Application of digital twins to the product lifecycle management of battery packs of electric vehicles

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Abstract
Lithium-ion batteries have become a core component of electric vehicles (EVs) because of their high energy density. However, several issues in lithium-ion batteries usage, such as safety, durability, charging time, and driving range, limit the development of EVs. Meanwhile, with the emergence of Industry 4.0, the digital twins technology has received widespread attention in the manufacturing industry because it provides real-time monitoring and intelligent management of the production process. The authors propose a framework based on digital twins, which can be used for real-time monitoring, intelligent management, and autonomous control of battery packs. The framework covers all aspects of a battery pack's lifecycle, including design, manufacturing, operation monitoring, and second use options. Such a framework can solve some critical issues inhibiting the usage of batteries. A case study of the application of the proposed digital twins-based framework to electric vehicle battery systems has been conducted. The results show that deploying digital twins into the battery packs of EVs will improve the safety and service life of the battery packs.

1 INTRODUCTION

One of the main contents of Industry 4.0 is to apply the cyber-physical system (CPS) to promote industrial transformation and realise intelligent manufacturing. Integrating information technology and production lines to meet the current needs of industrial manufacturing, such as being service-oriented and environment-friendly, are the main goals of intelligent manufacturing [1]. The key to achieving such goals is to realise the interaction of physical manufacturing and cyber information. Many enterprises have established initial production lines using CPS. However, due to the immaturity of the integration technology of entity information and virtual information, most of the existing intelligent production lines have the following shortcomings [1]: (1) the lack of integration of physical information and digital information; (2) low predictability and linkage of production planning; and (3) low intelligence of manufacturing process control and absence of global optimisation. Such disadvantages in the current CPSs have restricted the development of smart industries. The digital twins technology was thought to be an ideal technology for addressing the above shortcomings and was first proposed in the year 2002 by Michael Grieves [2] for product lifecycle management.

Digital twins technology is a virtual model of the physical asset that dynamically interacts with the asset and updates itself with real-time data from the asset. The physical asset that digital twins can model may be a component/subsystem of the system or a system of components/subsystems. The model in the digital twins of the asset is programmed according to the users' needs. It could be to analyse, simulate, predict, monitor performance, optimise asset functioning, or even evaluate new operating models. Digital twins technology also provides the operator with an insight into the asset's current state and relevant historical data on the crucial performance parameters stored in the asset's database. Figure 1 shows a schematic of the information flow between the digital twins and the physical asset.

The vital technologies of digital twins' development are:

\textbullet Data acquisition and transmission: To ensure the data acquisition and transmission quickly and reliably, it is crucial to build an information network that can transmit the

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Figure 1: Schematic representation of the concept of digital twins of any asset

measured state information to the digital twins system in real-time. The application of the Internet of Things (IoT) technology can interconnect the assets closely and enable the secure, cost-effective implementation of data acquisition and transmission. The construction of IoT-sensor networks should be done to collect all kinds of physical information of the system that ensures observability of the system’s state and on the principle of fast, safe, and accurate data acquisition, and transmission.

- **Models of asset**: The digital twins framework can make intelligent decisions after carrying out numerous simulations using the physical system’s data, which is different from the CPSs. The simulations in the digital twins are basically programmed models of the asset or the process. Besides the simulation models, it is also equally important to have accurate models that combine the statistical sensor data for other system states parameters online estimation.

- **Highly efficient computation**: The simulation models of the digital twins are generally computationally intensive. Cloud computing technology and optimal computing system architecture design technology have provided the required computing power to run the computationally intensive models for real-time decision making.

- **Data management**: High reliability of a digital twins system requires highly efficient collaborative data management of the physical information. The cloud server manages the massive data from the system in a distributed way to achieve high-speed data reading and safe redundant backup [3]. A blockchain-based data management system is ideal for the digital twins of products. Its change-sensitive characteristic can ensure data authenticity, its peer-to-peer network can facilitate efficient data sharing among participants, and its cryptographic data storage will limit data access to only eligible participants [4, 5]. Similarly, a layered reference model for IoT data management is suitable for the digital twins implemented using IoT [6].

- **Virtual reality (VR)**: The VR technology has provided an immersive experience in the form of vision, sound, touch, and other aspects to realise real-time and continuous human-computer interaction enabling inspection of each key subsystem of the complex system in multiple fields and scales in a safe and virtual environment [7].

