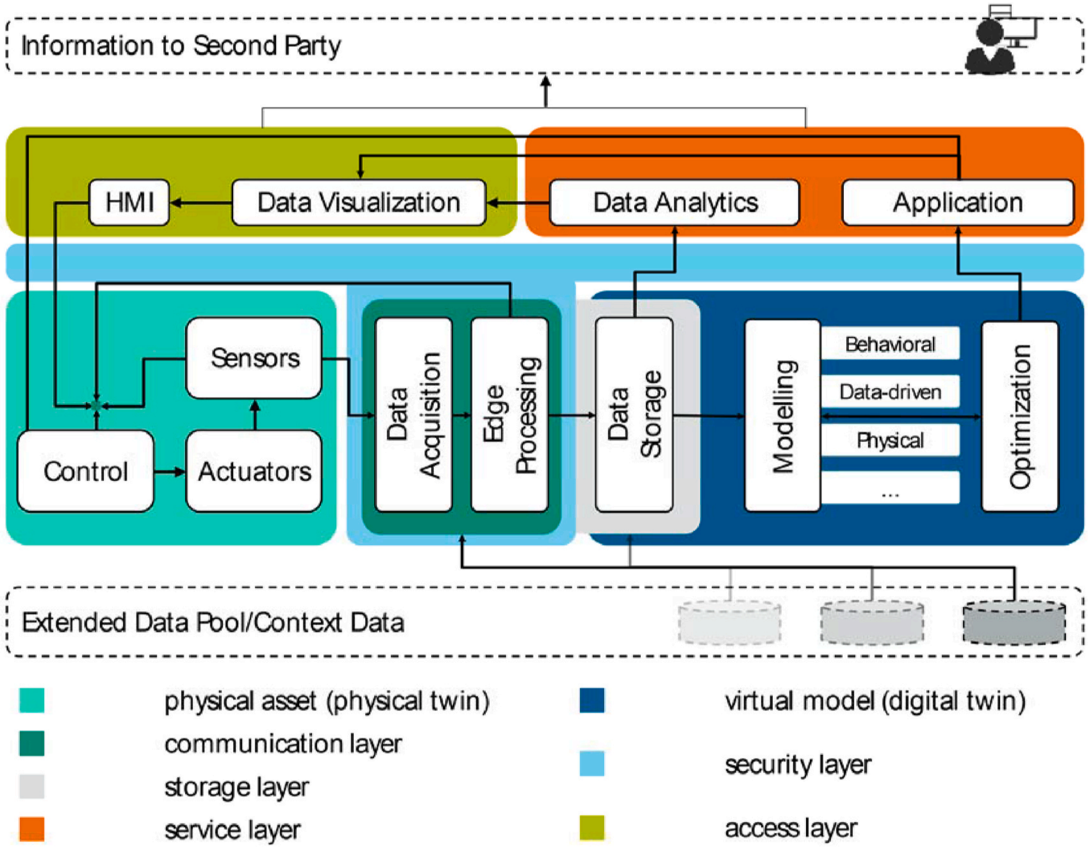


Fig. 17. The DT architecture proposed in [88].

Vehicle-to-Grid applications [99]. Reference [100] presents an orchestration of different IoT protocols in the electrical industry and a mapping of the protocols HTTP, MQTT, OPC UA, and LoRaWAN to use cases in different scenarios.

4.5. Data storage

The most appropriate technology to store data from battery PT is the time series databases since these are optimized for querying time series data [101,102]. Other types of data storage methods that are suitable for DTs can be based on the semantics that is normally used along with data models. A common technology for this is the resource description framework (RDF), which allows the storage of data using ontological or relational models as the scheme of the databases. This way, data can be stored and maintained on top of semantic models [103]. Description documents and metadata of DTs also need to be considered in large-scale DT setups and managing them in Git repositories with web servers for the DT Web, similar to the one proposed in Ref. [104]. Metadata and description files of the DT Web can also be mapped to RDF structures, enabling a bridge between static and dynamic data storage and querying using SPARQL, and even reasoning, such as presented in Ref. [105].

4.6. Visualization

Visualization tools have matured over recent years. Currently, it is possible to produce 3D interactive animations using tools such as Unity (https://unity.com), Qt (https://www.qt.io), iTwin (https://www.itwinjs.org), Gazebo, and dashboard interfaces with Grafana, Dash, to name a few.

