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# Data-Driven Online Prognosis of Rechargeable Batteries: Prospect and Perspective

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Along with the growing popularity of electric vehicles (EVs) and smart grids, rechargeable batteries are playing an increasingly important role in the field of energy storage. To ensure a safe and stable operation, it remains essential to estimate the states of batteries accurately and efficiently in advance. Herein, we provide a perspective on data-driven online prognosis of rechargeable batteries, where its scope and superiorities are first introduced. Four promising application scenarios in real world including battery manufacture, EVs, smart grid, and battery recycling are then discussed, followed by the challenges that require further investigation. We anticipate this perspective to attract more interest to this field, to illuminate potential directions for future researches, and to broaden the context of data-driven physical and engineering sciences.

## 1. Introduction

Due to the decreasing availability of conventional energy resources and the increasing amount of resulting environmental pollution, finding alternative, renewable energy sources remains an inevitable and essential task.[1–4] However, the large-scale utilization of renewable energies such as wind or solar still faces many challenges, such as their uneven geographical distribution and intermittent generation, which makes it imperative to develop efficient energy storage strategies.[5–6] Rechargeable batteries, in this case, emerge as a promising solution to efficiently storing energy.[7–12] For instance, lithium-ion batteries (LIBs) exhibit low self-discharge rate, long cycle life, and wide operation temperatures and thus have been widely adopted in mobile applications such as electric vehicles (EVs) and portable electronic devices, holding a large market share.[13–15] LIBs are also regarded as one of the most technically mature candidates for stationary storage, coping with the intermittent issue of utility-scale renewable power stations in smart grid.[16–20] Therefore, rechargeable batteries can help to realize reliable, green, and effective storage, transportation, and utilization of electricity.[21]

The above practical applications all require superior battery safety and long battery lifetime to achieve usage reliability and economic viability.[22–23] It is therefore vital to accurately evaluate the health states and lifespan of batteries to improve the battery safety and to reduce the economic and time costs in battery manufacture, screening, usage, and recycling.[24–25] Battery degradation remains the key factor twinning with battery safety and lifetime, which, unfortunately, usually complies with complicated mechanisms and is highly dependent on operation environments and conditions.[26–27] Therefore, effective real-time prognosis on the battery's states such as state of charge (SOC), state of health (SOH), end of life (EOL), and remaining useful life (RUL) is of paramount importance to adapt the battery to versatile environments and dynamic conditions, thereby ensuring a reliable operation over its entire service life.[28–29] Nevertheless, effective early prediction, especially online estimation, of battery is still challenging due to the normally nonlinear degradation process as well as the high variability even for the batteries working under similar conditions.[30]

As big data technologies and artificial intelligence (AI) advance, data-driven approaches utilizing machine learning (ML) tools stand out as promising solutions to overcome these challenges, because they have capabilities and versatilities in depicting complex, nonlinear correlations by predicting battery status without analyzing the complex degradation mechanism.[24,31–36] The adaptability of data-driven methods to diverse operating conditions significantly enhances the accuracy of predicting battery behavior. This adaptability, coupled with real-time responsiveness, allows for the prompt identification of changes in battery health, a critical aspect for timely maintenance, especially in high-stakes scenarios. The personalized predictions, which take into account each battery's unique characteristics, contribute to precision in estimating states and lifespan. Ultimately, by leveraging extensive battery performance data, data-driven methods provide cohesive and robust support for reliable online prognosis of batteries, proving essential for superior safety, longevity, and economic viability across various applications.

Despite the great potential established, data-driven online battery prognosis encounters challenges with dataset quality, availability, computational efficiency, model interpretability, and generality. Many researchers are actively addressing these issues, yet data-driven online battery prognosis is still at its infancy. To attract more contributors, we provide a concise

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outlook on the prospects and perspectives of data-driven online battery prognosis in this review. The advantages of online prediction and data-driven methodologies are first introduced by comparing them with offline estimation and model-based approaches, respectively. We then elaborate on four important application scenarios of battery prognosis including battery manufacture, EV, smart grid, and battery recycling, along with challenges encountered in each field. Lastly, we conclude the review with a brief summary on the obstacles and opportunities faced by the data-driven online prognosis of batteries, which is anticipated to propel its development and implementation in real-world applications.

## 2. Advantages of Data-Driven Online Prognosis

The advantages of data-driven methods for online battery prognosis are summarized in Figure 1. In this section, we will discuss the superiorities of online prediction and data-driven methods, respectively.

### 2.1. Why Online Prediction is Important?

Over the past decades, massive efforts have been devoted to offline experimental analysis.[37–39] Recently, researchers have started to turn their attention to online prediction due to its adaptability to diverse application scenarios.[40–41] Herein, offline estimation, or batch learning, refers to the estimation based on an algorithm using all the available data collected from previous batteries; while online estimation adopts the algorithm that utilizes real-time data collected from the target battery sequentially.[24] The data is often processed and stored in the battery management system affiliated with EVs or power stations. Offline estimation trains the model after acquiring the entire training dataset and then runs without learning anymore (Figure 2a). Online estimation, on the other hand, incorporates streaming data, where the model is optimized incrementally by real-time information and does not require the acquisition of a complete dataset beforehand, thus can adapt to change rapidly and autonomously (Figure 2b). The superiorities of online prediction are the most established in two scenarios, namely when the cell inconsistency remains non-negligible and when the strict requirement on input data quality needs to be alleviated.[42]