The first official application of digital twins technology is carried out by the U.S. Department of Defence to monitor operations and conduct spacecraft maintenance. Since then, digital twins technology is emerging to be one of the widely accepted digital transformation initiatives, and various firms have adopted this technology to increase their profits. Hence, here, we present the idea of using digital twins for batteries and discuss various methods which are essential for implementing it, such as IoT, CPS, cloud computing, and edge computing.

The rest of this article is organised as follows: Section 2 discusses some related studies, including the digital twins applications in manufacturing as well as in batteries. The reason for discussing the diverse applications shall be useful to understand the methods, models and, advanced intelligent and smart technologies used in formulating digital twins for complex systems. Section 3 presents a qualitative architecture of a digital twins approach for real-time monitoring, performance analytics, and intelligent control of battery packs. Section 4 describes a case study on the application of the proposed digital twins framework. Section 5 concludes the article and illustrates some promising research directions.

## 2 | RELATED RESEARCH

### 2.1 Digital twins applications in manufacturing and industry

IoT technology has provided the manufacturing sector with access to immense sensor-data from industrial tools. Access to a large amount of information has demanded the need for
its efficient management. Digital twins technology is proven to be invaluable for their ability to organise, analyse the collected data, and arrive at real-time optimal solutions to improve production efficiency. Figure 2 illustrates some of the salient features that could be integrated between the physical and digital information using the digital twins in the manufacturing sector. Kritzinger has given a categorical review of the application of digital twins in manufacturing [8]. Some of the applications and the corresponding impacts created by digital twins in the manufacturing sector have been discussed.

Wang proposed to optimise the IoT workshop by using the active scheduling mode. In this case, unskilled production line jobs and machines can be converted into interconnected and initiative individuals to improve production management [9]. Similarly, Woodward, a control systems manufacturer, is reducing the manufacturing costs, increasing the yield, and improving the quality based on a digital twins solution software which is called manufacturing information system (MIS) [10]. Volvo found the engine quality assurance (QA) process is time-consuming because a rigorous checklist could only be performed by highly trained technicians. Hence, Volvo used Parametric Technology Corporation (PTC)'s digital thread to digitise its QA process, which can immediately reflect any design-related changes in the QA checklist. The augmented reality (AR) technology of PTC-digital suite reduced the training period for QA-technicians [11].

Next, we discuss the role of digital twins in product design and manufacturing. Debroy has given a good insight into building digital twins that simulate the 3D-printing process, considering the crucial parameters that affect the properties of additively manufactured products to improve, optimise the product design, and the 3D-printers performance [12]. MX3D-ABB-Altair’s joint project is a typical digital twins industrial application case in the design and fabrication of a 3D printed robotic arm area. This project implements the digital twins to run design optimisation algorithms, and correspondingly sends feedback control signals to the WAAM (wire arc additive manufacturing) machine, so as to achieve a weight reduction of 75% and 80% in the fabricated lower and upper arms, respectively [13]. Lundin Norway's Oil and Gas platform is another typical digital twins industrial application case in process optimisation. This platform uses the Honeywell Forge Asset Performance Management Digital twins and its asset performance libraries to reduce CO₂ emissions by generating real-time energy loss reports and optimise the power requirements by adjusting the operating parameters [14].

Finally, the digital twins technology has also exploited in design and manufacturing to improve the customer experience and after-sales services. The digital twins-based model could diagnose faults in the products. Based on the digital twins model, the enterprise can modify the design or manufacturing process to prevent such faults from occurring [15]. The Dassault Inc. product design R and D group applied digital twins technology to set up a user experience platform and continuously improve its products with user feedback [16].

### 2.2 Applications of digital twins for batteries

The recent advancement of model-based battery system engineering is the use of digital twins technology to achieve intelligent battery management [17]. The models used for battery digital twins can have different accuracy and computational complexity. The high-fidelity [18] models can simulate the real battery process with high accuracy and precision, but the computational cost is higher; in contrast, the lightweight models can make fairly accurate predictions, but they are less computationally intensive and much faster than high-fidelity models. In this section, we start by briefly defining some of the important states associated with the batteries performances as these terms will be used frequently:

- **State of charge (SOC)**: SOC of a cell refers to the ratio of the current charging capacity of the battery to the rated charging capacity of the battery. The SOC of a fully charged battery decreases with use due to ageing. The critical parameters for SOC estimation include cell current, voltage, and temperature etc. [19].

