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Review article

Machine learning for battery systems applications: Progress, challenges, and opportunities

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HIGHLIGHTS

- Machine learning applications are reviewed for the full battery life cycle.
- Machine learning can revolutionize battery design, modeling, and management.
- Key benefits of machine learning are transferability and physics independence.
- Challenges include feature selection and the size/richness of data for learning.

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ABSTRACT

Machine learning has emerged as a transformative force throughout the entire engineering life cycle of electrochemical batteries. Its applications encompass a wide array of critical domains, including material discovery, model development, quality control during manufacturing, real-time monitoring, state estimation, optimization of charge cycles, fault detection, and life cycle management. Machine learning excels in its ability to identify and capture complex behavioral trends in batteries, which may be challenging to model using more traditional methods. The goal of this survey paper is to synthesize the rich existing literature on battery machine learning into a structured perspective on the successes, challenges, and prospects within this research domain. This critical examination highlights several key insights. Firstly, the selection of data sets, features, and algorithms significantly influences the success of machine learning applications, yet it remains an open research area with vast potential. Secondly, data set richness and size are both pivotal for the efficacy of machine learning algorithms, suggesting a potential for active machine learning techniques in the battery systems domain. Lastly, the field of machine learning in battery systems has extensive room for growth, moving beyond its current focus on specific applications like state of charge (SOC) and state of health (SOH) estimation, offering ample opportunities for innovation and expansion.

1. Introduction

This paper surveys the literature on machine learning for battery systems applications, with a focus on the potential of this emerging research area to revolutionize the battery energy storage domain. The paper is motivated by the ubiquity of battery applications in today's world, including powering our consumer electronics, stationary grid infrastructure, electrified transportation infrastructure, and other systems. Battery systems engineering is currently undergoing a fundamental transition where the traditionally separate fields of experimental research versus model- and data-driven research are converging. This transition is important, because it has the potential to enable the faster exploration and invention of new technologies, at a lower cost. In fact, one can argue that the emergence of modeling, simulation, and computer-aided design/optimization as a complement to experimental innovation has historically been one of the most important enablers for more rapid innovation in any engineering field, including the battery systems field.

The discipline of battery modeling is quite mature, and provides a rich portfolio of existing modeling approaches. These approaches include physics-based battery models spanning a broad range of fidelities and complexities, from molecular dynamics models all the way to reduced-order continuum dynamics models. These approaches also include equivalent circuit models that represent a battery using a simple combination of elementary circuit components such as resistors, inductors, capacitors, voltage sources, diodes, etc. One important question, in this regard, is: *why is there a need for data-driven machine*

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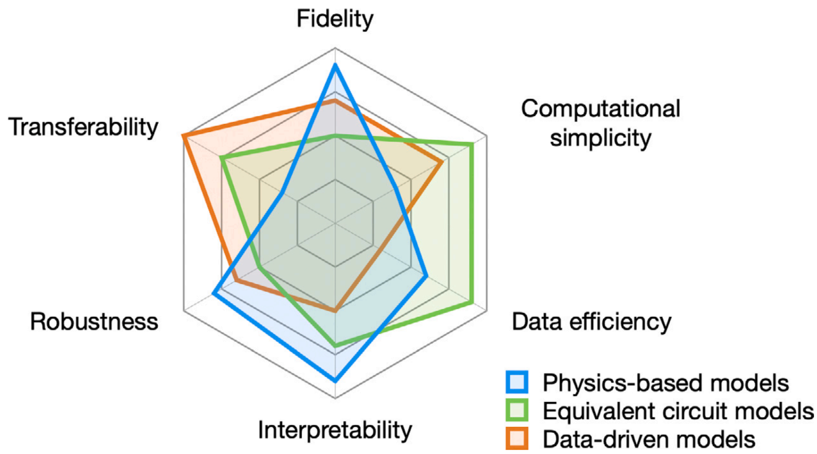

Fig. 1. Trade-off for different battery modeling methods.

learning models, given this rich existing portfolio of modeling paradigms? More specifically, what value can machine learning add to model-driven battery systems discovery, invention, and innovation? Fig. 1 provides some initial insights into this question, thereby motivating the remainder of the paper. Specifically, the figure identifies seven criteria for comparing different battery modeling approaches, namely:

- Fidelity, or the accuracy with which a model captures the underlying physics governing battery behavior.
- Computational simplicity/tractability.
- Data efficiency, or the degree to which one can parameterize a battery model using limited experimental data.
- Interpretability by a human expert.
- Robustness, defined in this paper as the ability of a model to predictively simulate battery behaviors beyond those reflected in the data used for training the model.
- Transferability, defined in this paper as the degree to which a given battery model is sufficiently general to be usable for multiple chemistries without needing to be reconstructed for each chemistry. A given modeling approach inherently provides better transferability if it is more "flexible" and/or "physics-independent". For example, both Ohm's law and the Butler–Volmer equation are fundamentally resistive in nature, in the sense that they both represent a relationship between an overpotential on the one hand versus a current or current density on the other hand. This means that a (potentially nonlinear) resistive law can be used for modeling both of these distinct physical effects, and may therefore potentially offer more "flexibility" and "transferability" than the underlying physical laws.

As one can see from the figure, the power of machine learning and data-driven methods lies predominantly in their flexibility, physics independence, and transferability. Machine learning models can perform well with respect to other criteria, too. For instance, these models are often more computationally tractable than physics-based models. However, it is reasonable to argue that the biggest selling point of machine learning for batteries is the degree to which it can capture battery system behaviors without necessarily requiring the in-depth modeling of the underlying physical processes. This is extremely valuable, for a number of reasons. First, when novel battery chemistries are developed and explored, the underlying physics are not always fully understood. Machine learning can help accelerate battery system development in such a context. Second, the advent of networked computing means that substantial volumes of data can become easily available for any battery chemistry, especially once it is commercially deployed. Machine learning excels at constructing models from the resulting datasets, perhaps to the point of unveiling which physical phenomena contribute to the aging and degradation of a given chemistry in the field. This is particularly important in light of the fact that many phenomena typically contribute to a battery's aging and degradation. The ability to discern which of these phenomena are dominant in the field is, therefore, quite valuable for practical battery system deployment. Third, the flexibility of machine learning methods can be extremely valuable for transferring the insights gained from one generation of battery products and chemistries to the next. This minimizes the need for "reinventing the wheel" as the energy storage industry embraces newer battery products and chemistries.

In addition to the above advantages, perhaps the greatest degree to which a novel battery modeling approach can add value to the literature stems from the degree to which it can potentially augment, as opposed to replace, existing modeling approaches. Physics-based, equivalent circuit, and data-driven models are not mutually exclusive. In fact, there is a growing literature on hybrid combinations of these modeling approaches, especially hybrid physics-based/data-driven battery modeling. Aykol et al. provide a conceptual summary of the different ways one can integrate physics-based and machine learning models [1]. Fig. 2 presents some of these model hybridization methods pictorially. In contrast to the "black box" nature of purely data-driven models, hybrid physics-based/data-driven, or "gray box" models, offer a more transparent and theoretically grounded approach to battery modeling. By integrating the deterministic laws of physics with the adaptability of machine learning algorithms, gray box models utilize the strengths of both domains. For example, a physics-informed neural network (PINN) ensures that the network's predictions do not violate the laws of thermodynamics or charge conservation [2]. Similarly, physics-based feature engineering can be employed to inform the model's input features with domain knowledge, enhancing the model's ability to learn relevant patterns from data [3]. Additionally, existing physics-based models can be refined using data-driven techniques to correct or update their predictions, an approach known as physics-based model correction [3]. This can be particularly useful when dealing with phenomena that are not fully understood or are too complex to be captured by traditional models. Lastly, the incorporation of physics-based activation functions within neural networks can introduce known physical relationships directly into the learning mechanism of the model [4]. These methods exemplify how the incorporation of physical principles into data-driven approaches can lead to more reliable, interpretable, and generalizable battery models, which are crucial for advancing battery technology and its applications.