In reality, cell inconsistency inevitably exists in batteries.[43] Even cells of the same type from the same manufacturing line might exhibit variations in performance.[44] This also implies that the performance of large-scale battery packs cannot be reliably inferred from the behavior of one single cell, whose performance is extremely sensitive to the varying currents among parallel strings stemming from cell-to-cell deviations, thermal disparities, and interconnects.[45] In addition, battery performance is highly dependent on the operation conditions and can

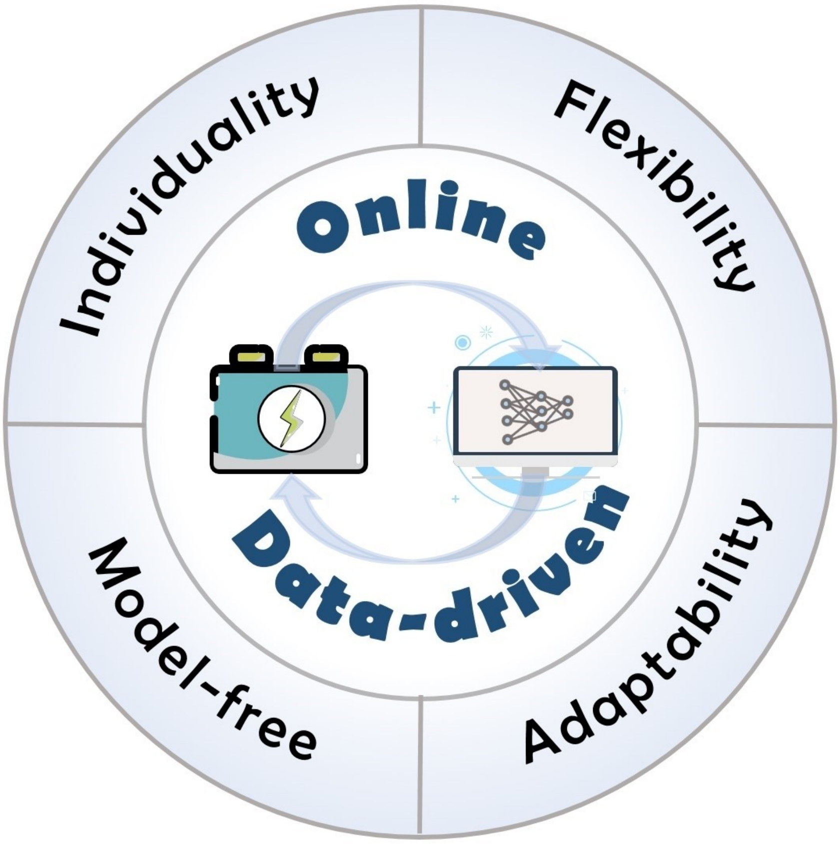


**Figure 1.** Advantages of data-driven online prognosis method.

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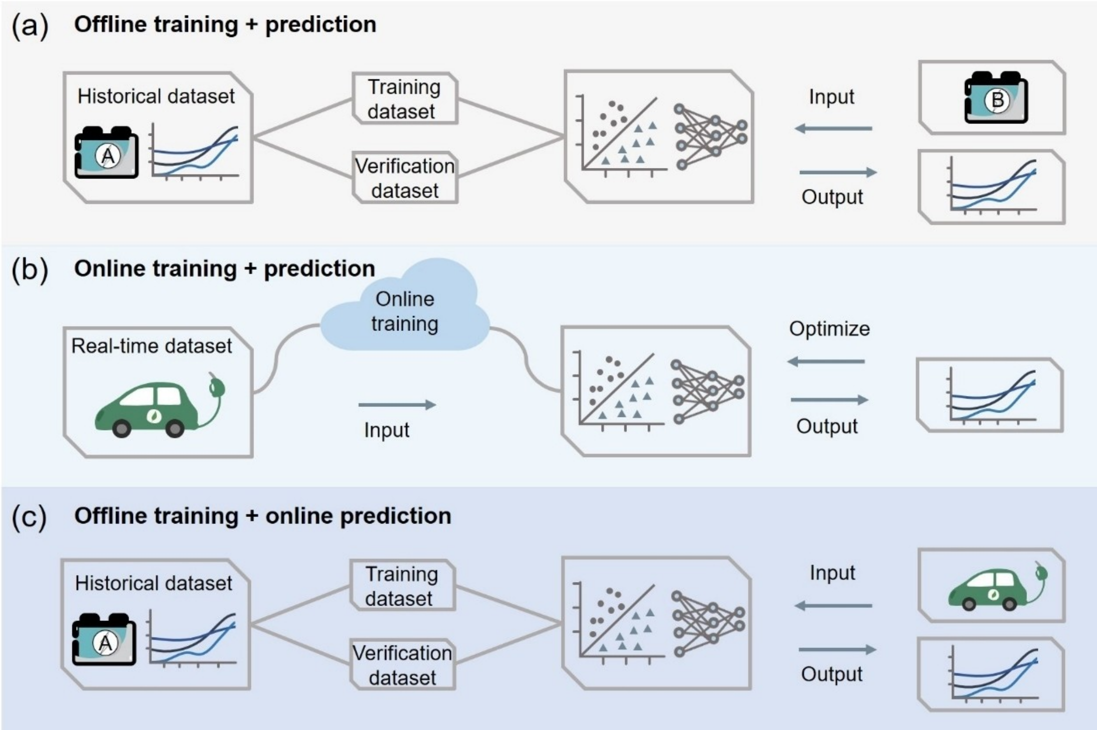


**Figure 2.** Workflows for (a) pure online prediction, (b) offline prediction, and (c) a combination of offline training and online prediction.