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**Figure 2** Illustration of the integration of physical and digital information in the digital twins
• **State of health (SOH):** SOH is a measure expressed in percentage to estimate the condition of a battery, and is used to estimate the usage of a battery (or battery pack) compared with the fresh battery. Factors such as cell’s internal resistance, cell’s charge acceptance, operating voltage and self-discharges are considered in the SOH estimation [20].

• **Remaining useful life (RUL):** The RUL is defined as the number of charging-discharging cycles when the battery can be subjected to a specified operating power. It is another state of the battery that is estimated from its SOC and SOH, and the cell-to-cell variation of a battery pack causes significant deviation in RUL estimation [21],

Based on the methodology used, the battery models used are classified into:

• **Physics-based models:** These models are derived from the first principles of physics and battery chemistry. The battery models are multi-physical models because they are developed by integrating the chemical, electrical, and mechanical behaviour of the battery to accurately simulate the process that occurs in the battery.

• **Data-driven models:** These models are developed from the tools of artificial intelligence (AI) like machine learning (ML), deep learning (DL) etc. which have been used off late to estimate SOC, SOH, and RUL and find the degradation of the battery. These are the models that are used when it becomes difficult to design the physics model or when it is cumbersome to solve mathematical equations of the model.

• **Hybrid models (data and physics combined):** In recent times, the hybrid models are gaining prominence and are being implemented as they combine the advantages of both the data-driven and physics-based battery models, for example, Kalman-filters-based battery state estimation.

Some of the recent peer-reviewed research works related to the concept of digital twins for batteries that have been described here:

• Peng et al. developed a cost-effective digital twins platform and implemented it by using LabVIEW-software to monitor battery packs in spacecraft. The tool uses battery degradation algorithms to estimate the RUL, which can be loaded flexibly according to the battery type [22].

• Li et al. discussed implementing a cloud-based battery management system (BMS) that performs robust online estimation of the SOC of lithium-ion and lead-acid batteries using an adaptive extended H-infinity filter. The system used particle swarm optimization (PSO) to estimate battery SOH and monitor fade in capacity and power with ageing [23].

• Merkle et al. described a digital twins architecture using unified modelling language (UML) metamodel to provide digital services for battery systems, catering to the various stakeholders involved in battery manufacturing and its lifecycle [24].

• Cheng et al. have proposed a block diagram of a BMS for SOC-estimation in electric vehicles (EVs) using Coulomb counting and open-circuit voltage method, and the errors introduced by noise were further corrected by the Kalman-filters [25].

• The following are some recent works and attempts in the industry to implement digital twin technology in battery-powered systems and EVs: ION Energy and Twaise are among the leading companies in battery design and management, currently working to provide digital solutions for battery management. While ION Energy is building a digital twins platform to perform intelligent battery analytics for predictive maintenance [26], Twaise’s software tools and battery simulation model perform timely and accurate prediction of energy storage performance [27].

• Northford and Siemens are collaborating to build an intelligent battery manufacturing plant and apply digital twins to set up a product-lifecycle management (PLM) system using closed-loop manufacturing [28].

• Maclean has developed a digital twins-based monitoring system that collects and transmits real-time performance data from EVs to remote servers for analysis to enable the operations personnel to make better maintenance decisions [29].

3 | PROPOSED DIGITAL TWINS FRAMEWORK FOR BATTERY PACKS OF ELECTRIC VEHICLES

This section describes a digital twins qualitative framework for the real-time monitoring and intelligent management of batteries. Since the digital twins concept has a physical space and a digital space, physical and digital space parts of the battery that make up this framework are first identified.

In the physical space of this framework, we have the battery packs with the battery management system (BMS). The BMS is an electronic system that comprises battery sensors and a battery control system. The sensors and the control system form the two-way mode of communication between the physical space and the digital space. Next, in the digital space of this framework, we have the battery-data cloud, data-processing unit, and assessment unit. The battery and its digital twins are a part of the IoT-network in this framework. Subsequent paragraphs of this section present a detailed discussion about implementing the digital twins framework for batteries.