One of the most valuable aspects of machine learning for battery systems is that machine learning is not a single, monolithic tool tailored to a specific battery application. Rather, it is a portfolio of tools for solving many interconnected problems, as illustrated in Fig. 3. The power of machine learning lies at least partly in its ability to advance

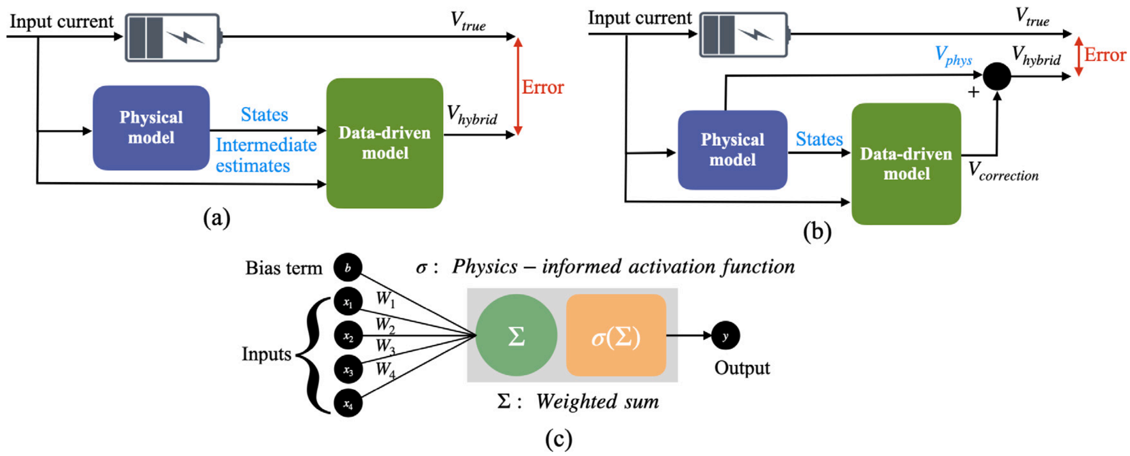

Fig. 2. Examples of hybrid battery modeling approaches, including: (a) physics-informed machine learning models; (b) models utilizing machine learning to correct physics-based predictions; (c) machine learning models with physics-informed activation functions.

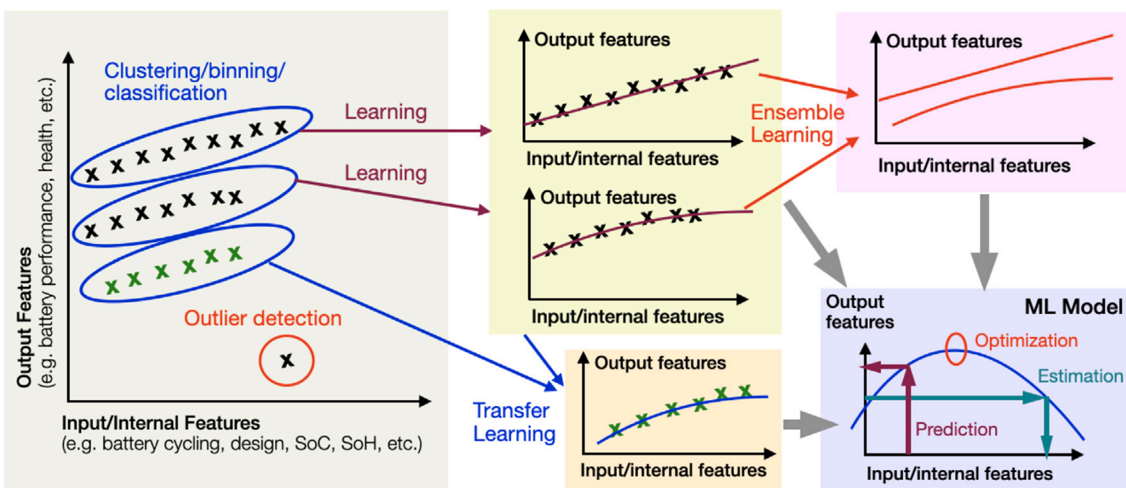

Fig. 3. Classifying battery machine learning problems and their interconnections.

various stages of battery development by employing diverse modeling techniques as illustrated in the figure. This encompasses the classification of batteries into clusters, the learning of battery dynamics, and the extrapolation of unforeseen scenarios through the application of ensemble learning and transfer learning to analogous cases. Moreover, machine learning provides capabilities for the accurate prediction and estimation of key parameters, as well as the optimization of input–output relationships. This involves leveraging machine learning algorithms to forecast and refine battery performance metrics.

The intent of the above discussion is to highlight the value added by machine learning to the battery systems engineering discipline from a very broad perspective, regardless of the specific machine learning application at hand. It is reasonable, however, to argue that machine learning has specific benefits to impart at specific stages of a battery's life cycle. Moreover, it is reasonable to argue that different machine learning algorithms may be better suited to different battery systems applications. These insights motivate the structure of this survey paper. Specifically, the paper begins by metaphorically traveling with a battery cell or chemistry through its full engineering life cycle, and examining how machine learning can add value at every stage of that cycle (Section 2). This leads to a discussion of: the prerequisites for the successful application of machine learning in the battery system domain (Section 3); the databases available for battery machine learning (Section 4); and some of the cross-cutting insights and open opportunities for research in this broad field (Section 5).

The existing literature on machine learning offers a rich and large portfolio of both original research papers and review papers, as surveyed below. The novelty of this particular review paper stems at least partly from its structure, especially its use of a metaphorical journey through a battery's life cycle to structure its literature review. This makes it possible to provide an extensive survey of a broad spectrum of battery machine learning applications, ranging all the way from material discovery to end-of-life management, in a structured manner. It also makes it possible to contextualize different battery machine learning applications, especially those related to online battery management, within the broader literature. Last but not least, this structure helps highlight some of the cross-cutting challenges and opportunities appearing throughout the battery machine learning domain. One important conclusion from this discussion is that machine learning for batteries remains at its infancy, with many exciting potential future explorations to come.

2. Applications of machine learning in the battery domain

Machine learning has become a centerpiece of the battery systems domain, and has seen extensive use at every stage of the life cycle of battery technologies [5], as illustrated in Fig. 4. The discussion below is structured to follow this life cycle, showing the value of machine learning at every stage from initial battery material innovation to end-of-life battery management.

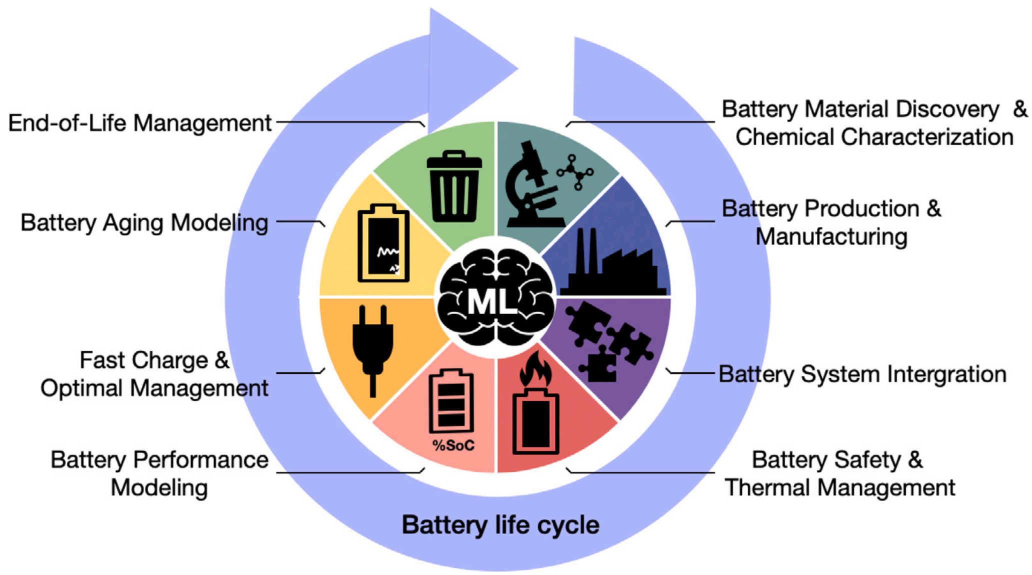

Fig. 4. Machine learning applications in a battery life cycle.