The challenge remaining is the ability to create such interfaces quickly from CAD and semantic models of the battery. For example, it should be possible to, use such interfaces; selectively visualize the 3D battery PT and its environment; spawn new what-if simulations from current and historical data; replay past states; and display predictive maintenance results.

It can be challenging to strike the right balance in detail, as data visualization needs to promote real-time, perceptual, and scalability [106]. For more details, the reader can refer to Ref. [107].

4.7. State estimation

Key battery state variables include SoC, SoH, and SoP. Other states such as state-of-safety, state-of-temperature, state-of-energy, and state-of-function can be of interest in some use cases. Battery state variables are highly correlated and vary with time. State estimation combines the available sensory data and battery models to indirectly elicit these state variables. State estimation methods are very diverse and can be generally categorized into model-based, data-driven, and hybrid methods. The model-based methods can be based on stochastic techniques such as KF and its variations (extended Kalman filter, Unscented KF, etc.), PF, H-infinity filter, etc., or deterministic techniques such as state observers. Many data-driven methods have been proposed for battery state estimation-NNs, long short-term memory networks, and SVM to name a few. Model-based methods fall short in certain operating conditions due to low fidelity, e.g., during the fast charging of the battery. On the other hand, the data-driven methods have better generalization capability, but they rely on an extensive amount of experimental data to be trained. Obtaining the data requires time-consuming and expensive laboratory tests. Hybrid methods combine the advantages of the other two approaches. An Example of the hybrid method is presented [108] which combines PFs and NNs to predict the battery SoH. A detailed review of the battery state estimation can be found in Ref. [109].

4.8. Monitoring and anomaly detection

Monitoring is crucial for the evaluation of the PT's behavior and for checking whether the original assumptions about the environment in which the PT operates still hold [110]. In the SotA [111,112], one can distinguish between online and offline monitoring techniques. Online monitoring is done as each new data sample arrives, whereas offline monitoring is suitable for use cases where an added delay is tolerated. In offline monitoring, a time series database stores all data from the PT and is consulted at leisure by the monitor. Monitors can also attempt to identify the cause of problematic behavior by replaying the historical data through models of the system, while artificially injecting faults in the system until they find a potential explanation for the problematic behavior observer [113]. Monitors are not limited to checking for undesirable situations. They can also check for expected and desirable behavior of the DT services themselves, and not just the PT. For example, concerning the safety of the battery PT, it can be very valuable to be able to monitor when the discrepancy between the monitored and predicted behaviors starts and thereby enable anomaly detection. The reader can refer to the SotA in run-time monitoring [111,112] and advanced battery monitoring strategies [114].

4.9. What-if (Co-)simulation

A DT foundation as a decision support system is the ability to run simulations using hypothetical scenarios reproduced from historical data or containing predictions of the future environment of the PT. For instance, after an anomaly is detected, many simulations can be run to investigate what the probable cause is. Naturally this forces such simulations to be faster than real-time, so as to find a solution and intervene before the anomaly becomes a fault. In cases where the system is represented by coupled sub-models that have been produced by different tools, then co-simulation [115] can be used to realize the coupling. What-if simulations can also be used to optimize the battery configurations as the battery operates in new conditions or environments. However, one of the challenges is to quantify and manage the uncertainty inherent in these simulations and subsequence choices based on them.

4.10. Self-adaptation

Self-adaptation can be denoted to the process of optimizing the PT configuration as a response to changes in its environment, as proposed earlier in autonomic computing, thereby increasing its resilience. DTs are perfect candidates to deploy self-adaptation loops. However, designing these loops requires domain experts who, incidentally, do not usually possess the software engineering background to deploy these loops. In this regard, complex event processing frameworks [116] which provide a useable interface to encode behavioural rules can be of help. Domain specific language engineering provides the tools to quickly create such code-free development environments that can be used by domain experts [113].

After a new configuration for the PT has been found, it is necessary to make sure not only that it is safe, but also that the act of changing the PT from its current configuration to the new one, is safe. Here formal methods [117,118] and reachability analysis [119–121] can play a role.

As for the main steps in any self-adaptation loop, the reader can refer to the MAPE-K Loop, proposed in Ref. [122] and detailed in Ref. [123], as a reference architecture for designing self-adaptive loops. The work in Ref. [94] adapts the MAPE-K loop to the context of DT.