The following paragraph highlights in detail, the parts of the digital twins framework that were identified in the last paragraph. Sensors collect measurable data from the battery in real-time. The key measurable data that affect the battery pack performance are [30]:

• **Polarisation Data:** It is the voltage versus current data of the battery in operation. The polarisation data is used to estimate many other cell parameters, such as its internal resistance. Tessier’s method can be implemented for the
real-time online estimation of lithium-ion cell's internal resistance in EVs [31]. Monitoring the voltage and current of each cell within a battery pack plays a crucial role in estimating its overall health, and limiting the cell’s charge/discharge rate [32] which is vital for efficient operations and longevity of the battery pack. A hall-effect sensor in the BMS can be used for measuring the discharge current.

- **Temperature**: Monitoring the battery temperature of each of the cells in a battery pack is of utmost importance for two reasons. Firstly, a big current is generated during the safe operation of the battery, causing the battery to heat up, which leads to the decrease in the internal resistance of the battery [33]; thereby generating more discharge current, on further heating, and causing thermal runaway of the battery. Second, it is also crucial to prevent the ageing process, which is otherwise accelerated by high temperatures in the battery [34]. Since there are several cells in a pack, the best method to measure their internal temperature is to use fibre Bragg gratings as explained in [35]. These fibres also aid in measuring the strains within the cells that will help in carrying out simulations that estimate degradation due to chemo-mechanical and thermo-mechanical effects.

The control system is made of a microcontroller that maintains the battery's operating parameters and environment based on the input signal, which is received from the simulations occurring in the digital space. For example, a feedback signal of the hall-effect sensor's current measurement to the controller can limit the cell's charge/discharge rate. Since the BMS is connected to the IoT gateway, the abundance of data collected from different battery packs is effectively stored and analysed in cloud storage. Cloud storage serves as a data repository for the data-processing unit to train neural networks or machine learning algorithms. These models that are trained in the data-processing unit are the data-driven models. The next unit in the digital space is the assessment unit, in which the models of the battery pack are loaded and made to run. These models form the main functional feature of the digital battery pack and estimates the other observable states of a battery.

This paragraph describes some approaches in the literature that have the potential to be loaded as the battery pack models and estimation algorithm in the assessment unit of the digital twins framework. The Newman model is the most common physics-based model for lithium-ion batteries that is based on governing differential equations of mass and charge transport (Maxwell-Stefan equations) between the electrode and electrolytes. This model can be used to simulate the lithium-ion battery pack's current and future performance. Next are the methods to estimate the two basic states of a battery – SOC- and SOH-based on which the degradation process of the battery can be understood. For SOC estimation, the method described in the article by Plett [36] using Kalman-filters to eliminate sensor noise can be implemented. For SOH estimation, the method based on differential thermal voltammetry (DTV) [37] can be used in the assessment unit. The data-driven linear regression method of differential voltage described by Severson [38] can be a good method for RUL estimation in this framework.

Here, we describe the implementation of the battery's digital twins framework in the IoT-network architecture. In theory, the digital twins can be implemented in any part of the IoT topology such as edge computing nodes, operational technology infrastructure, or information technology systems. However, when it comes to the practical implementation of the framework, the sophisticated high-fidelity battery models are loaded in the powerful cloud processors of the OT/IT systems as they are for simulations that are computationally expensive. The high-fidelity models need large time scales to run, to process the data, and produce accurate results because of their computational complexity. Since the digital twins are often required to make quick decisions, the data processing and simulations must run at faster time scales. This invokes the need to also have a lightweight battery-model in the framework. The lightweight battery-models are locally run in the edge computing nodes of the IoT topology. The lightweight model at the edge lowers latency, accelerates the evolution of digital twins, and supports localised decision-making for supervisory control of battery operation. In the interest of maintaining the accuracy of the lightweight models, the model parameters are also updated in scheduled intervals by using the results from high-fidelity models. Such parameter updates are lined up to take place automatically when the operating range is close to superseding an acceptable tolerance in the operation of the battery. By implementing this framework, we can achieve accurate and rapid prediction of the model at the same time. Hence, this digital twins framework has its different models working in various locations and platforms remotely, sharing data and updating themselves when required. Figure 3 is a schematic depicting the information exchange, locations of the lightweight and high-fidelity models of the digital twins in IoT.