2.1. Machine learning for battery discovery, invention, and manufacturing

Before a battery chemistry is even commercialized, one can use machine learning to develop its underlying chemistry [6,7]. This can potentially include the use of machine learning to invent and discover new battery chemistries [8–10]. Liu et al. provide a thorough survey of the literature on this topic, with an emphasis on both electrode and electrolyte discovery [11]. The literature presents many examples of such use of machine learning for **battery material discovery**. For example, Guo et al. survey the use of machine learning to improve the computational efficiency of the atomistic simulation of different battery materials [12]. Hu et al. and Qiu et al. argue that machine learning can be particularly valuable for the rapid discovery of a broad spectrum of solid battery electrolytes [13,14]. Kilic et al. argue that machine learning can also be valuable for the discovery of new battery chemistries, including Lithium–Sulfur chemistries, provided there is sufficient data to train the learning algorithms [15]. Huang et al. explore the use of machine learning on the experimental side of battery material development, by showing that image processing algorithms can be used for the automated detection of lithium plating from operando X-ray computed tomography images of battery materials undergoing experimental cycling [16]. Moreover, Sun et al. show that machine learning methods can both predict the X-ray electron spectroscopy of battery materials and assist with the problem of dimensionality reduction in this domain [17]. Machine learning can also be used for characterizing transport mechanisms in experimental batteries [18], estimating the operating voltage window for novel electrolytes [19], relating battery material mesostructure to battery performance metrics [20], and predicting the force field information needed for the atomistic simulation of novel battery chemistries [21].

Once a novel battery chemistry is invented, machine learning can prove quite valuable for optimizing its **production and manufacturing**. For example, Liu et al. train a regression model to predict the impact of fabrication process parameters on battery performance metrics, then use this regression model for fabrication process optimization [22]. Moreover, Severson et al. show that machine learning models can be trained using early cycling data to predict long-term cycle life [23]. This is an important capability because it makes it possible to classify production batteries into different batches based on initial estimates of quality and cycle life. Stock et al. demonstrate such use of machine learning for the classification (or "binning") of batteries early in their life cycles, based on measurements of electrochemical impedance spectroscopy [24].

To summarize the above applications, machine learning can help bring new battery chemistries to life, both in the laboratory by facilitating the invention of these chemistries and in the market by facilitating their manufacturing, quality control, etc. In other words, machine learning is valuable in the early stages of a battery system's engineering life cycle, including product conceptualization, invention, planning, and design. A common challenge present in all of these applications is the lack of prior in-depth understanding and/or data when one wishes to invent or deploy a new battery chemistry. Machine learning is valuable, in this context, because it can assist with the discovery of new chemistries and/or "binning" of newly fabricated batteries by searching for previously unmodeled patterns in battery image data, sparse testing data sets, and/or sparse battery material databases.

2.2. Machine learning for integrated battery system deployment and design

Machine learning can be used for optimizing not just the design and production of battery cells, but also the **integration** of these cells into different energy systems. There is a significant volume of existing literature on the use of machine learning for integrating batteries into different application systems, including electrified vehicles: a topic explored in depth in a bibliometric analysis by Chen et al. [25]. Examples of such systems include grid-connected battery systems [26] and hybrid battery systems [27]. Managing battery **safety** is critical for successful integration into broader energy systems. This motivates the use of machine learning for developing methods for **predicting battery failure** as surveyed by Zhao et al. [28]. Catastrophic battery failures are sometimes driven by thermal events, such as **thermal runaway**. Moreover, the performance of a battery can be very strongly temperature-dependent: a fact that has motivated an extensive study of the use of machine learning for modeling battery thermal behavior by Zhang et al. [29]. This potentially drives the interest in the literature in using machine learning for **battery thermal management**: a topic surveyed extensively by Ghalkhani et al. [30]. Extensive research has been done in this area. For example, Zheng et al. use machine learning to model and monitor battery temperature dynamics [31] and Wei et al. propose a strategy to address the over-temperature risk associated with fast charging [32]. Finally, Tang et al. apply machine learning to the problem of designing an active liquid cooling system for a battery pack [33], and Zhang et al. discuss the use of machine learning for the design of phase change materials, which can be valuable for the passive regulation of battery temperature [34].

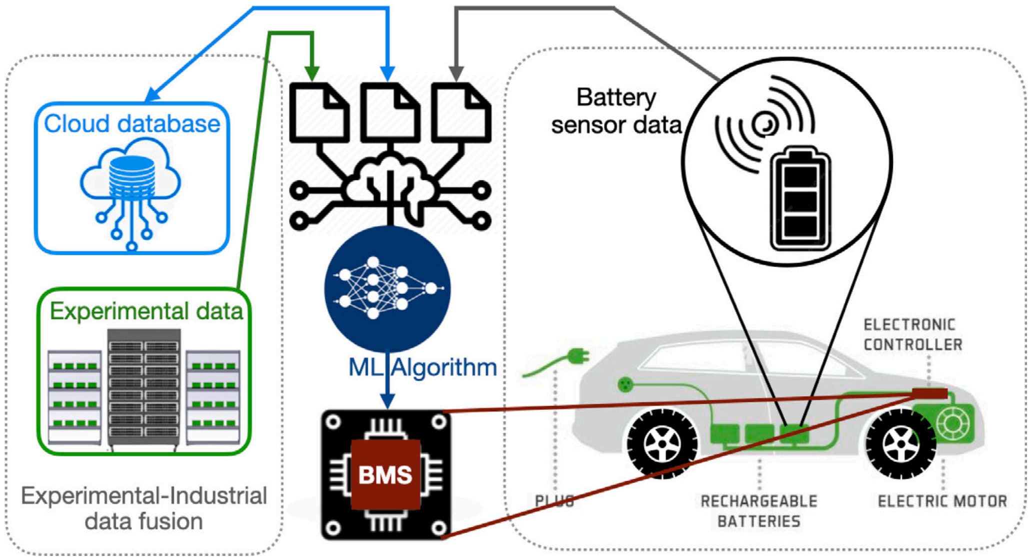

Fig. 5. Machine learning as an enabler for cloud-experimental data fusion.

All of the above applications take machine learning a step further, where it becomes an enabler for not only battery cell engineering but also system-level design and integration. The challenges associated with this stage of battery innovation are fundamentally different from those associated with cell-level engineering. For example, the use of machine learning to optimize a battery cell requires modeling the behavior of the cell on its own. In contrast, once machine learning is deployed for system integration, the ability to model the complex interactions between battery cells and their environment (including other subsystems) becomes critical. Machine learning tools are particularly well-suited for this task because of their ability to integrate different models of disparate engineering systems, potentially with different underlying levels of model uncertainty, in a seamless and straightforward manner. Fig. 5 highlights this fact by showing the degree to which machine learning algorithms can learn seamlessly from laboratory test data, online sensor data, and cloud-based databases of prior cycling data. Such seamless data fusion is useful not only for battery systems integration but also for battery management system deployment, as discussed in the next section.

2.3. Machine learning for online battery performance management

Once a battery system is commercially deployed, machine learning becomes particularly attractive for the system's online **management**. Such use of machine learning in **battery management systems (BMS) engineering** is central to the scope of this paper, and has been studied very extensively in the literature. There are at least two broad, interconnected categories of online battery management applications, namely: managing a battery's **performance** and managing its **aging/health**. This subsection explores the application of machine learning to battery performance management, whereas the next subsection focuses on health management. Broadly speaking, questions related to battery performance focus on shorter time scales, perhaps on the order of one day of utilization or much less. These questions include: *how does a battery's charge pattern affect its terminal voltage, temperature, and/or state of charge?* In contrast, managing battery aging focuses on longer time scales, on the order of months and years, with the overarching question being how to model, monitor, and/or manage battery deterioration and end of life.

Within the battery performance management domain, machine learning can be used for solving three broad classes of problems, namely: performance **modeling**, performance **monitoring/estimation**, and performance **optimization**. Each one of these classes of problems is explored in more depth below.