4.11. Privacy and security

This aspect of battery DTs is especially important for industrial use because compromised security could lead to dangerous situations such as unstable operation of the battery, physical and economic damages, and accidents leading to injury or death [124]. To this end, the battery DT can be perceived as a prime target for potential attackers, similarly to supervisory control and data acquisition (SCADA) systems [112,125,126]. Several ways of preventing attacks at industrial and specifically CPSs have been proposed, such as among others, the use of formal methods to create secure architectures [127], integration of different security controls [128], or the use of state estimators [129,130], where attack resilient state estimators have been proposed [131]. Securing DTs consequently requires not only considering access control, network security, and transmitted data integrity but also the integrity of the model itself.

As examples of a DT as a security tool, one has [132,133] both proposing using the DTs assets in the design of the security aspects and attack modeling and mitigation. In Ref. [132], the authors propose a framework to generate DTs from specifications for SCADA systems. In addition to being a security tool, the work of [133] proposes to use the DT in training and simulation, testing exercises for security engineers. Further information on this topic can be found in Refs. [134–136].

Relevant standards that apply to the DT domain in terms of security and privacy include IEC 27400–2022 entitled "Cybersecurity — IoT security and privacy — Guidelines" and IEC 62443 which defines cybersecurity for industrial automation networks.

5. Review of the existing DT platforms

The implementation process of the battery DTs is twofold: development and integration. For each phase, several commercial and open-source tools and platforms are available, which are reviewed in the following subsections.

5.1. Development platforms

The development of DTs includes the design and establishment of the appropriate battery models which could replicate the real battery behavior to the desired purpose. Several tools can be used for battery DT development, which are reviewed in the following.

5.1.1. ANSYS Twin Builder

ANSYS Twin Builder offers multiphysics system solvers which involve applications in 1D and 3D space with easy and fast system setup. It makes simulation models closer to the real batteries by combining 3D physics solvers and the reduced order models and thus, the electrical, thermal, and mechanical models can be coupled and tested in synergy. ANSYS heating/cooling library offers a wide range of models for TMS components such as heat exchangers, turbomachinery, valves, etc. It is also possible to model two-phase flows which are needed to model the TMS's refrigeration cycles. ANSYS Fluent and ANSYS Twin Builder have been applied by Electronic Cooling Solutions Inc. For thermal prediction and optimization [137].

A typical battery DT developed in Ansys is shown in Fig. 18 [138]. The battery DT simulation steps are shown in Fig. 19.

Fig. 20 shows how the PT and DT can be connected using ANSYS Twin Builder. The real-time data measured by sensors are transmitted to the battery DT using IoT. The DT perceives the data as input, performs all the simulations, and sends feedback to the battery PT.

5.1.2. COMSOL Multiphysics®

COMSOL Multiphysics® is a commercial Finite Element software with strong tools for battery DT development. The battery's electrical, thermal, and mechanical aspects can be numerically investigated in synergy. Similar to ANSYS, the COMSOL DT incorporates lightweight models such as reduced order models and lumped models to improve computational efficiency. The concept of COMSOL's battery DT is shown in Fig. 21. To link the battery with its DT, COMSOL offers an application programming interface communication tool powered by Java. The web service transfers the measured battery data to the DT. Upon stimulation