be greatly influenced by factors such as operating temperature, maintenance frequency, and charging/discharging protocols.[46] In this case, online prediction algorithms that continuously incorporate historical data from the target battery, as well as changes in data distribution to build and revise the models, remain indispensable, as prompt responses to dynamic changes in the external environment can be simultaneously ensured, indicating their capability to establish individualized estimation method for each battery.[47]

Online prediction also presents higher flexibility than offline estimation in terms of the input data required. The offline model is incapable of learning incrementally and often constructs features from cell data with a fixed cycle length. This can be unfeasible in practical applications, as predictions can only be made if all data until a certain cycle is obtained.[48] Additionally, to learn up-to-date data, a new version of the model needs to be trained from scratch on the full dataset, which generally takes a lot of time and computing resources. In contrast, online method compatible with streaming data can readily utilize cell data from any previous cycle to generate estimations, which enables the online estimation process to be fast and cost-efficient and allows the model to continuously learn from new data in real time.[49] In this sense, input flexibility endows online prediction with more opportunities in practical applications than offline estimation.

In addition, online estimation is sensitive to abnormal data, which leads to a decline in model performance due to low-quality data input. To achieve satisfactory accuracy in real applications, most studies are conducted on a combination of offline training and online prediction (Figure 2c), where the model is still trained with a complete, offline dataset but readily applicable to generate predictions on real-time streaming data.[50–52] Numerous efforts have been made to optimize online prognosis models that are trained offline in previous works. For instance, Liu et al. used a novel health indicator (HI) that combined the discharge rate with voltage sequence, realizing online estimation from offline training dataset with high accuracy.[53] In addition, the adaption algorithms are embedded in online estimation process to mitigate the prediction error due to the discrepancy between the offline training dataset and real-time measurement, as Zhang et al.[54] and She et al.[42] described.

## 2.2. Why Data-Driven Methods are Advantageous?

Recently, significant progress has been made in the field of battery prognosis, where the approaches can be in general divided into model-based methods and data-driven methods.[55] Model-based approaches are particularly emphasized on the development of various physics-based or empirical models, while data-driven approaches aim to directly derive hidden correlations from the data itself through statistical theories or ML methods.[28,55] In simple terms, model-based methods attempt to choose the most appropriate model and parameters for a specific dataset where the model itself usually remains unaltered. On the other hand, data-driven methods optimize the model to fit the data based on the information obtained from particular batteries.

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Taking the EOL or RUL prediction as an example, model-based approaches utilize physics-based models of degradation behavior or construct empirical models to depict battery dwindling trajectory, which usually consist of a set of algebraic and differential equations or an empirical equation. Representative approaches include electrochemical models,[56] empirical models,[57] and equivalent circuit models (ECM).[58] The electrochemical approach utilizes various partial differential equations to estimate battery states by describing their electrochemical and thermal dynamics that are closely related to battery degradation. However, this type of approach usually requires the identification of a large number of variables and the high computational cost, yielding it less practical for real-time predictions. The empirical model employs different forms of regression models (such as linear and exponential) or empirical formulas to describe battery degradation behavior and forecast future decay trends through extrapolation. Though this approach is simple to implement owing to ignoring the internal mechanism, the requirement of large amounts of data and the difficulty in accounting for cell-to-cell variations bring obstacles to practical applications. The ECM is created based on the combinations of various electrical elements to depict battery dynamics. Because of its simplicity in mathematical representations and the resulting minimized computational intensity, it has received much attention for battery prognosis. Nevertheless, this method is mostly applied to battery systems under very similar conditions, the accuracy of which remains limited when predicting battery characteristics across a wider range of scenarios.

Empowering with higher flexibility and computational efficiency, data-driven methods have gained ever-growing popularity in recent years.[59] Aligning with the advancements in data-mining techniques and AI, the superiorities of data-driven battery prognosis can be fully leveraged, making it favorable for real-world applications.[60] The key strength of this type of method lies in its ability to describe abstract, complex relationships without the necessity to construct an explicit mathematical model, making data-driven methods more applicable to dynamic conditions.[48] The data-driven models treat batteries as black boxes focusing on establishing the mapping relations between inputs and outputs instead of analyzing battery degradation behaviors. Since the health status of batteries is greatly influenced by the operating environment inducing diverse degradation mechanisms, data-driven method shows greater potential in online prognosis due to its model-free nature. Specifically, when applied to real-time online predictions, the data-driven model can be continuously iterated, optimized, and upgraded to incorporate newly available information, and the model accuracy and robustness can be consequently improved.

## 3. Real-World Application Scenarios of Online Prognosis

Excellent versatility and robustness have yielded data-driven online methods extremely promising for practical battery prognosis. Figure 3 summarizes four major application scenarios, which will be elaborated in this section respectively.