- First, machine learning methods can be used for the **predictive modeling of battery performance dynamics**. This topic has been explored in the realm of electric vehicle batteries to model battery performance [4,35,36], among other application domains. It is certainly possible to build predictive models of electrochemical batteries based purely on machine learning. For instance, recent research by the authors utilized machine learning for predicting the terminal voltage of a lithium–sulfur battery cell given its input current profile [37]. However, it is also possible to augment an existing battery model with machine learning, perhaps with the goal of increasing its prediction accuracy. For instance, Tu et al. utilized machine learning as a correction algorithm for low-order battery models in order to improve their prediction accuracy without significantly increasing computational cost [3]. Moreover, it is possible to train a machine learning model to match the predictions of a physics-based model. This can be particularly valuable for partial differential algebraic equation (PDAE) models, where machine learning can enable index reduction, thereby dramatically improving computational tractability: a problem explored in recent research by Li et al. [38]. Finally, machine learning methods can be used for the parameterization of existing battery models. For instance, Hashemi et al. employed machine learning to capture the intricate relationships between battery State of Charge (SoC) and health within an equivalent circuit model, facilitating fault diagnosis in electric aircraft [39]. Also, Guo et al. leveraged machine learning methods to identify parameters in a physics-based fractional order model (FOM) [40].
- Second, machine learning has been used extensively in the literature for the **online battery state monitoring and estimation** for different applications (e.g. electric vehicles [41–43], aircraft propulsion systems [44], and unmanned aerial vehicles [45]). Kim et al. and Ren et al. provide extensive surveys of the use of data-driven methods for different battery state estimation applications [46,47]. The "state" of a battery refers, broadly speaking, to its operating condition. Online state estimation can, therefore, refer to any problem where the goal is to estimate one or more aspects of a battery's operating condition, or state. Previous work by the authors, for example, examined the problem of using a data-driven approach for determining whether a lithium–sulfur battery is operating in its high or low plateau region [48]. This, in a sense, is a state estimation problem where the "state" of interest is a discrete metric indicating which plateau the battery is currently operating inside. Perhaps the most extensively studied

battery performance-related (as opposed to health-related) state estimation problem is **state of charge (SoC)** estimation [49]. Traditional SoC estimation essentially relies on modeling and utilizing the relationship between battery cycling history and terminal voltage in order to infer SoC. This can be achieved using machine learning, as done by Chandran et al. [50]. In doing so, it may be valuable to account for battery temperature as part of the SoC estimation process, as done by Chemali et al. [51]. Moreover, it may be valuable to utilize clustering algorithms to map different clusters of battery cycling features onto different SoC ranges, as explored by Hu et al. [43]. Beyond battery voltage, current, and temperature measurements, however, there is growing interest in the literature in estimating battery SoC using novel sensors and online measurements. For example, machine learning-assisted SoC estimation has been explored using strain sensor data, as explained by Raoofi et al. [44]. One can also estimate SoC using electrochemical impedance spectroscopy (EIS) data: a topic examined by both Babaeiyazdi et al. and Li et al. [52,53]. Finally, a battery's acoustic signature can also potentially be used for SoC estimation, as shown by Galiounas et al. [54]. Machine learning methods can be especially valuable for SoC estimation using such novel sensor measurements because the underlying physics may not always be fully characterized in the literature. For example, machine learning can excel in scenarios where there is a mapping between a battery's acoustic signature and SoC that enables SoC estimation, but whose underlying physics may not yet be fully modeled and characterized in the scientific literature.
- Finally, machine learning can be used for **optimizing battery system control**. This includes applications such as optimizing **fast battery charging** as well as using machine learning for **health-conscious battery control**. For example, machine learning algorithms can be used for battery fast charging protocol development [32,55]. The ability of such algorithms to potentially model and detect lithium plating is particularly important in this context because it allows machine learning algorithms to optimize charging protocols that avoid such plating [56]. Machine learning methods enable life-extending health-conscious control by improving accurate battery capacity fade prediction [57]. With this potential, machine learning methods can assist battery optimization to reduce the need for frequent battery recharging, which is extremely important for resource-constrained environments such as wearable sensors in the healthcare context [58].

The above review highlights the popularity of machine learning methods for online battery performance modeling, monitoring/estimation, and control. Fig. 6 illustrates the adoption of machine learning for such applications expanding from cycle data feature selection to performance modeling, estimation, and optimization. The driving force for this popularity is the degree to which online battery performance management requires careful navigation of the tradeoff between model complexity and fidelity. Online controllers cannot use excessively complex battery models, given the computational tractability issues associated with such models. However, it is important for online battery performance management to utilize models of sufficient accuracy to eke out the best achievable levels of battery performance. Machine learning methods are particularly well-suited for navigating this tradeoff between computational complexity versus prediction accuracy. In fact, one can push the machine learning paradigm even further by using it to optimize battery cycling *directly*, as opposed to using it in an *indirect* manner where a battery model is learned first, then embedded within an optimization/planning routine. Perhaps these facts explain the degree to which machine learning algorithms have become popular for BMS applications: they are flexible in terms of how they can be used, and they excel at navigating the tradeoffs between model fidelity and tractability.

2.4. Using machine learning to manage battery health, safety, reliability, and end of life

Machine learning methods can be used to manage both the performance of a given battery as well as its aging, degradation, safety, reliability, and ultimately end of life. These families of BMS applications are intertwined in practice. However, due to the sheer volume of research in machine learning-based battery management, this paper surveys the machine learning-based management of battery performance versus safety/health/reliability separately. Within the context of managing battery safety, reliability, and health, one can find at least four significant bodies of work in the literature:

- First, machine learning can be used for the **predictive modeling of battery aging/degradation dynamics** [59–62]. Xue et al., for instance, combined machine learning with semi-empirical methods to model battery degradation [63]. Similarly, Kohtz et al. mixed physics-of-failure (PoF) and machine learning approaches for battery state of health prognostics [64]. The importance of machine learning within this class of problems stems from the sheer number of phenomena contributing to battery aging, as well as the difficulty of building physics-based models spanning all of these phenomena. Research by Gasper et al. highlights this fact by employing machine learning methods for battery aging prognosis, and showing that machine learning is more accurate in this context than human subject matter experts [65]. One particularly important challenge in modeling battery aging is the existence of significant heterogeneity in how batteries age. Different battery chemistries may exhibit different aging dynamics, for example. Moreover, significant heterogeneity may exist among different production batches of the same chemistry, or even different battery cells within the same batch, due to factors such as production quality control and variations in initial battery faults/flaws. At least one family of machine learning tools – namely, ensemble learning – can help address this heterogeneity issue by blending the life predictions from multiple machine learning models: an idea demonstrated by Shen et al. and She et al. [66,67].
- Second, machine learning has also been used extensively in the literature for the **online monitoring of battery state of health (SoH)** [68–73]. Compared to SoC, the term SoH is somewhat nebulous in the sense that there is a lack of a single, unified definition of SoH in the literature. However, there are at least two commonly used metrics for SoH in the scientific community: *(i)* **capacity fade** (i.e., the degradation of a battery's charge capacity with time and/or usage); and *(ii)* **power fade**, often quantified in terms of **impedance growth**. Different learning methods are utilized in the literature to monitor these SoH metrics in a robust and flexible manner. These include adversarial learning [74] and transfer learning [75]. Machine learning is particularly valuable for SoH estimation because it can learn battery aging behavior from large data sets, potentially using distributed cloud computing methods, as shown by Sun et al. [76]. Machine learning is also valuable because it can help navigate the coupling between battery performance and aging dynamics, thereby enabling combined SoH/SoC estimation. For example, Li et al. propose a hybrid approach that combines SoC and SoH estimation, incorporating surface strain and temperature measurements [77]. Moreover, Alamin et al. use a digital twin for lithium-ion batteries to learn and capture SoC dynamics as a function of SoH [78]. SoH monitoring can be performed using different types of measurements, including online EIS measurements, as explored by Zhang et al. and Babaeiyazdi et al. [79,80]. Research by Harting et al. pushes this idea further by utilizing nonlinear frequency response for SoH estimation [81]. The ability to predict long-term battery cycle life using early cycling data can be a particularly important aspect of SoH monitoring, and is explored by researchers including Celik