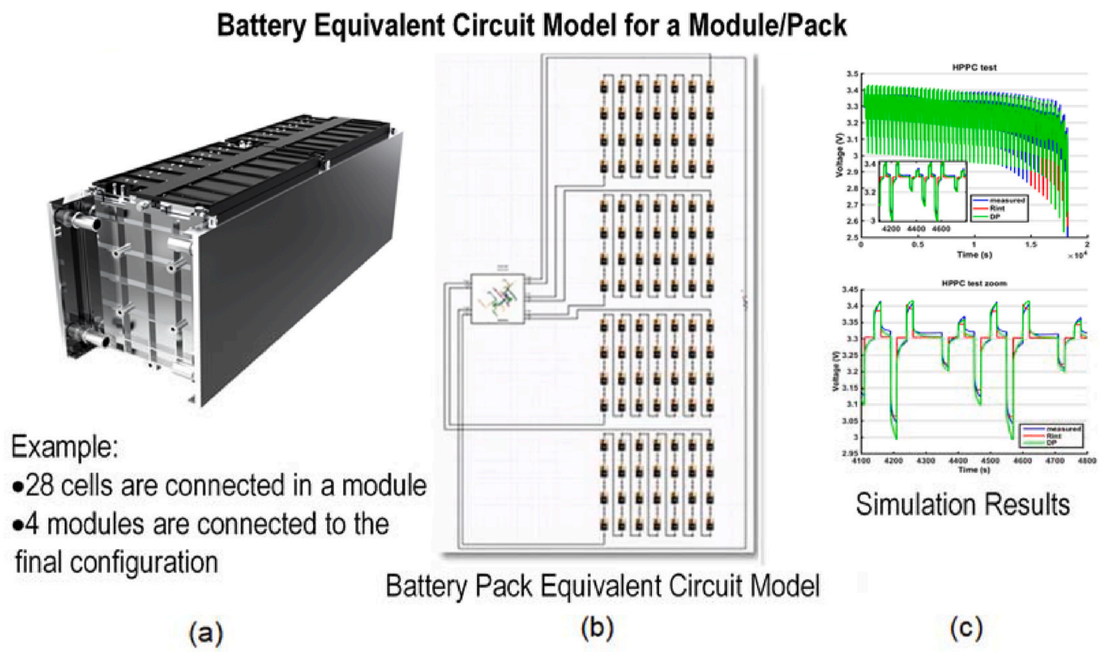


Fig. 18. (a) A battery pack example with 28 cells, (b) battery pack configuration with connections of 4 modules, (c) Visualization of results.

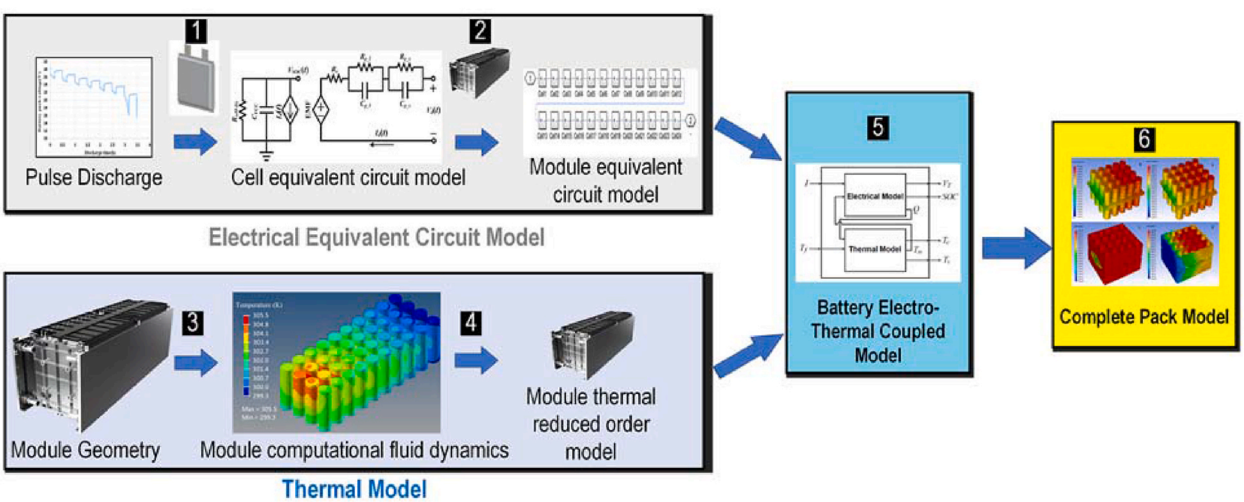


Fig. 19. System simulation steps of battery DT in the Ansys Digital Twin Builder [138].

of the scenarios, the control parameters and reports are sent back to the battery. Additionally, COMSOL Multiphysics comes with a dedicated and effective Battery Design Module, which can be used to develop a range of models for battery DTs at different scales from cell level to pack level. The DT models can be easily structured and calibrated to cover the right modeling and simulation needs, e.g. modeling of different aging phenomena, thermal runaway, etc.

5.1.3. *Siemens Simcenter Amesim and digital twin*

Simcenter Amesim software is an integrated, scalable mechanical system simulation platform that enables design engineers to virtually evaluate and optimize system performance. This will increase the evolution of systems engineering, from producing more realistic simulations at earlier design stages to final performance verification and control calibration. The software seamlessly combines system simulation and testing, helping to predict performance on critical features ahead of time and throughout its entire lifecycle. Simcenter Amesim allows you to practically build models and perform realistic analysis by combining ready-made multi-physics libraries with applications and solutions that enable accurate analysis supported by powerful platform features. Simcenter can be easily integrated into computer-aided design, computer-aided engineering, and control software packages [47].