In the proposed framework, besides utilising IoT for just running the models of the digital twins in the cloud, we also leverage the benefit of being in the IoT-network by allowing the digital twins of the battery to connect to the larger system of devices with which the battery closely functions together, and their digital counterparts, that is, the battery packs digital twins exchanges information with the digital twins of the other sub-systems in the power-generation system. This promotes the better performance of the system in a holistic manner when the digital twins of the various sub-systems could communicate with each other to predict, optimise, and control the performance of the entire system. This framework also allows us to remotely receive and monitor all the relevant battery data such as operating parameters, utilisation, notifications on malfunctioning, and warning in one place.

While the notion of digital twins came into its existence to address PLM, we have extended this idea and introduced the concept of battery lifecycle management in the proposed digital twins framework (Figure 4). We conceptualise battery lifecycle management as a closed-loop optimisation and intelligent management of the batteries right from its development.
in the research labs, manufacturing in the industry, operations phase, after-sales services, and second-life services after retirement. The cyber hierarchy and interactional network (CHAIN) proposed by Yang [39] is a suitable framework to achieve PLM in battery's digital twins. In the coming paragraphs, we discuss the features that are included in the framework for PLM of battery packs.

In the battery research and development (R&D) stage, the traditional trial and error method is used to develop better designs of the cells and the battery packs leads to high consumption and wastage of raw materials. To avoid this, the cloud server of the digital twins at the R&D will integrate the data of all technical fields into one model for simulating, testing, and optimising the performance of the battery in an entirely virtual environment. Therefore, before the pack is actually manufactured, the digital twins model can identify and repair potential problems based on its analysis. The performance reports and customer feedback that are received by the digital twins network of functioning batteries are also stored in the cloud. This will help raise the battery's performance standards and customer satisfaction in product development. When designing or optimising the current design to meet the actual operations need in the battery, the performance report provides real-time data that provide insights into the operating cycle of the battery pack, the working environment of the battery pack, and other valuable information that cannot be obtained through laboratory experiments. Thus, the digital twin promotes data-driven battery development and research.

Likewise, we would allow the battery's digital twins to exchange information with the digital twins of the production line. First, this would influence the cell manufacturers to virtually design, test, plan, and verify the assembly process thus enabling the battery pack manufacturing to become flexible and, dynamically adjust their production plan to incorporate...
changes brought in by the R&D. The second goal is achieved by linking the digital twins of the battery and production line to extract data relevant to the cell-to-cell variation of the manufactured cells, and ultimately explain the variation-based error in the RUL estimated by the battery’s digital twins. Also, reducing the variations among the cells of a pack has been identified as one of the major means to decrease the rejection rate of the manufactured battery packs and increase pack longevity [40]. The method described by Santhanagopalan to quantify such variations in cell components and achieve quality control measures has good potential for implementation under this digital twins framework [41].

In the operations stage, battery ageing is one of the concerns with modern-day batteries. Several charge and discharge cycles ultimately lead to the decrease in the batteries' SOC, SOH rendering them unusable finally. In this background, the proposed digital-twin framework will prove to be a good candidate to improve the battery pack's durability by running its models to carry out hundreds of future scenario simulations to operate the battery pack in an optimal state that would decelerate its degradation. Under this framework, the digital twins model is programmed to immediately flag operational behaviour of battery that deviates from expected (simulated) behaviour that might ultimately lead to failure and a possible downtime during operations. The twin alerts such an expected downtime in advance, schedules maintenance, and the battery is operated at sub-optimal levels until maintenance. The data stored in the cloud storage of the digital twins is also used to facilitate remote commissioning, diagnostics of battery to accordingly procure the necessary equipment and parts, thus lowering service costs. The RUL estimated by the twin will indicate the remaining cycles, operating hours, or kilometres for given indications of accuracy, and confidence and the twin throws a proximity alert to the end of battery life so that new ones could be replaced before the current ones are completely rendered unusable.

Besides all this, the battery’s digital twins model is also programmed to provide battery-related auxiliary services that can help the customer use the battery more efficiently, thereby improving customer experience. For example, the customer could have an application running in his mobile or car, which could provide a visual display of the crucial information about the state of the battery (like charge, health, temperature, life), scheduled maintenance, warranty manager etc.