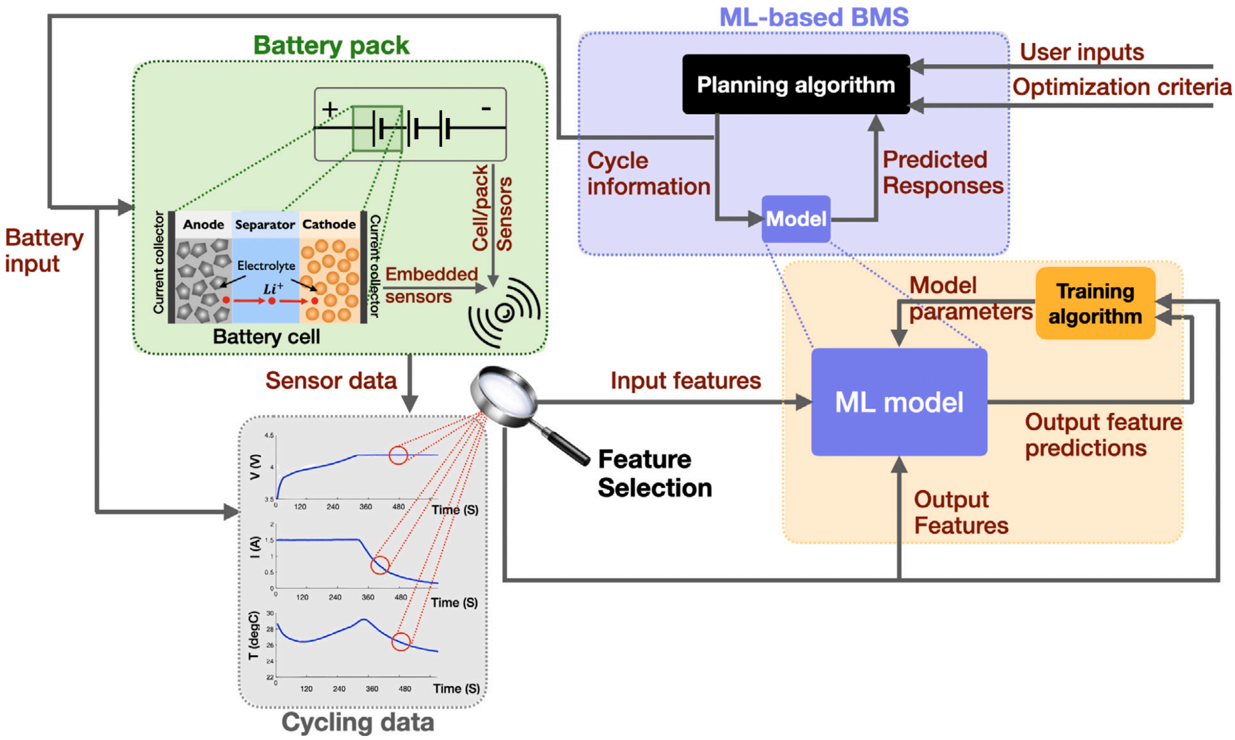

Fig. 6. Example of machine learning-based online battery management.

et al. [82]. Fei et al. argue that the nonlinearity of battery aging and the low variability in initial battery aging data can cause such battery life prediction from early cycling data to be very difficult [83]. To address this difficulty, Fei et al. suggest that the careful selection of specific features from a manually compiled list of battery cycling features can help with the early prediction of battery lifetime using machine learning [83]. This idea that careful feature selection is a critical precursor for the successful application of machine learning to battery SoH estimation appears frequently in the literature. For instance, Choi et al. and Hu et al. utilize selective features to perform capacity estimation [84] and SoH estimation [85] for battery life prediction.

- Third, machine learning methods are particularly valuable for **predicting the remaining useful life (RUL)** of a battery. For example, Bai et al. harness machine learning for battery capacity fade prognostics and estimating RUL [86], Aitio et al. forecast the end of life for grid-connected lead–acid batteries [87], and Li et al. estimate RUL using thermal voltammetry [88]. Facilitated by the compatibility of machine learning methods with large-scale data, Zhang et al. adopt cloud-connected li-ion battery data for RUL prediction [89]. Aykol et al. integrate machine learning methods with physics-based models for improved prediction of remaining useful life [1]. Similar to other machine learning applications, researchers such as Yang et al. worked through feature selection for battery RUL prediction [90], and Zhao et al. even highlighted that the ideal feature selection might be different for cell versus pack level estimation [91]. Additionally, Yang et al. exploited machine learning for binning or screening electrochemical batteries based on RUL performance [90].
- Fourth, machine learning is also particularly valuable for **fault detection, classification, and diagnosis** in battery systems. For example, Samanta et al. review different methods for machine learning-based battery fault detection and diagnosis [92]. An interesting application of machine learning in this regard is identifying/classifying failure modes in different chemistries (including Li–S, e.g., [93]). The literature also explores machine learning capabilities to assist with battery degradation modeling [94] and aging mode identification [95] where important features from battery cycling such as dV/dQ, Coulombic efficiency, capacity fade, etc. can assist with differentiating distinct aging phenomena from Li-plating, in particular [96].

To summarize, machine learning has emerged as a very popular tool for managing battery aging, safety, reliability, and end of life. One important reason for this popularity is the fact that it is very difficult to build comprehensive physics-based models of battery degradation, given the multiplicity and complexity of fundamental phenomena contributing to this degradation. Machine learning provides an attractive alternative to such physics-based modeling by inferring battery health, remaining useful life, and degradation projections from data. As battery systems see growing deployment in the field, coupled with growing communication network connectivity, very extensive data sets are becoming available to industry practitioners capturing field degradation data. This underscores the potential utilization of machine learning algorithms as a catalyst for incorporating field-acquired data and experimental battery cycling data as schematically shown in Fig. 5. This integration is instrumental in formulating the BMS design, enabling efficient control of battery performance by integrating monitoring data from battery sensors. Subsequently, this information can be seamlessly integrated into cloud databases, paving the way for forthcoming modeling practices. Such cloud-based integration of battery data sets promises a new era for machine learning-based battery management in industry, but raises an important question regarding academic research in this field. Specifically, the question arises of whether the scientific community can potentially access similarly large and rich battery aging databases, to the point of being able to continue to push this particular field of research forward in the open literature. As discussed in the next section of this paper, this is one of several critical questions that must be addressed as the battery machine learning literature continues to evolve.

3. Critical requirements in machine learning for battery systems

In order for machine learning to generate precise predictions of battery behaviors and dynamics, the data sets and algorithms used for machine learning must satisfy multiple key prerequisites. Examining the literature helps identify some of these critical prerequisites as follows:

- **Large data sets** are often needed for machine learning to genuinely impact the battery field [7]. This becomes even more crucial when using machine learning for modeling battery aging and predicting battery life, where large data sets covering diverse cycling conditions over long time durations are needed for model accuracy [97]. Berecibar et al. reviewed machine learning techniques to predict battery life and highlighted the fact that a large cycling data set is an important key to effectiveness [98]. Given the cost of generating such data sets, researchers have worked towards remedies that can reduce the size of these required data sets. Tang et al., for instance, highlight that machine learning facilitates data fusion from the field to provide extensive data sets for model training [99]. Additionally, Zhu et al. explored active querying for intelligent fault prognostics and reported that this method can be a remedy when facing data limitations [100].
- **Rich data sets** covering a broader spectrum of battery cycles are particularly valuable for enabling machine learning algorithms to discern subtle differences between these cycles, thereby enhancing modeling accuracy. In fact, one can argue that the richness of a data set is potentially much more important than its size, and that the need for "rich data" in battery machine learning supercedes that for "big data". Divena et al. for instance, suggest that more aggressive cycling (which is closer to real-life cycling condition) can help improve the learning accuracy for SoC prediction by improving the richness of the underlying data set [101]. Similarly, Harting et al. suggest that optimizing the frequencies used in nonlinear frequency response can facilitate SOH estimation [81]. In order for rich battery data sets to produce the greatest value for the scientific community, it is important for richness to be coupled with **uniformity** in areas such as which battery signals are measured, how the test results are converted to data archives, etc. Dufek et al. argue that such uniformity is still lacking in areas such as battery test protocols, and suggest that deeper community commitment to uniformity in battery testing is necessary, as a precursor to the sharing of battery test data for applications including machine learning [102].
- **Proper selection of features and/or health indicators** is an important aspect of using machine learning since it can add to the richness of the dataset, which ultimately affects the quality of algorithm outcomes [84,85]. Multiple researchers, for example, recognize that the good selection and optimization of health indicators is essential for accurate battery health management and prediction [103,104]. Fig. 7 illustrates five features commonly used in the literature for battery aging and SoH prediction. The idea is that a battery cell's capacity, dV/dQ slope, impedance, and rate of change of capacity/impedance with cycling can all serve as examples of simple but common features extracted from battery cycling data for the purpose of machine learning. That said, there is certainly room in the literature for additional innovative and/or optimal choices of features for battery machine learning. Some examples of innovative attempts at optimal feature selection are: (i) the use of automated partitioning of battery discharge and/or characteristic curves to facilitate feature selection by Sheikh et al. [105], (ii) feature selection for efficient utilization of cloud computing settings by Shu et al. [106], and (iii) time–frequency image analysis (TFI) of multi-domain features to extract diagnostic characteristics on the degradation of LiBs beneficial for capacity prediction by El-Dalahmeh et al. [107]. It is also important to tailor feature selection to the specific battery problem at hand. Zhao et al., for instance, suggest that there is a distinction between proper features for pack versus cell RUL prediction even for the same battery chemistry [91].
- The **ability to transfer knowledge** from one portfolio of battery tests and/or applications to another is particularly critical for the long-term success of battery machine learning methods. Battery testing is expensive and time consuming: a fact that makes it potentially prohibitive to revisit such testing from scratch in every new battery application or for every new battery design/chemistry. Therefore, the degree to which one can transfer knowledge from one set of battery tests to another and/or merge knowledge from multiple sources of battery data is vitally important in practice. **Transfer learning** has emerged as a popular solution to this problem in the literature. It leverages knowledge gained from a source task to improve learning for a related but different target task and is well-established in the field of battery dynamics modeling using machine learning [75,104,108–120]. One application of transfer learning is to retrain a machine learning model for a new battery of interest (i.e., target battery) with a limited amount of data by transferring the knowledge contained in a well-studied battery (i.e., source battery) with sufficient data [121–123]. Moreover, transfer learning facilitates generalizability of battery SoC and SoH estimations to different battery chemistries [124–127], various charging/discharging protocols [128,129] or new untested temperatures [130] as well as adapting to cell variability [131–134]. To exemplify, Chen et al. use transfer learning for adaptive online capacity prediction under fast charging which amplifies cell-to-cell variability [135], since transfer learning allows for using prior knowledge followed by fine-tuning. On top of that, transfer learning facilitates dealing with long-term dependencies in battery aging dynamics [136,137] in different ways: first, it enables machine learning methods to utilize different datasets for training versus testing for SoH estimation [138,139]. This can be training and fine-tuning on separate datasets such as laboratory versus real-world data [140], synthetic versus real-world data [141], or accelerated versus normal-speed datasets [40,142]. Second, it allows for cloud-based learning transferred to collective battery data [143]. Finally, transfer learning empowers BMS algorithms to be trained offline and tuned online for fast and accurate future capacity prediction [144]. These capabilities significantly reduce the data collection challenges typically linked to battery cycling. Additionally, Wang et al. find the potential in transfer learning to be used to reduce the computational burden when predicting battery core temperature [145] and Ma et al. exploit transfer learning for optimally selecting historical test data to train the machine learning model [146].
- Finally, **algorithm certifications** is highlighted by Raoofi et al. as a critical prerequisite for the deployment of battery machine learning in safety-critical applications, one example being electrified aviation [44].