A brief comparison of the battery DT development platforms is provided in Table 4.

5.2. *Integration platforms for battery DTs*

Since DT technology has been a trending topic in recent years for both industry and academia, the necessity for ready-to-use DT platforms has increased. The backbone of these platforms lies in the IoT infrastructure for the connectivity layers with additional modeling, simulation, and visualization layers. The available options vary from commercial to open-source solutions and can be also combined with other toolsets for DTs, such as [140,141]. There is also the ISO standard ISO 23247:2021 [142], which proposes a set of consensual terms for DTs and common criteria for DT frameworks. According to the standard, a

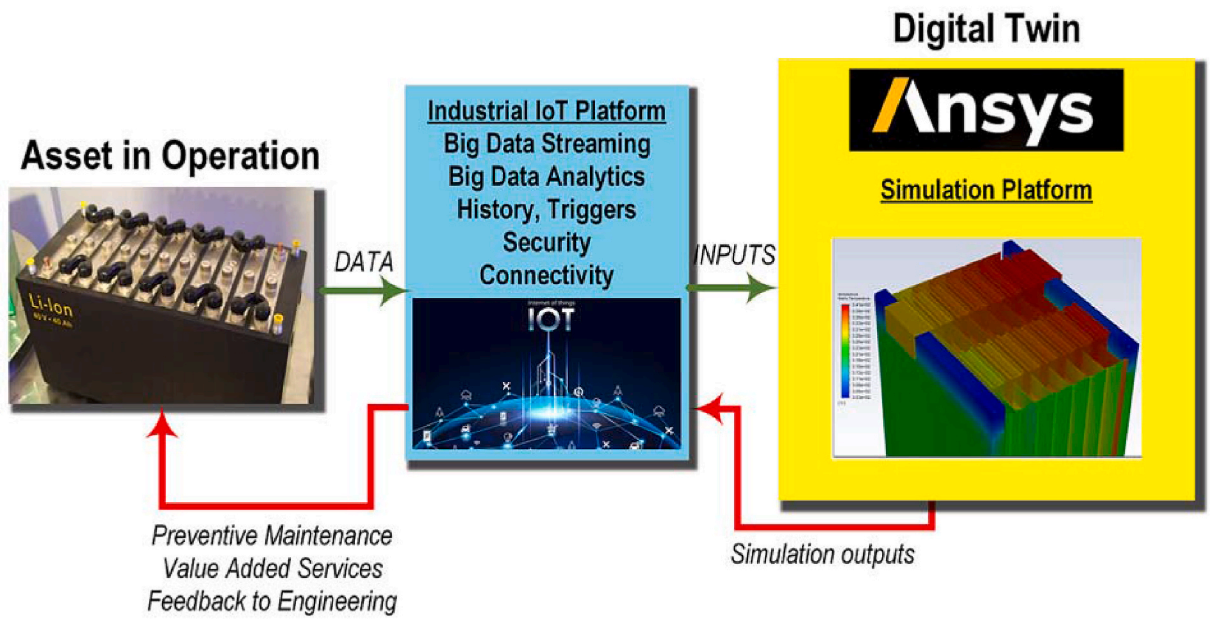


Fig. 20. Connectivity of battery and DT in ANSYS Digital Twin Builder [138].