4 | CASE STUDY ON THE APPLICATION OF THE PROPOSED DIGITAL TWINS FRAMEWORK

Global warming has become the most critical climate concern in the modern world. Many countries have put forward specific carbon reduction targets based on the existing climate treaties. The use of environmental-friendly EVs has become a way for many governments to achieve carbon reduction in the atmosphere. Lithium-ion batteries are the most widely used source of electric power in EVs for their high energy and power density. Currently, the EVs have not hit the market as much as the conventional fuel-engine powered vehicles for many reasons that are not conducive to their use. However, given this background, the use of battery-powered EVs will drastically increase in the future. The battery industry needs to further adapt to this growing demand and foster innovation to develop robust and user friendly battery systems. This section discusses the proposed framework of the battery’s digital twins for EVBS to improve the feasibility of using the battery-powered vehicles. Figure 5 shows the complete schematic of the proposed digital twins framework applied to EVBS.

The long-time required for charging and inaccessibility to charging points while driving are the most common reasons that hinder people from choosing EVs. The concern with implementing fast charging is the problem of lithium plating [42]. However, the digital twins technology is applied to the battery and charging port to implement the model and protocol is described by Lee [43] and Mai [44]. Taking into account the health and temperature of the battery, the battery can be quickly and safely charged in the charging station to obtain the optimal charging voltage and current. With this being implemented, the SOC in vehicles battery pack could be replenished in no time. It is also an important measure to improve the accessibility to charging points to popularise EVs. Thus by implementing the concept of EV-Battery Telematics through the proposed digital twin framework, it would serve to be an excellent solution to such a problem. The concept of EV-Battery Telematics is a cloud-based multi-faceted approach of collecting, integrating, and analysing the vehicular data (like power requirement, driving cycle, travel distance, speed, fleet etc.) and battery data (like polarisation, battery states temperature, RUL) to arrive at an optimal solution for problems related to vehicle charging, charging stations, and imminent failure. Suppose a hybrid electric vehicle is running out of charge. In that case, the SOC data from the digital twins of the battery pack and other relevant data from digital twins of the internal combustion (I.C) engine and electric motor of the hybrid electric vehicle are used to formulate an optimisation problem. The constraint to such an optimisation problem is to maintain a minimum SOC of 5% in battery. Optimisation algorithms can be implemented in the cloud servers to arrive at an optimal power distribution between the engine and the battery. Thus the digital twins will operate the vehicle in the calculated optimal state till it reaches the closest charging facility located by the vehicle’s GPS. In a smart city empowered with digital twins, Battery Telematics can also coordinate among the fleet of EVs and charging stations to minimise vehicle pile-up, waiting time, and charging time in the charging stations. The digital twins data also aid in evaluating the design, deployment plan, and distribution of the charging piles [45].

Another reason for the apprehension among the users in using EVs is battery degradation and unforeseen breakdown. To decelerate battery ageing, the digital twins can update its energy management strategy through method dynamic programming optimisation and tuning fuzzy logic membership function as discussed in [46]. It is also important to monitor battery degradation. Thus, a method suitable for online
implementation in the digital twins is the Long Short-Term Memory-based model [47] that virtually discharges the lithium-ion cells and compares it with the actual discharge of the cell to assess the health of the battery pack. Overcharging and undercharging of a battery also have a detrimental effect on battery life, but the twin may be deployed to maintain the battery’s SOC within its thresholds limits by controlling the charging process. To address the problem of sudden breakdown of batteries, the digital twins can be programmed to implement the interclass correlation coefficient (ICC) method [48] to diagnose faults and schedule maintenance. For example, the twin would detect a faulty cell in the pack and disconnect it from the circuit temporarily and alert its replacement to the user. Since it is difficult to carry a replaceable battery in the vehicle, a cloud-connected BMS, as described by Tazizawa, will maximise the value of shared

FIGURE 5 Proposed framework of digital twins to EVBS
batteries by using location data from the cloud to continuously connect to batteries and monitor their SOC [49]. Such a cloud-connected battery sharing system would encourage the usage of EVs for long distances as the replaceable batteries are made available even at remote locations.