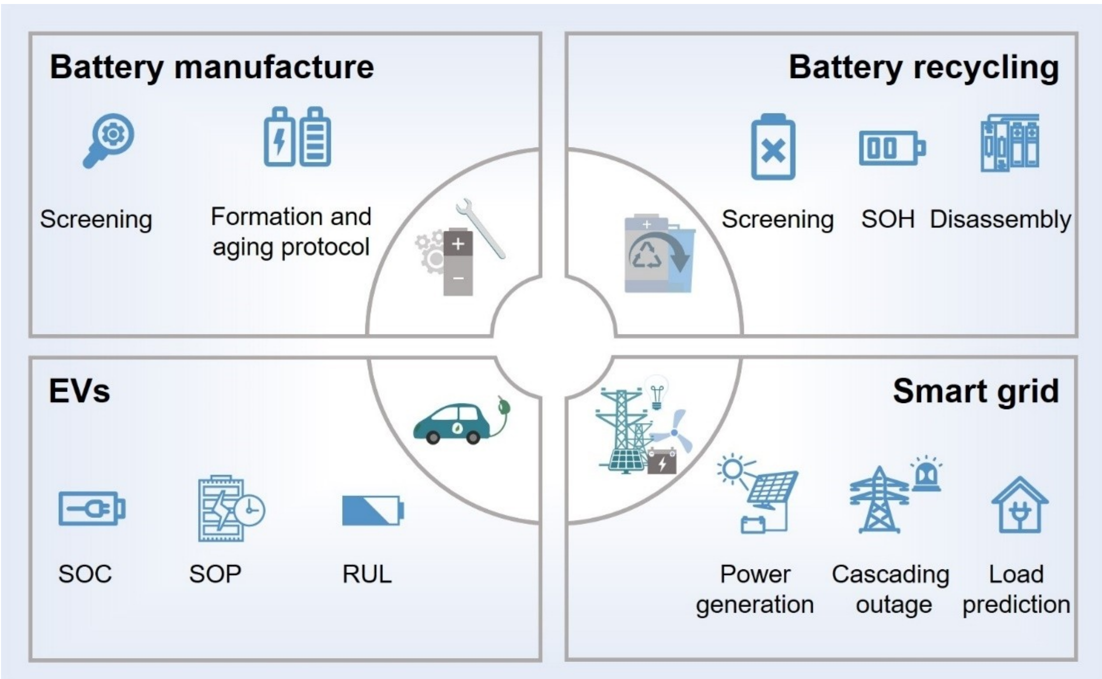


**Figure 3.** Major application scenarios of data-driven online prognosis methods.

### 3.1. Battery Manufacture

Along with the increasingly widespread application of batteries, the optimization of their manufacturing cost has attracted much attention both in academia as well as in industry.[61] According to The Boston Consulting Group, the production of batteries is an extremely complex process and can be roughly divided into three stages, electrode production, cell assembly, and cell finishing, which account for 39%, 20%, and 41% of the entire production-related costs, respectively.[62] For the cell finishing that accounts for the highest proportion, cell formation and aging are the most cost-intensive processes, the optimization of which remains vital to improve battery processing time and yield rate.[63]

In the formation stage, batteries are activated through charging and discharging at low cycling current so that they can last for the indicated lifetime. While being the major bottleneck in battery manufacturing as the charge and discharge cycles that activate the material in a fresh cell can take up to twenty hours, this process remains crucial in determining the final quality of the product.[64] Although some fast formation protocols have been developed, it might be unwise to apply them to all batteries since cells with various electrodes, electrolytes, and even assembly modes might comply with distinctive electrochemistry and respond differently to a specific formation process.[65] To develop a new formation protocol and to improve its efficiency, it is therefore vital to develop low-cost and rapid prognosis approaches to estimate battery lifespan, as months or years need to be spent to measure true battery cycle life. The adoption of online lifetime prediction models built by data-driven methods is then promising to help realize individual optimization of formation protocols for every single type of batteries, single batch of batteries, or even single battery without long-time testing.

Following the formation process is cell aging, where finished batteries are stored for several weeks for solid electrode interphase formation, micro short circuits identification, as well as consistent battery screening.[66] Only after this process can suitable batteries be selected for packaging and deployed to the market. During the aging period, thousands of batteries are stored in the warehouse with strict requirements on environmental stability and safety prevention measures. In this case, the implementation of data-driven online prognosis approaches can be highly valuable as real-time battery safety monitoring can be readily achieved, and the batteries can be screened automatically as well. While several environmental and operational factors such as temperature and storage time remain crucial in determining the cell's response to aging, online battery prognosis can assist the aging protocol optimization by unearthing hidden correlations between the protocol and individual battery performance.

Formation and aging processes are essential to ensure high-quality rechargeable batteries but significantly increase manufacturing costs. Most studies established fast predictive quality models based on data-driven methods to assess cell quality before entering the formation and aging step to reduce the process time and costs.[67] For instance, an early quality classification and prediction model was developed by Stock et al. using inline measurement data, achieving reliable detection of defective cells before the aging process.[68] Besides time reduction, design parameters also can be optimized. Attia et al. demonstrated an early outcome prediction combined with Bayesian optimization to optimize parameter space.[37] In addition, several data mining methods were implemented by Schnell et al. to predict battery quality before the cumbersome and costly formation and aging procedure, which accelerated the identification of battery production and key quality drivers.[60]

### 3.2. Electric Vehicles

The exhaustion and environmental concern of fossil fuels have spurred a shift from fuel vehicles to EVs that are powered by rechargeable batteries. However, potential thermal runaway, unsatisfactory service life, as well as range anxiety have remained the major obstacles to the large-scale deployment of EVs.[29] Estimating battery accurately based on its real-time electrochemical characteristics is therefore of vital importance to avoid cell lifespan shortening induced by several reasons such as overcharging, as well as potential safety hazards brought by battery thermal runaways.[69] To achieve the goal of efficient battery monitoring, several critical cell parameters are focused on, which will be elaborated in the following paragraphs.