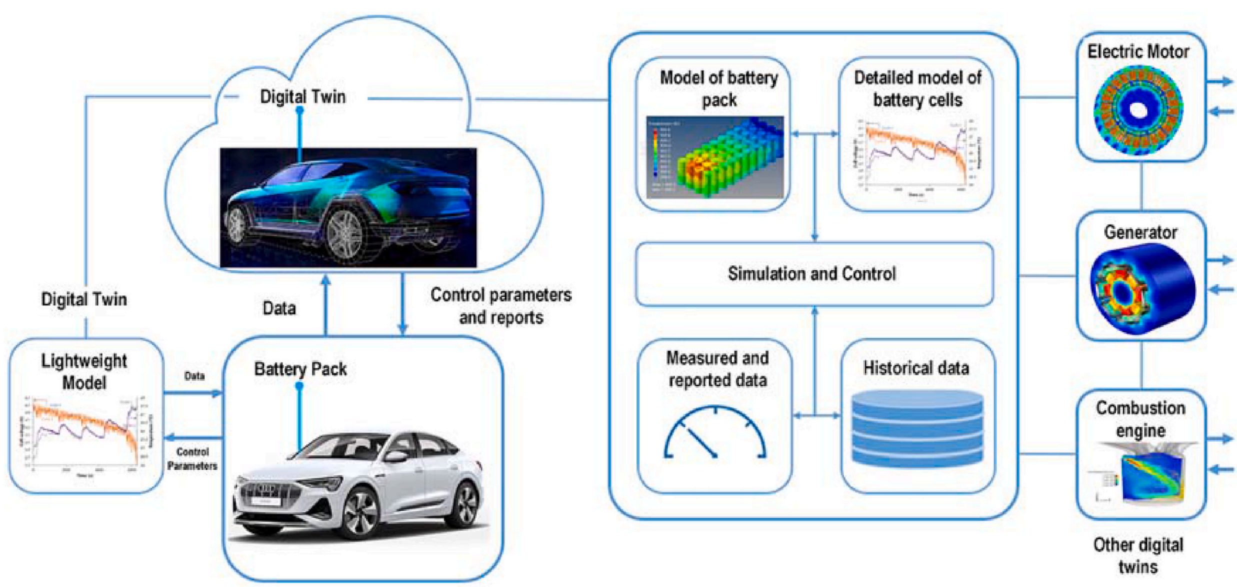


Fig. 21. Battery DT concept in COMSOL Multiphysics® [139].

DT framework requires accuracy to describe at an appropriate level of fidelity, communication that enables synchronization, data acquisition with local or remote sensors, built-in data analysis, data integrity to correctly describe the state of the PT, compatibility to a range of applications, granularity for different levels of detail, identification of the data to a unique PT, management for resource optimization, coverage of different product life-cycle phases, security to communicate only with authorized agents, built-in simulation, synchronization (data, state estimation, etc.) between DT and PT, dynamic viewpoint according to objectives, and support hierarchical modeling to fit in a defined hierarchy.

Regarding the available frameworks [143], reviewed and analyzed Amazon web services (AWS) IoT Greengrass, Microsoft Azure DTs, and Eclipse Ditto in conjunction with Eclipse Hono and Eclipse Vorto in seven dimensions, covering 13 requirements in total. The frameworks are assessed regarding overall functionality, the performance of resource usage, compatibility to exchange information with other systems, usability to effectively achieve user goals, security of the connection, maintainability to adapt the software product, and portability of software and hardware artifacts.

The asset administration shell (AAS) is a German industrial framework initiative for DTs [144], which has several open-source implementations, including Eclipse BaSyx, SAP I4.0 AAS, NOVAAS, and AASX Package Explorer. AAS intends to provide a consensual metamodel for DTs hand to hand with industrial standards.

iTwin and Unity offer a toolkit for 3D-enabled DTs. The former is open-source while the latter is commercial that has free licenses for students.

Going to a different domain, TerriaJS and digital twin cities centre platform, both open-source, provide a foundational geospatial data DT framework, where the data associated with the PT can be mapped to identify patterns in the geospatial context.

Table 4
Comparison of well-known software packages for DT development (● = High-performance, ◐ = Mid-performance, ○ = Low-performance).

DT Platforms	DT development process	Compatibility	Computational cost	Processing power, performance, and scalability	Visualization	3D-modelling
ANSYS Twin Builder	●	●	◐	●	●	●
COMSOL Multiphysics	●	●	◐	●	●	●
Siemens Simcenter Amesim	●	●	◐	●	◐	●

When analyzing the requirements for DT frameworks with the reviewed platforms, it is possible to identify the strengths and weaknesses of each one in the following dimensions.

DT development process: The DT development process is not trivial with the currently available DT frameworks. This is mainly because DT engineering is a complex task that requires several components. Integrating the models into the connectivity layers and visualizations requires time and handwork to set it up. Although, modular implementations, such as commercial platforms, facilitate this by providing user-friendly components that can reduce the complexity considerably.

Connectivity: Since most of the DT frameworks are built upon IoT infrastructure, the connectivity is usually good and flexible. The frameworks integrate IP-based communication protocols, such as MQTT, AMQP, HTTP, and WebSockets, which enable communication within the system and with third parties. However, some frameworks are not built upon and oriented to connectivity and their communication capabilities make them less prone to external integrations and less flexible regarding interoperability and synchronization.

Security: Common security aspects rely on the security of the connectivity layer, such as authorization, authentication, and encryption. However, other security aspects regarding access control, security self-aware DTs, and similar are not covered by the existing frameworks.