4. Battery machine learning databases

The above survey highlights the sheer number of ways in which machine learning can support battery systems engineering and applications. Given this large volume of applications, there is a need for both rich and large databases supporting battery machine learning efforts. Multiple efforts exist supporting the creation and open sharing of such databases among scholars in the scientific community. Hasib et al. summarize the main datasets associated with lithium batteries in the public domain [147]. Some of these efforts that we found commonly used in the reviews literature are listed below:

- **The NASA Prognostics Center of Excellence database**: NASA provides datasets related to the health and performance of lithium-ion batteries used in aerospace applications. This database is valuable for research in battery prognostics and health management, as it provides records of impedance as a damage criterion during the charging and discharging of Li-ion batteries at different temperatures [148].

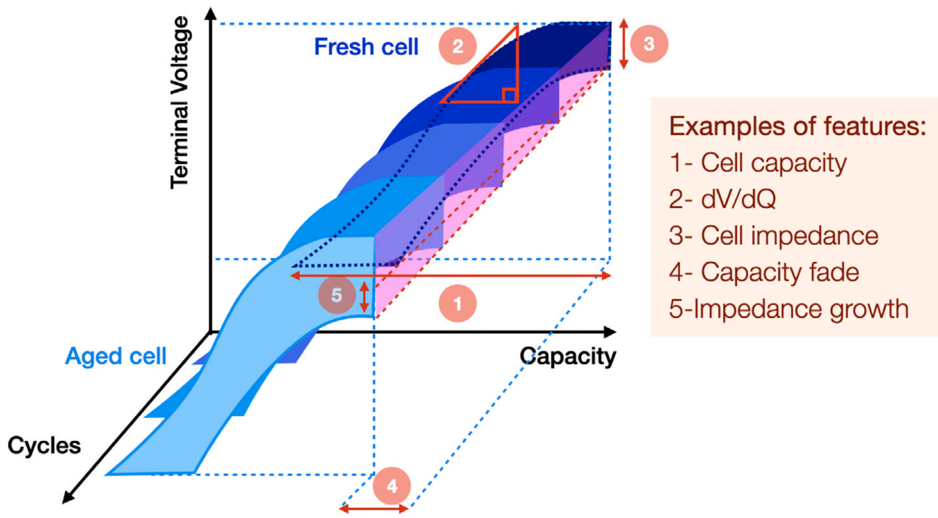

Fig. 7. Various selection of features for machine learning algorithms in battery modeling and prediction.

- **Battery test data from CALCE, the center for Advanced Life Cycle Engineering**: the CALCE battery team at the University of Maryland offers various datasets for battery reliability, aging, and life cycle analysis. These datasets include information on different battery chemistries, cycling profiles, and temperatures [149].
- **The NREL transportation and mobility research databases**: The National Renewable Energy Laboratory (NREL), provides access to a wide range of battery datasets for Li-ion batteries. It offers data on battery performance, aging, and degradation under various conditions. For example, the **Battery Microstructure Library** contains X-ray nano-CT data of calendared and uncalendared positive and negative electrodes from lithium-ion batteries [150]. The **Battery Failure Databank** [151] contains radiography and calorimetry data from several hundred abuse tests conducted on lithium-ion batteries. Finally, the database for **Battery Capacity from Electrochemical Impedance Spectroscopy** [152] contains hundreds of measurements from commercial cells, recorded at varying temperatures, states of charge, and health.
- The **Sandia R&D data repository**: the research and development data repository from Sandia National Laboratories [153] offers a rich resource for battery thermal analysis as well as cycling, abuse, and EIS tests.
- The **Stanford University Li-ion Battery Dataset**: the Stanford Energy Control Lab offers experimental data of Li-ion batteries. This includes galvanostatic discharge test data at different rates and temperatures of operation for NMC, LFP, and NCA as well as an aging dataset based on electric vehicle real-driving profiles [154].
- The **MIT-Stanford LFP Battery Fast Charge Dataset**: this is an extensive dataset consisting of 124 commercial lithium iron phosphate/graphite cells cycled under fast-charging conditions, valuable for life cycle and capacity degradation analysis [23,155].
- The **PNNL Battery Data Center**: the Pacific Northwest National Laboratory (PNNL) provides a collection of battery datasets that mainly facilitates cell performance research for vanadium redox flow batteries [156].
- The **UW-Madison experimental dataset**: this Panasonic 18650PF Li-ion data set offers a series of tests including HPPC and EIS performed at five different temperatures, specifically on Panasonic 18650PF battery cells. [157].
- The **Oxford dataset**: the Oxford battery dataset records the battery aging experiment data produced by the University of Oxford, beneficial for battery degradation modeling [158].

Table 1 summarizes the focus field of each dataset and provides a brief description of the specification of the data provided by each of the references.

Collectively, the above databases are useful for battery modeling, diagnostics, and machine learning research in general. The availability of these databases is important because they can potentially facilitate the entry of academic researchers into the battery machine learning field, even if such researchers are unable to access the much larger proprietary data sets potentially available to the battery industry. In fact, these databases are already seeing extensive use in today's published battery machine learning literature. An opportunity exist for further growth in the literature grounded in the use of these databases to define "benchmark problems" for battery machine learning, in a manner akin to the use of large databases to define benchmark problems in other machine learning domains, such as machine vision. Such a potential future research direction can be valuable, as the literature matures, in terms of helping understand the benefits and tradeoffs between different machine learning algorithms for different battery applications.

5. Discussion and lessons learned

To summarize the above literature survey, machine learning *(i)* already adds significant value to the battery systems domain, with the caveat that *(ii)* different machine learning approaches and algorithms may be better suited for different applications. Moreover, there are many *(iii)* novel potential battery applications of machine learning that remain relatively unexplored. This section revisits each of these three important facets of the literature, with a particular focus on future opportunities for machine learning research in the battery systems discipline.

5.1. A perspective on the value added by machine learning in the battery domain

The role of machine learning in the battery domain has been a topic of increasing interest and scrutiny. Gasper et al.'s study undertook a comparative analysis of machine learning models in battery lifetime modeling, pitting them against models developed by human subject matter experts. The results of this study strongly advocate for the adoption of machine learning, citing its significantly superior accuracy and resource efficiency in battery modeling [65]. Furthermore, the transformative potential of machine learning in the battery domain is demonstrated by Tang et al., who suggest that machine learning can revolutionize how field data is processed, effectively creating a

Table 1
Summary of datasets for battery machine learning applications.