SOC, defined as the percentage of remaining charge with respect to the fully charged condition, is the key parameter to optimize battery usage and prevent overcharging or overdischarging.[59] SOC significantly impacts battery voltage and output current, and is akin to the vehicle's "fuel level", influencing power output efficiency and energy management. Considering the variances in battery degradation introduced by different operating conditions, online parameter identification is more suitable for tracking the real-time behavior of the battery, as well as for improving the reliability and accuracy of SOC estimation. Along this line, an online parameter identification algorithm based on the recursive least squares method and adaptive extended Kalman Filter or adaptive unscented Kalman Filter are utilized simultaneously to realize accurate SOC estimation online, as Li et al.[70] and Zhang et al.[71] demonstrated, respectively. Similarly, Luo et al. have proposed a partial least squares-based model for SOC prediction in EVs, where a small number of streaming data is incorporated to update the model in real time.[72] Considering real vehicular operating conditions, Hong et al. proposed a joint-prediction strategy using long short-term memories (LSTM) and multiple linear regression algorithms to perform real-time multi-forward-step SOC prediction.[73]

Range anxiety has remained one of the key factors determining the market penetration and customer adoption of EVs.[74] While it can be overcome by developing new rechargeable battery chemistries with high energy density or fast-charging capability, effective battery management presents as another solution to maximize the utilization efficiency of battery packs on an EV. Here, state of power (SOP) defined as battery peak power capability stays a key index.[28] Accurate prediction of SOP allows for in-time adjustment of EV's power system to meet users' driving habits, modulate energy output/input, and protect battery from abuse.[75] For instance, precision in estimating allows efficient absorption of feedback energy during braking and acceleration with increased power, ensuring higher acceleration without compromising the battery. This approach also prevents power loss due to undervoltage or overcurrent protection, even with a low SOC. Current SOP prediction models have suffered from several practical limitations such as the imprecise estimation of vehicle operations, while data-driven online prognosis presents an effective solution to address operational uncertainty and the resulting large parameter variance. For example, Rhode et al. have proposed a data-driven method employing vehicle sensor data. A specific class of kernel adaptive filtering algorithms was employed to realize quick adaption to real-time charging conditions. This approach was demonstrated to provide a high degree of accuracy in controlling the autonomous vehicle, thus paving a road for enhanced safety and efficiency in autonomous driving systems.[76] The data-driven method was further combined with the ECM-based method by Guo et al., achieving accurate online SOP estimation in a lengthy prediction window ranging from 30 s to 120 s.[77]

To quantify the amount of service life left, RUL is commonly adopted, which is defined as the available time left before the cell degrades to an unacceptable level.[25] After a battery reaches its EOL, a sharp decrease on capacity will normally appear and the increasing likelihood in cell failure can induce catastrophic safety problems. Forecasting the battery life state is therefore nontrivial to guarantee a safe operation of EVs. Additionally, precise RUL predictions help reduce maintenance and replacement costs, extend battery lifespan through refined management, and improve the overall economic viability of EVs. Similar to SOC, RUL is also susceptible to various factors such as road conditions, environmental temperatures, charging modes, and even the driver's behaviors, yielding it necessary to employ online estimation. For instance, Cai et al. built a fast online RUL prediction algorithm based on whale swarm algorithm and LSTM, realizing high accuracy under direct current, where a dynamic data-driven application system was applied to ensure the real-time combination of condition monitoring data and simulation system.[78] Aiming close to the application, Wang et al. have established an online ML model using real-world data to estimate RUL rapidly, where an aggregated model was created for all vehicles and personalized parameters were utilized to reflect individual characteristics.[79]

### 3.3. Smart Grid

With the trending exploitation of sustainable, distributed energy sources, smart grids are built across the world to ensure stable, economic, and effective production and utilization of renewable energies.[80] The success of these smart grids greatly relies on the underlying infrastructure for information communication, as well as the efficient processing of floods of data generated from various sources. In this case, various data mining techniques can be highly valuable as they present effective tools for data analysis, which can be applied to intermittent power generation, equipment failure prevention, and load forecasting.

Smart grid can adopt various kinds of renewable energy generation systems such as photovoltaic (PV) and wind turbine. However, it is still challenging to uniformly forecast the generation of sustainable energy due to the large variance in power quality and stability induced by distinctive geographical location and environment.[81] The lack of additive coherency of the predictions generated by different power plants has necessitated the implementation of online forecast to allow for a quick adaption to changes according to their underlying characteristics. Along this line, Modica et al. have proposed a constrained regression framework for online wind power prediction, where the estimator is derived recursively and adaptively. The optimal reconciliation tracking is therefore enabled in a fully data-driven manner, yielding the framework effective to reconcile any out-of-sample forecasts.[82] The superiorities of online methods were also proven by S. Ferlito et al., who have compared eleven data-driven forecasting models of PV power both in online and offline training modes and concluded better forecasting performances of the online training models.[83] In addition, an ML model trained by solar off-grid system field data for battery SOH estimation and EOL prediction was demonstrated at large scale by Aitio et al., indicating the opportunity to analyze large field data through data-driven methods.[84]

Despite across multiple power plants, inconsistency might also exist between various infrastructures within a single complex power system, which induces risks in plant control and monitoring. One major challenge is cascading failure, where a single event can trigger multiple power outages and lead to a total blackout eventually, bringing catastrophic damages to the critical infrastructure, economy, and traffic.[85] In this case, prediction of cascading failure is crucial for accident avoidance, by supplying early warnings on possible errors and proposing corresponding strategies. For instance, Du et al. have suggested a framework for failure identification based on deep convolutional neural network and a depth-first search algorithm, achieving a computational efficiency thousands of times faster than the traditional model-based approach.[86] The great potential of data-driven online method for cascading failure prediction is thereby demonstrated.