Processing power, performance, and scalability: Depending on the scope of the framework, the processing power, performance, and scalability of DT platforms can be different. Frameworks, such as iTwin, which is oriented to 3D scenarios, require more processing power than IoT-based DT frameworks, such as Ditto. The same happens with the scalability; the more processing power a framework requires, the fewer instances of DT - PT pairs it can run at the same time. On the other hand, the overall performance depends on several aspects because the DT application is composed of different components, such as communication, modeling, data analysis, data storage, and so on.

Data storage: The current DT frameworks are built upon IoT frameworks, which means that they already implement a data storage layer as part of the system, which is an advantage. Additionally, they can provide different data storage methods, such as SQL and No-SQL databases, but also plain text and structured files, such as CSV and JSON, respectively. Metadata is also relevant to be stored because the semantics of data and systems can be strategically used for extracting valuable inferences and learning from data, systems, and their composition. Here, structured data with common schemes, standardized meta-structures, and RDF structures can be used within aware systems and entities.

Visualization: Visualization applies to both 2D and 3D visualizations, which can be required in different contexts, depending on the purposes and scope of the DT use case. If the requirement is regarding 3D aspects or the PT requires a 3D representation, DT frameworks like iTwin and Unity can supply this aspect. In case geospatial 2D graphs are required, TerriaJS can be a better option. It can also be the case that 2D visualizations are needed for monitoring. For these cases, any of the frameworks can be integrated with dashboards to obtain built-in 2D visualizations.

Modeling and simulation: This aspect is not completely covered by the current available DT frameworks. Modeling categories that are covered by the frameworks include data models, 3D models, or ML models. Simulation, on the other hand, relies on high-fidelity physical models, which are not offered as built-in modules so far. Development platforms described in subsection 5.1 can be useful here.

An empirical analysis of the frameworks is shown in Table 5 [143].

Table 5
Qualitative comparison of different DT integration platforms (● = High-performance, ◐ = Mid-performance, ○ = Low-performance).

Name	DT development process	Connectivity	Security	Processing power, performance, and scalability	Data storage	Visualization	Modelling and simulation
Microsoft Azure DT	●	●	●	◐	●	●	●
AWS IoT Greengrass	●	●	●	◐	●	●	●
Eclipse Ditto	◐	●	◐	●	●	○	○
AAS	●	●	○	●	◐	○	◐

6. Discussions on challenges, gaps, and opportunities

The challenges and gaps of the battery DTs are discussed as follows:

- Lack of Standards and legislation: There is no standard or consensus about the definition, architecture, functional requirements, mandatory or nice-to-have features of the battery DTs. The transparency of battery data throughout its value chain will expose the technical and trade secrets of manufacturers, recyclers, etc. Therefore, proper legislation concerning the privacy and transparency level of the data is required.
- Cybersecurity of battery DTs: There is a certain risk that the communication channels between the battery DT and PT can be compromised and manipulated by adversaries. Manipulation of the sensory data or DT feedback misleads the battery control and protection algorithms which can lead to risks of battery fires and accidents. Therefore, research should focus to identify the DT security gaps and potential hazards that may arise and their effect on the PT operation and accordingly devise appropriate countermeasures to maintain the cybersecurity and integrity of the DT.
- Complexity and cost of implementation: Battery DT development requires significant design effort to develop multi-disciplinary system designs and frameworks and relies on expensive infrastructures such as gateways, cloud servers, super-processors, and potentially additional sensor units. Despite that the additional cost and complexity can be justified in the medium-term due to the benefits for a wide spectrum of stakeholders, this still poses a challenge to the initial investment and development of the pilot set-ups or full-scale development at higher technology readiness levels.
- Technical barriers: The VIT data of the cells and heterogeneous data from other sensor units (e.g. gas or pressure sensors) should be collected and communicated to the cloud at a relatively high rate. The EV battery pack may include thousands of cells which means millions of real-time data will limit the communication bandwidth. This necessitates using advanced communication technologies to facilitate real-time data connectivity. The use of new generation communication interfaces such as 5G technology is thus needed for the implementation of the battery DTs. In addition, processing a huge amount of data on the cloud requires strong processors and deep fusion via advanced signal processing algorithms to achieve precise mapping and a fast flow of data, and sharp responsiveness of the DT.