Data source	Focus	Specifications
NASA	Cell performance and damage prognostics	Charge and discharge profile under multiple temperatures with impedance records
CALCE	Cell performance, aging, reliability	Multiple cycle profile (low-current and dynamic cycles), multiple chemistries (NMC, LFP, LCO), and multiple temperatures
NREL	Cell performance, material microstructure, failure, aging	Battery Microstructure Library (X-ray and nano-CT data), ...
SANDIA National Lab	Cell performance, aging, thermochemical, safety	Thermodynamic reactions and calorimetric data
Stanford Energy Control Lab	Cell performance, aging	Galvanostatic discharge test (NMC, LFP, NCA), electric vehicle real-driving profiles aging data (NMC)
MIT-Stanford	Cell Performance, aging, fast charge	Fast charge cycle data (124 LFP cells)
PNNL Battery Data Center	Material performance	Multiple charge–discharge cycles for hundreds of cells, performance data of vanadium redox flow battery with various current densities
UW-Madison	Cell performance	HPPC, drive cycles, and impedance spectroscopy at five different temperatures for Panasonic 18650PF cell
University of Oxford	Cell performance, aging	Long term battery aging data for SLPB533459H4 lithium-ion pouch cells

vast distributed cyber–physical battery testing facility. This can be accomplished by applying classical machine learning techniques to a smaller laboratory dataset to identify critical features, which in turn enables the utilization of field data for more comprehensive learning and predictive purposes [99]. Additionally, Zhang et al.'s work highlights the capabilities of machine learning in the hierarchical modeling of battery aging and degradation. By harnessing machine learning, a broad population-wide model can be initially trained on an extensive dataset, and subsequently refined using more individualized aging and degradation models. This hierarchical approach not only improves the overall accuracy of predictions but also allows for a more nuanced understanding of battery performance at both the population and individual levels [34]. In summary, the collective evidence from the literature suggests that machine learning has the potential to add significant value in the battery domain by enhancing accuracy, resource utilization, and the utilization of field data.

5.2. Perspectives on the choices of machine learning algorithms for different battery systems applications

The selection of machine learning algorithms in battery systems is a nuanced process, where the intricacies of specific applications and the underlying principles of different algorithms play crucial roles. To use a simple analogy, a good carpenter always knows when to use a hammer versus a screwdriver or a saw. Similarly, making the best use of machine learning algorithms for different battery systems applications requires a deep understanding of which algorithms are best suited for each application. In certain battery machine learning application domains, this understanding is still evolving. As a result, there is a notable lack of clear consensus within the academic community regarding which machine learning tools to use for those applications. A case in point is the set of diverse perspectives on machine learning-based SoC estimation algorithms. Numerous studies within the literature extensively evaluate machine learning algorithms for estimating the state of charge. However, the absence of a unanimous identification of the proper algorithm underscores the context-dependent nature of this selection. Different algorithms may demonstrate superiority under distinct conditions, emphasizing the ongoing quest for a universally applicable solution. As another case in point, the exploration of the suitability of any given machine learning algorithm across different battery chemistries remains relatively unexplored in the literature. While it is plausible that diverse machine learning algorithms may be well-suited to different battery chemistries, the literature predominantly focuses on Li-ion batteries. This skewed emphasis neglects the nuanced differences even among various Li-ion chemistries. As a result, the question of whether machine learning algorithm can be tailored for different chemistries, even within the family of Li-ion chemistries, remains open for future research.

With the above caveats in mind, it is exciting to note that there are some examples of emerging consensus in the literature regarding the suitability of different machine learning algorithms to different battery applications. Drawing from the literature, one can see the following collective insights regarding specific roles for the different categories of machine learning algorithms highlighted in Fig. 8:

- *Ensemble Learning can help with addressing battery heterogeneity*: Ensemble learning is gaining prominence in the literature because of its potential to help with addressing the battery heterogeneity challenge. Researchers advocate for its utility as it enables the training of multiple models to recognize diverse degradation mechanisms within a battery system. Moreover, the adaptability of adjusting model weights in real-time applications enhances the robustness of this approach.
- *Gaussian Process Regression (GPR) can help with capturing complex inter-dependencies in battery systems*: Within the battery machine learning literature, a notable emphasis is placed on Gaussian process regression. This preference is attributed to the suitability of GPR for representing nonlinear maps within a given state space. Its application extends to capturing complex relationships inherent in battery systems.
- *Long Short-Term Memory (LSTM) networks can help facilitate battery health modeling*: LSTM networks find particular relevance in health modeling within the broader battery research field. Given the dynamic nature of degradation, often embedded in time series data, LSTMs offer a solution for capturing temporal dependencies influenced by the historical usage patterns of the battery.
- *Classification algorithms can help with enabling fault diagnostics*: In the realm of fault diagnostics, the application of classification algorithms, such as support vector machines, is well-justified. The inherent characteristics of fault diagnosis, where discrete classes of faults need identification, align well with the capabilities of classification algorithms.
- *Transfer learning can help address dataset multiplicity and inter-chemistry dynamic modeling*: A growing body of research is dedicated to understanding the dynamics of one battery chemistry and

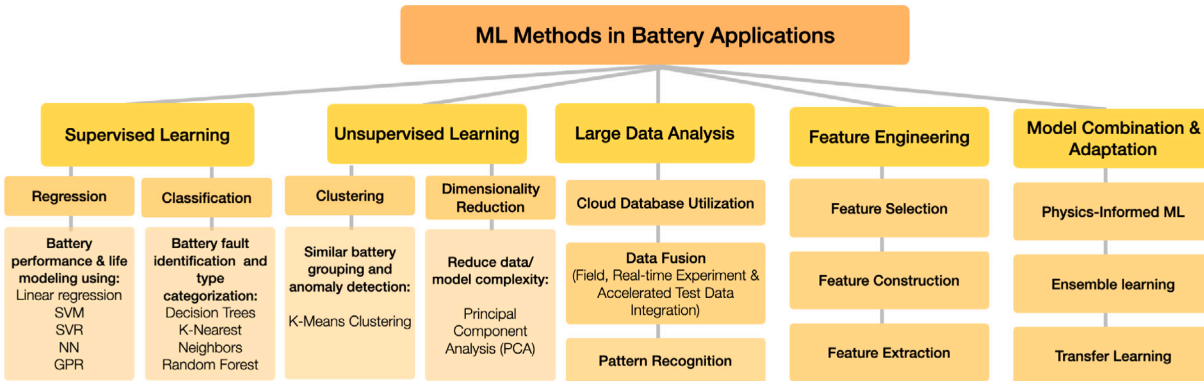

Fig. 8. Machine learning methods applied to battery systems domain.

leveraging transfer learning to adapt to another. This exploration addresses the challenge of knowledge transfer between different chemistries within the machine learning framework for batteries, opening avenues for cross-chemistry model adaptation and understanding. Moreover, transfer learning is employed to solve the challenge posed by dataset diversity. This approach is particularly well-suited when combining data from disparate sources, such as laboratory and field datasets or multiple laboratory datasets. Transfer learning facilitates the adaptation of knowledge gained from one dataset to another, enhancing model generalization.

- *Feature selection can help boost battery data utilization*: Feature selection is rapidly emerging as a critical aspect of battery machine learning. Various methods, including gradient boosting and manual selection, are employed to automate or manually curate relevant features. Despite its recognized importance, the literature on this topic is still evolving, with no consensus on a definitive algorithm for feature selection.