While real-time, stable, accurate prediction of smart grid remains beneficial for warranting economic saving, effective planning, and secure operation, the uncertain and intermittent nature of electric load has brought additional challenges for the realization of steady and continuous forecasting. It is therefore vital to introduce data-driven methods to digest the large amount of data generated by smart grid and yield accurate and timely load forecast as well.[87] In this case, Vrablecová et al. have demonstrated the effectiveness of online support vector regression to short-term power load forecasting, where small amount of in-memory data was leveraged to supply online

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predictions with high accuracy.[88] In addition, Cheng et al. have revealed that the short-term load forecasting based on the improved online kernel extreme learning machine increased the prediction accuracy and outperformed the existing offline prediction methods.[89]

### 3.4. Battery Recycling

Most batteries nowadays are retired when their capacity retention drops to 70%–80%, which leads to a waste of the remaining capacity. Battery recycling in this case can be useful by endowing them with second service life in lower-request energy storage systems, which contributes to the reduction of resource waste, economic cost, as well as environmental pollution.[90] In the traditional battery recycling process, intensive time and labor costs are required for cell screening, classification, and disassembly, while online battery prediction provides a nondestructive alternative to assist all these processes.[91]

First, data-driven methods can reduce the cost of battery screening before re-utilization.[92] Due to the poor consistency of the cells after usage, a retired battery pack is not directly reusable. As the performance of the entire pack is determined by the worst cell, unqualified cells must first be identified and replaced to enhance the overall performance of a recycled battery pack. Online prognosis on each cell individually therefore presents great value as the time and resource-consuming pack disassembly and cell testing can be circumvented. In addition, online battery prediction can also assist cell classification, as retired batteries might exhibit diverse characteristics due to their different operating conditions. Along this line, Zhou et al. adopted principal component analysis method to achieve real-time battery clustering and the improved K-means algorithm to efficiently and stably reach the global optimal result.[93] By categorizing them according to different degradation chemistries, retired batteries with diverse qualities can be applied to different scenarios correspondingly.

Second, data-driven methods also play a pivotal role in the efficient usage of recycled batteries during their second service life, where an accurate estimation of SOH remains critical to quantify battery's ability to store and release energy. Since SOH is susceptible to a variety of factors such as charging rates, discharging depth, and the external environment, online approaches with high flexibility and versatility are especially preferential, where no prior knowledge of cell degradation mechanism is required. For instance, Cheng et al. have reported an optimal dispatch approach for online SOH estimation of second-life batteries, achieving impressive accuracy by a combination of frequent short-term capacity estimation method and infrequent long-term data-driven prediction model.[90]

Lastly, data-driven approaches can be applied to the recycling of batteries incapable to continue servicing as well. Conventionally, mechanical process is adopted to discover valuable electrode materials from these cells, where subsequent hydrometallurgical and pyrometallurgical processes usually require extensive energy input and yield low material recovery rate.[94] Alternatively, battery-grade materials can be recycled directly without the destruction of their chemical structures. The involvement of manual disassembly, however, exposes workers to harmful materials and presents a potential hazard. Automated disassembly is therefore more ideal as the cells can be pre-processed with higher precision and efficiency without human participation, where online prognosis participates in an intelligent streamline for material classification, real-time prediction, and safety detection. For instance, combined with the streaming temperature data captured from the thermal camera, a data-driven model was proposed by Lu et al. to predict the location of temperature spikes, which can then be avoided by the implementation of a subsequent closed-loop control.[95]

## 4. Challenges and Possible Solutions

Despite the huge potential and broad prospects in real-world applications established by data-driven online prognosis, it is still at an early stage of exploration with several major challenges to be resolved, which we will elaborate below, together with possible solutions showcased by existing efforts (Figure 4).

### 4.1. Data Quality and Availability

Data-driven method derives hidden correlations solely from the data, the performance of which is therefore highly dependent on the sampling frequency, completeness, and quality of the training data. To ensure satisfactory model prediction accuracies, it remains vital to improve data quality and data availability.

Harsh and dynamic environment can degrade sensors and transmission devices and introduce large noise and nonnegligible disturbances to the data acquired, affecting the performance of online prognosis model.[96–97] To improve data quality, efforts such as raw data denoising and cleaning have been devoted. For instance, Qu et al. have adopted the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise to eliminate data noise before predicting RUL of LIBs., improving the accuracy of prediction.[98] Nevertheless, defects such as mode mixing exist in Empirical Mode Decomposition methods. In future studies, more attention is required to handle missing data, outlier data, and large noise.

There are certain limitations for available data on the quantity and quality of online prediction such as the challenge of obtaining ample and diverse experimental data, the diversity of battery types, variability in environmental conditions, and restrictions in accessing real-world application data. Obtaining accurate time-related labels and addressing data privacy concerns further contribute to these limitations. The need for real-time processing in certain applications also poses constraints on data accessibility. To enhance model performance, various attempts have also been devoted to improve data availability or to construct model compatible with small number of samples. For instance, Chen et al. have achieved highly