Taking these challenges into account, it is very important to consider more targeted DT applications and use cases to avoid excessive resources on tasks that do not provide too much value. To investigate the industrial potential of the DT, a technical questionnaire was recently developed as part of the European Project HELIOS and a few partner companies in the BMS/EV sector were asked to complete it. The feedback revealed that a major bottleneck is related to the DT cost which hardly can be justified for some use cases such as SoC estimation since the achievable results on BMS are already good. Concerning the SoC estimation, another bottleneck is the real-time performance which is difficult to realize due to the high sample rates required, communication delays, and computational burden related to cell-level SoC estimations. The use of DT for SoH estimation could make more sense as the required update intervals are much longer. The advanced life extension algorithms operated by DT could improve the lifetime and thus reduce the life cycle cost of batteries. It would also be worthwhile to consider DT use cases that provide value for a fleet and not individual EVs. Concerning this, use cases related to fleet management, repurposing of batteries, and battery passports can be very promising.

7. Concluding remarks

This work provides a comprehensive review of the battery DTs. Different existing and potential use cases of the DTs are discussed and the SotA related to each use case is reviewed. The number of published research papers on the battery DT topic has increased by about 200% since 2020, which demonstrates the increasing interest in the concept. Among these research works, the majority have focused on using battery DT for SoX estimation, design optimization, manufacturing, and monitoring of batteries. More recently, the application of battery DTs for predictive maintenance and 2nd life applications has also gained interest. The potential use cases that can be developed within the battery DT framework such as energy optimization, optimized battery charging, lifecycle management, and battery passport are also introduced. The reports show promising results for battery DT application, e.g. 60% reduction in maintenance costs, a 15% improvement in the lifetime using optimized charging protocols, and a DT-based SoC estimation MAE of 0.14%.

The multi-disciplinary elements and requirements of the battery DTs are categorized into three groups, namely software, hardware, and IoT. Each group is then reviewed and the corresponding technical aspects are discussed in detail. Possible sensor networks to measure the key battery information such as VIT sensors, gas sensors, and GPS data, and IoT/connectivity options such as 5G to transmit the data to the cloud-located DT and vice-versa are reviewed. In terms of software requirements, several key topics are covered including the co-simulation of multi-scale models, cyber-security, review of databases suitable for time-series data, and so on. The battery DT architectures are also reviewed. The three main layers in the DT architecture are the connectivity layer to receive and pre-process various types of data, the twin layer to operate the battery multi-scale models and algorithms, and the service layer which provides higher-level services such as visualization, user interfaces, application programming interface, etc. It is worthwhile in the DT architecture to include the metadata and metamodels related to different types of data (such as master data, transactions data, etc.) and models (cell models, module models, BMS, TMS, etc.), which will improve the findability and interoperability of the data and models on the battery DT.

The study also contributes to the review of the existing DT development platforms including ANSYS Digital Twin Builder and COMSOL Multiphysics. The commercial integration platforms such as Microsoft Azure and AWS and open-source integration platforms such as AAS and its different implementations such as NOVAAS and AASX are reviewed and compared in terms of their security and capabilities in modeling, processing, visualization, connectivity, and storage of the DT data. The comparison provides valuable information to decide the best development/integration platform depending on the requirements of the implemented use case(s) and the specific modeling/simulation needs.

Finally, the existing challenges in front of the battery DT technology are reviewed. The strategic challenge is the lack of standards and legislation, which complicates the transparency of data across the battery value chain. The economic challenge is related to the large investment costs due to the need for additional sensor networks, cloud services, etc. Concerning the technical barrier, the complicated modeling and algorithmic processes can be pointed out. In addition, communication and online processing of a massive amount of real-time data related to a large number of cells is a challenging task. The review also summarizes the results of an industry survey about the effectiveness of the existing battery DT use cases. Companies believe that the additional costs associated with the battery DT must be carefully justified considering the use cases. In this regard, SoC estimation on the DT is considered to be less effective because the achievable results on the BMS are already good. Use cases such as health estimation, battery passport, and predictive maintenance that will benefit a larger number of stakeholders such as EV users, fleet operators, leasing and car-sharing companies, etc. Are deemed to be more promising.

While the use cases are comprehensively outlined, a detailed review of each use case was not included due to space limitations. However, the work can be used to judge if it would be worthwhile to do a full systematic review of each use case. In terms of open-source DT platforms, only the most known ones are considered in the review. Therefore, future work can evaluate a wider range of DT platforms and assess the possibility of applying them in the battery context.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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