5.3. Open challenges and opportunities for battery machine learning research

Machine learning has emerged as a transformative force in battery research, offering unprecedented potential for enhancing performance, efficiency, and reliability. However, a comprehensive review of the literature reveals several open challenges and untapped opportunities that merit attention for the advancement of this field. At least seven clusters of research topics are particularly promising for future battery machine learning research:

- First, there is a need for more studies **quantifying the benefits** of machine learning for battery applications through rigorous assessments of these benefits versus the associated costs. One example of such costs is the large **energy usage** associated with the large-scale training and deployment of battery machine learning algorithms. This energy cost remains inadequately explored in the literature, necessitating a deeper understanding of the sustainability and efficiency gains of machine learning in battery systems. Most of the literature on assessing battery machine learning algorithms focuses on comparing one algorithm to another, often in terms of metrics such as performance and accuracy as opposed to data efficiency or energy needs. Moreover, with any machine learning algorithm, especially transfer learning, there is a tradeoff between how much it costs in terms of computations and data offline, prior to deployment, versus online, after deployment. This kind of tradeoff analysis has not yet been explored in depth in the literature. The question of the feasibility of implementing machine learning algorithms online, either on embedded platforms or on the cloud or both, for real-time BMS applications, has not yet been fully addressed in the literature. For example, it is not clear which algorithms would be best suited for such practical implementation, and why. Finally, the current literature has a predominantly "inward" focus on the battery as the subject of battery machine learning. This comes at the price of less emphasis on the "outward" focus on how battery behavior may be driven by factors such as battery user behaviors. There is untapped potential, for instance, in using machine learning for user education and training to optimize electric vehicle or airplane performance. This area presents a wide-open field for investigation into the implications of introducing machine learning to battery applications through a **user-centric perspective** rather than a singular focus on the battery itself.
- Second, there is a need for more extensive research on **safe and bounded machine learning** for batteries. Despite the critical role that safety plays in battery applications, the literature on **safe** machine learning for batteries is surprisingly sparse, with the exception of fast-charging applications where safety is considered a main factor. This sparsity might be a result of the limited exploration of **active** machine learning in the literature (where the machine learning algorithm actively probes the battery to maximize the richness of the resulting test information). Such active learning, in and of itself, can be an extremely worthwhile research path. Furthermore, **explainable and trustworthy** machine learning is particularly valuable in the battery context, because of its safety implications. For example, a machine learning algorithm that can provide not just a warning against catastrophic battery failure events (e.g., thermal runaway) but also an explanation for this warning that can potentially better help human battery operators in avoiding these events. This is widely recognized as important in the broader machine learning literature, but remains an open research topic in the battery area. The absence of a robust emphasis on safety considerations in battery machine learning poses a potential risk to the robustness and dependability of the resulting battery systems. Similarly, significant gaps persist in the realm of **bounded** machine learning. The lack of constraints on data during algorithm training is a noteworthy issue, as it raises concerns about the generalizability and adaptability of models in real-world scenarios. Therefore, the exploration of safe and bounded machine learning approaches in battery research stands as a promising and open avenue for future investigation.
- Third, there is a significant potential for advancing **multi-scale, multi-domain (MSMD)** battery modeling by facilitating seamless connections between different aspects of battery behavior, such as mechanical deformation, electrical characteristics, and thermal dynamics using machine learning algorithms. Despite the excitement surrounding this application, it remains relatively unexplored in the literature, potentially due to its intersectionality across multiple domains. That said, even in the battery control domain, machine learning has been underutilized for the **integration of multi-level control** algorithms. For example, integrating

a predictive model of stationary battery pack performance into a higher-level model for grid energy management remains relatively unexplored. This includes the regulation of energy demand at the battery pack level based on predictions of grid load and/or renewable energy availability, etc.

- Fourth, the **transition from cell-level to pack-level behaviors** remains a relatively underexplored area in the battery machine learning literature. This is unfortunate, given the degree to which machine learning algorithms (especially ensemble learning) could play a pivotal role in addressing this challenge. Opportunities lie in utilizing these algorithms to bridge the gap and enable more accurate predictions and optimizations at larger scales while utilizing the cell-level model findings. Moreover, ML is not extensively utilized in **battery pack design and optimization**. Applying machine learning to questions of layout optimization, thermal management system design, and safety packaging of the pack/enclosure, etc. could lead to more efficient and reliable battery packs. Machine learning can also serve as a strong enabler for detecting and analyzing heterogeneity in a battery pack, before and after development, including for applications such as **pack balancing** and **outlier detection**. Machine learning can additionally help with analyzing and comparing battery performance data with databases to detect battery flaws, for **reliability** reasons, and even for the prediction of imminent failure, at the full pack (as opposed to cell) level. As an illustration, a given machine learning algorithm can be trained to do early anticipation of venting, thermal runaway, etc., for reliability purposes. The proven capabilities of machine learning in image analysis can furthermore be employed for the visual inspection and visual inspection-based quality control of battery system products. This includes detecting events like the swelling of battery cells, cracks and leaks in battery cells, flaws in battery material structure, etc.
- Fifth, the utilization of cloud-based machine learning algorithms, particularly in the context of online battery management applications, remains a relatively unexplored research area. Questions such as which portions of a machine learning algorithm to deploy onboard versus on the cloud, in a robust manner, are only beginning to receive attention in the literature. Furthermore, such cloud computation requires a degree of attention to the **cybersecurity** of battery machine learning algorithms: a topic that also remains relatively unexplored in the literature.
- Sixth, one of the main difficulties when using machine learning models is the fact that they are not always easy to interpret by a human user. This stands in contrast to both physics-based and equivalent circuit models, where the scientific community has developed a deep understanding of either the physical mechanisms being modeled or the intuitive meaning of different elements in a given model or both. There is certainly some research on the **interpretability** of machine learning models of battery systems (see, e.g., [22,93]), as part of the broader domain of research on the interpretability of machine learning models in general. However, one can argue that much remains to be explored in this research area. Key challenges include developing models that can offer a deeper, more nuanced understanding of the complex relationships between material properties, manufacturing parameters, and their outcomes. There is also a significant need for machine learning methods that can provide clear insights into how different variables interact and affect material performance. Opportunities lie in creating more transparent, explainable models that facilitate the identification of critical factors for optimization, enabling a more informed and efficient discovery process for new materials. To provide maximum benefit to their users, interpretable battery models should not only uncover hidden patterns in complex battery chemistries, but also translate learned patterns into useful knowledge for the user. For example, perhaps the greatest benefit of an interpretable machine learning model, when it comes to battery material design, is the degree to which it can give the battery designer insights regarding how to improve the material design, and why.
- Finally, while the existing literature applies many machine learning algorithms to the battery systems domain, one can argue that specific algorithms remain relatively less explored. Examples of such **relatively less-explored algorithms** include the use of **regularization**, **Bayesian approaches**, and **uncertainty quantification** approaches for battery machine learning. Incorporating these methods could contribute to more stable models, as well as address challenges related to overfitting and uncertainty in battery systems. Additionally, **integrating physics-based and machine learning models** deserves more attention from the research community as it helps leverage the strengths of both approaches and offers the potential to advance modeling accuracy and reliability. Exploring the linkage between low-order and high-order battery models can also provide an enhanced balance between computational efficiency and a robust connection to the underlying physics. The development of a systematic integration approach for this purpose can, therefore, be a valuable addition to the existing literature. The extensive dependency of machine learning to data for accurate performance is commonly deemed as a limitation, but it also provides the unprecedented advantage of enabling the use of large scale could data. The literature lacks a rigorous examination of these opposing perspectives, leading to a deeper understanding of when to deploy machine learning and when to refrain from doing so. The integration of ML with **cloud computing** is an emerging topic, but its exploration is still in its early stages. Addressing challenges related to feature selection for minimalistic yet useful communications is crucial for advancing this area. Cloud computation enabled by machine learning can be effectively tuned to combine learning from field data and experimental test data. This in turn brings up a noteworthy concern as there can potentially be a very significant **variability in the quality and integrity of different datasets** used for battery ML. For example, datasets generated in the laboratory will often employ much higher-fidelity sensors than field datasets. However, laboratory cells still undergoing experimental research can be of much lower quality control than commercial cells. In this regard, there is a very slim body of research focusing on: *(i)* the fusion of different battery databased in a manner that explicitly accounts for the heterogeneity in their quality. *(ii)* the sanitization of battery datasets to remove outlier patterns happening in batteries under development stage, e.g., "glitches" in cycling data resulting from internal shorts, etc.

Addressing these open challenges and capitalizing on the identified opportunities has the potential to propel battery machine learning research into a new era in terms of the value it adds to the overall battery systems discipline. In fact, one can argue that the biggest gaps and opportunities in battery machine learning involve exploring new problems such as those listed above, as opposed to new solutions to problems that are already well-explored.

6. Conclusions

This article examines the substantial body of literature devoted to the application of machine learning within the battery domain. A significant portion of this research is directed towards the invention and discovery of innovative battery materials, the predictive characterization of material behaviors, the estimation of critical battery state variables such as state of charge (SOC) and state of health (SOH), and the modeling and prediction of battery aging. The comprehensive scope of application areas is supported by a diverse array of machine learning approaches, indicating a relative maturity in the field concerning both the foundational tools and their practical applications. Nevertheless, as elucidated in the latter sections of this article, significant opportunities exist for machine learning to make further contributions to the realm of battery systems. These potential advancements encompass areas such as battery cell to pack up-scaling, quantifying machine learning benefits and costs including energy implications, and delving into user-centric applications.

CRediT authorship contribution statement

Zahra Nozarijouybari: Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation, Conceptualization. **Hosam K. Fathy:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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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