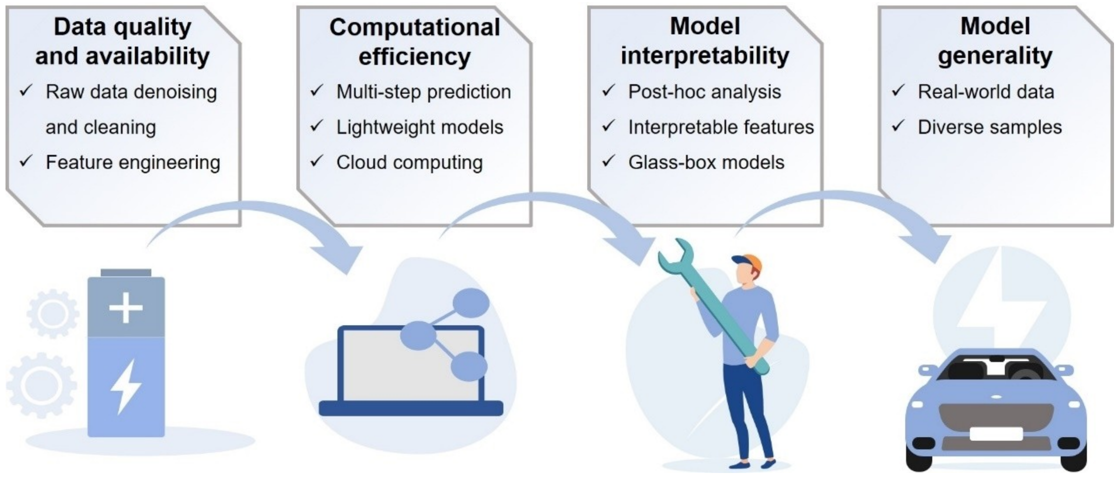


**Figure 4.** Major challenges of data-driven online battery prognosis and possible solutions.

accurate SOH estimation by combining correlation-based ideas and data-driven approaches. They adopted the increase of mean ohmic resistance as a novel HI for battery aging characterization, thus alleviating model's requirement on training data size. By constructing a recursive least-squares with a forgetting factor for the Thevenin model, rapid HI extraction can be realized and efficient real-time SOH prediction can be consequently achieved.[99] Though feature engineering is effective for data reduction, data quality and operation conditions need to be considered before feature extraction. Moreover, current feature engineering methods largely lean upon domain knowledge or experience, automated feature engineering is regarded as an important task in future research.

### 4.2. Computational Efficiency

Scalability remains one central concern for the practical deployment of ML models. To realize the industrialization of online battery prognosis, it is therefore important to balance model complexity and its computational intensity. While significant progress has been made in improving the accuracy of online prediction, the enhancement of computational efficiency has rarely been investigated. For on-board scenarios, accurate RUL prognosis is required only when the battery is near its EOL. Along this line, Patil et al. have proposed a fast estimation method potentially applicable to real-time RUL estimation of EVs. The Support Vector Machine-based approach was divided into a classification stage and a regression stage. The gross RUL was first estimated by a classification model, where subsequent prediction can be realized through the highly accurate regression model. By eliminating the necessity to train a massive regression model across the entire battery lifecycle data, this two-stage framework presents a simple RUL estimation method with reduced computational complexity, yielding greater model efficiency and scalability.[100]

In the past, most deep-learning methods such as Neural Network have achieved high accuracy. Due to the long-term dependence of data, networks are prone to problems such as gradients vanishing and gradients exploding problems, as well as increased computational and storage complexity. In this case, Shi et al. adopted linear regression algorithms, which is one of the simplest and least computationally intensive models. Due to the simplicity and efficiency of the linear model, a quite small amount of calculation and low computation costs were realized.[101] Deep learning models especially in larger configurations, tend to demand longer computational times, ranging from milliseconds to seconds, owing to complex matrix operations during both feedforward and backpropagation. This complexity often translates into higher resource requirements, including substantial central processing unit (CPU) and memory usage, and potential utilization of hardware accelerators like graphics processing unit (GPU). In contrast, simpler models like linear regression models, typically exhibit shorter inference times, often completing within milliseconds. Its resource requirements are generally lower, involving modest CPU and memory usage. The choice between these models hinges on the task's complexity, precision requirements, and available computational resources. For simple tasks or scenarios with limited computational resources, lightweight model architectures may be more practical.

In practical applications, the computing capacity of onboard chips may be limited, posing challenges in handling intricate prediction tasks such as deep learning and consequently compromising efficiency in the pursuit of high accuracy. Cloud computing, however, presents an opportunity to mitigate this constraint through its in-could, shared robust computational resources.[102] Large-scale data processing and complex model training performed in the cloud enable the onboard system to prioritize real-time prognosis, thereby enhancing overall system efficiency. For instance, Ma et al. proposed an end-cloud collaboration method for battery SOH online estimation, achieving an optimal balance between fusion result accuracy and system resource consumption. This method utilized a data-driven model and an empirical model for accurate cloud-side offline estimation and on-board online estimation, respectively,

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showcasing an efficient synergy between the two components.[103] In addition, the effective storage and data management services of the cloud platform facilitate convenient storage, management, and retrieval of extensive battery data, providing ample support for model training. Building upon this foundation, Zhang et al. devised a cloud platform-based in-situ methodology, leading to high-precision battery life prediction and classification.[104]

### 4.3. Model Interpretability

Most data-driven approaches still adopt black-box models to realize accurate prognosis. While presenting impressive prediction performance, these models usually supply limited information on their internal workings, causing concerns on their physical sanity. Rationalizing the prediction of proposed methods can help to uncover hidden physical correlations, shedding light on future strategic optimization under specific application scenarios especially at the researcher and manufacturer sides.[105] For instance, Li et al. have introduced the Shapley additive explanation (SHAP) approach to quantify the impact of different features on SOH estimations. The well alignment between SHAP analysis results and established physical understandings instills confidence in the sanity of the model. The transparency of the model is largely improved through the interpretation of each estimation.[106]