The thermal runaway is the critical problem when it comes to the safety of EVs. As mentioned earlier, thermal runaway is feared as it triggers a series of events leading to an exponential increase in current and thermal power dissipated once it begins. The BMSs were introduced for closely monitoring the battery pack temperature. However, the current BMSs are not adaptive to the specifications, unable to give accurate results as they are offline and with no data storage feature. By introducing the proposed digital twins framework with the conventional BMS, we can outdo the above mentioned disadvantages and enhance the thermal safety of the battery packs. For example, in an EV with regenerative braking system, the digital twin could limit the maximum recharge current caused due to excessive braking if the temperature indicates any risk of thermal runaway. The battery packs of vehicles are also prone to mechanical damage and fatigue. Mechanical damages are dangerous as they could lead to short-circuit and fire. To diagnose external short circuit and related faults, the method described by [50] is suitable for online implementation in the digital twins. Similarly, a digital twins model to monitor the structural health of the battery pack could provide solutions to avoid such damage caused by short-circuits and also monitor stress concentrations in the electrodes of the cell. The interaction of such a structural digital twins with the battery pack would be less compared with the digital twins models that simulate the pack’s electro-chemical behaviour because its models of the structural digital twins run in larger time scales in comparison with the latter.

Digital twins are also helpful in the development of batteries as the researchers could have real-time access to the various important data (like the driving cycle, temperature, current voltage, power requirements etc.) that play a crucial role in developing a better battery design. For example, the R&D of GE Global Research is working to build smaller and efficient battery packs that could deliver the same amount of power as the former packs. The GE team used their sensors and the physics-based digital twins models developed by the University of Michigan to improve the efficiencies of electro-chemical and thermo-mechanical processes occurring in the batteries. The digital twins used by the research team has helped them to get a good insight into the changes that occur in a battery during different vehicle driving conditions. Digital twins also drive the development process to be faster and cut down on cost as it avoids real testing. For example, the discrete element method models the electrode calendaring process and its effect on battery electrochemistry [51]. Another example to this is the hybrid solution strategy [52] that uses multi-scale models and data-driven methods to arrive at an optimal electrode design under the CHAIN framework that we discussed in the last section.

Retired EV batteries are generally considered E-waste and are disposed of after use for recycling. However, these batteries can be put to second-life use as they still retain significant residual ability to deliver power before recycling. Recruiting the cells for second-life services from vehicle batteries is a cumbersome process characterised by time and expensive process of disassembling the modules of the battery, manual inspection of individual cells-SOC and SOH with costly testing instruments. But these steps could be bypassed with the digital twins of battery, which already has all the necessary information to consider a cell for second-life energy storage systems. Further, the digital twins could also connect the user with the different second-life demands in the market and classify the battery's fitness for the corresponding reuse. Since we proposed to implement the proposed digital twins platform in the IoT platform, the cost of setting will be cheap. The benefits like battery longevity, fast charging, safety, energy conservation, and other auxiliary-services available by using the battery's digital twins far supersede the initial setting up cost. Hence, the proposed framework is very feasible in terms of implementation.

5 | CONCLUSIONS

From the proposed framework and case study, it is evident that the application of the digital twins in batteries would provide a good solution to solve critical issues that are hindering the development of batteries and EVs. Digital twins can be used in a battery pack to ensure their safety and reliability in real-time. Besides, the intelligent batteries with the digital twins would also function efficiently and have higher life which would directly conserve energy.

Some of the future directions of research that would complement the digital implementation are:

- Research on the virtual models that the digital twins run – geometric models, physical models, behaviour models and rule models. The geometric model is the three-dimensional model of the battery. The physical model is generated to simulate and analyse the structure, fluid, electric field, and magnetic field characteristics of the battery model. Behaviour model is to describe the real-time response prediction of the physical model under the external interference of different space and time. The current models used are not robust and are computationally expensive.

- Better IoT – Architectures suitable to cater to the need of digital twins (such as reduced latency). The current network speed is low and unstable, which makes the performance of cloud applications not high. The popularity of cloud computing depends on the development of network technology.

- Improvements in cloud computing technology, such as data privacy and security: It is essential to ensure that the privacy of the data stored in the cloud service provider is not used illegally.

- Data and physics hybrid method: Data and physics hybrid models are gaining prominence and are being implemented as they combine the advantages of both the data-driven and physics-based battery models and avoid their respective
disadvantages for example, Kalman-filters-based battery state estimation.

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