To design and optimize next-generation batteries at the stage of research and design, mining potential correlations between interpretable features and a targeted battery property is of vital importance. For instance, understanding the correlation between interpretable features and electrolyte performance aids in optimizing electrolyte selection and formulation.[107] This includes modifying solvents, salt concentrations, or adding additives to enhance electrolyte conductivity, stability, and safety. Interpretable features identify factors contributing to cyclic or calendar degradation, enabling adjustments in battery design for improved cycle stability. Furthermore, comprehending the relationship between predictive features and battery capacity/efficiency allows precise adjustments for maximizing energy density and overall efficiency in battery designs. Focusing on battery degradation, our group has extracted trend and seasonality features from voltage curves by combining time series forecast techniques and multivariate linear regression.[49] In the model, trend feature reflects the median voltage, representing the evolution of battery polarization and internal impedance. The seasonality feature, on the other hand, represents the shape variation of the voltage profiles, which could be related to the compositional and structural changes induced by crystallographic transformation and oxygen release, or the fluctuation of anode potential with respect to 0 V vs. Li/$Li^+$. Thus the primary reason for battery degradation can be probed by quantifying the relative contributions of these two features to the whole capacity fading, which further guide the optimization and re-design of high-energy lithium metal batteries.

### 4.4. Model generality

So far, most models are constructed with cell data measured with well-controlled conditions.[108] To ensure compatibility with practical applications, it is preferential to train the model with datasets from real world. Along this line, Zhang et al. have adopted three kinds of datasets to develop a predictive model for battery aging trajectory and EOL estimation. The first and the second datasets were collected on lithium-iron-phosphate cells under a well-controlled laboratory environment, and lithium-cobalt-oxide cells with simulated random real-world battery usage, respectively. The third dataset was obtained directly from the traction battery systems of plug-in hybrid EVs comprising lithium nickel–manganese–cobalt oxide-based pouch cells. By a combinatory adoption of these datasets, a thorough assessment on the accuracy and applicability of the proposed framework under wide-ranging operating conditions can be thereby realized.[54]

Several challenges exist in utilizing datasets from real world, such as the various uncontrolled usage conditions, data quality issues, and lack of clear validation data, therefore most models are still built with lab data.[109] To ensure their applicability to real-world scenarios, however, a more complex, dynamic environment needs to be considered. For instance, Lin et al. have proposed a data-driven model adapted to non-constant current charging. This model was shown effective in predicting battery capacity in non-constant current charging and variable-temperature operating scenarios, presenting great value for cell estimation in real vehicles.[110]

## 5. Conclusions and Outlook

The data-driven online prognosis method of rechargeable batteries exhibits substantial promise. Through customized model development, this approach fully considers the individual characteristics of each battery or battery batch, encompassing factors such as chemical composition, cycling history, and temperature. Consequently, it reflects the distinct aging patterns of various batteries and delivers more accurate and real-time predictions for key indicators such as battery lifespan, power, and residual capacity. Integration of real-time data streams facilitates continuous updates, enabling models to swiftly adapt to evolving battery states for heightened responsiveness. The incremental updating feature allows autonomous and cost-effective continuous learning, reducing storage and computation expenses. While challenges exist in achieving optimal accuracy with purely online predictions, the combination of offline model training with online prediction mitigates this limitation. This hybrid approach not only leverages the strengths of data-driven online prediction but also addresses potential drawbacks, establishing a solid foundation for widespread application in battery forecasting.

Nevertheless, challenges for data-driven battery prognosis persist in terms of data quality, computational efficiency, model interpretability, and model generality. To address these challenges, specific solutions can be adopted (Figure 4). Firstly, rational feature engineering to reduce sample size and effective data denoising/cleaning techniques are recommended to ensure the accuracy and completeness of the data. Secondly, in tackling computational efficiency, the exploration and adoption of multi-step prediction and cloud computing, as well as the construction of lightweight models, are suggested to enhance computational efficiency and ensure real-time applicability. Regarding model interpretability, architecting glass-box model structures, selecting inherently interpretable features, and employing post-hoc analytical tools are essential for enhancing user understanding of the model's decision-making process. Lastly, to improve model generality, the introduction of diverse samples and the application of real-world data are advised to enhance the model's performance on data under dynamic conditions. By systematically implementing these solutions, we anticipate fruitful opportunities to enhance the reliability and performance of data-driven online prognostic methods in practical applications.

As long as above critical issues are addressed, the data-driven online prognosis method is poised to play a more significant role in the future. Through real-time monitoring prognosis, this approach could transform battery industry by optimizing formation and aging protocols, refining manufacturing parameters, and enhancing overall battery production efficiency. With more accurate predictions of battery lifespan and performance, sectors such as EVs and portable devices will benefit, elevating the reliability and intelligence of battery usage. Incorporated with user feedback mechanisms and regular model evaluations and iterations, the adaptability and accuracy of data-driven online prognosis method can be further fortified. In the scope of a renewables-powered future, data-driven online prognosis emerges as a crucial tool for optimizing energy storage systems, improving efficiency, and extending into fields like smart grids and distributed solar/wind energy management. Moreover, data-driven online prognosis is playing a key role in planning and executing effective strategies, minimizing environmental impact, and maximizing resource reuse, both of which promote sustainable practices of battery recycling. In summary, data-driven online prognosis is paving an avenue towards intelligent, sustainable, and efficient battery applications in the near future.

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## Conflict of Interests

The authors declare no conflict of interest.

## Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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