Machine Learning Approaches in Battery Management Systems: State of the Art

Remaining useful life and fault detection

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***Abstract*—Lithium-ion battery packs have been widely applied in many high-power applications which need battery management system (BMS), such as electric vehicles (EVs) and smart grids. Implementations of the BMS needs a combination between software and hardware, which includes battery state estimation, fault detection, monitoring and control tasks. This paper provides a comprehensive study on the state-of-the-art of machine learning approaches on BMS. It differentiates between these methods on the basis of principle, type, structure, and performance evaluation.**

***Index Terms*—Machine learning, battery management systems, state of charge, state of health, remaining useful life, fault detection.**

I. Introduction

Since the invention of electricity, the scientists across the world have been investigating a method to store the energy and to use it when it is required. This resulted in the creation and evolution of the energy storage (ES) industry [1]. Increasing the accuracy and efficiency of battery model is a hot research which can enhance the development of several sectors. Such these sectors are the electric vehicles (EVs), which include ES and consider to be a green energy and draw the attentions for many researchers. The focus on the reduction of green house gases, such as carbon di-oxide(CO_2), and the aim to use a cleanly renewable energy in transportation increase the penetration of energy storage systems [2]. Batteries are used to improve the stability and reliability of microgrids with high renewable energy penetration [3]. Among the various types of batteries in the market, lithium-ions are the most efficient in electrical systems. This is due to the high energy and power density of this type as well as the wide temperature operating range, small size, long lifespan, fast recharging characteristics, and low self-discharge rate [4]. Battery Management Systems (BMSs) are essentially important for increasing the efficiency of battery state monitoring and protection from over current and voltage as well as internal and external short circuits. Although in the last decade many studies and patents were developed on BMSs and their applications, many are still open for further investigations [5]–[7]. In [8] shows the publication work in Li-Ion batteries among the countries, where China has paid more attention in BMSs and has the largest share of studies in the world with up to 36%. The organization of this paper is as follows. Section II presents an overview on the battery management systems, while III overviews the machine learning approaches. Section IV investigates the machine learning approaches in BMS applications and compares them. The conclusion and recommendations are presented in section V.

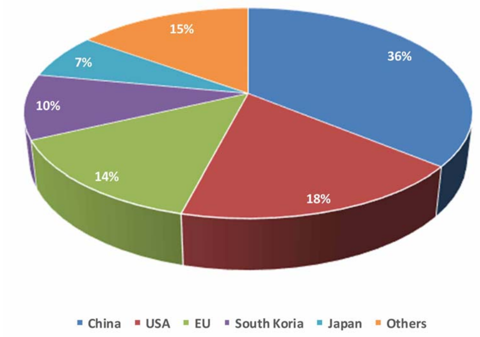

Fig. 1. Percentage of research publications on Li-ion battery technology in different countries.

II. Overview of Battery management systems

Comparing with other chemistry types, Lithium-ion batteries have been used in industry for several applications, such as electric vehicles, due to the unique features as mentioned in the introduction. Therefore, it is quite demanding to apply monitoring and control methods, i.e., BMS, to prolong the battery life cycle and to avoid sudden catastrophic events. To implement BMS effectively, its different parts have to be discussed in detail and some solutions to overcome their shortcomings and to improve their performances need also to be investigated. For reference discussions and investigations, the main parts of the BMS is shown in Fig 2.

As EVs face many challenges due to the battery packs, the battery conditions should be monitored in normal and abnormal conditions during run-time. Battery cell monitoring in-

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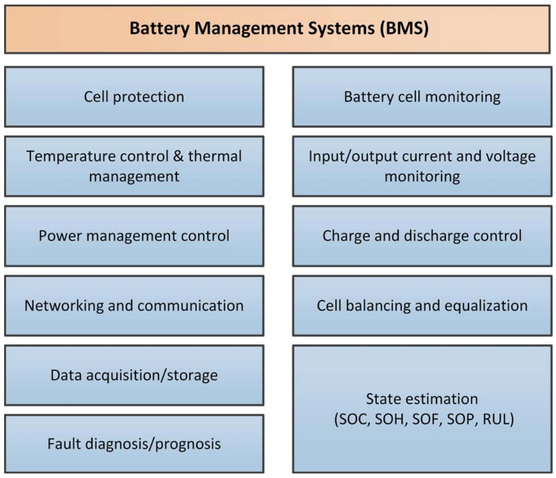

Fig. 2. Overview of battery management system.

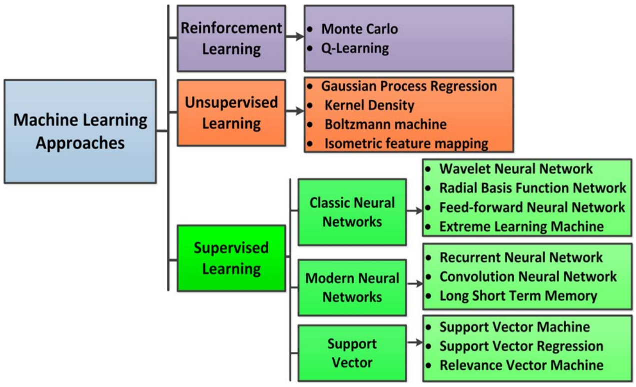

Fig. 3. Machine Learning Approaches in BMS Applications.

cludes battery status and operation indications [9]. Monitoring the voltage, current, and temperature are also essential to protect the battery cells from over-current and over-voltage [10], [11]. Recording the voltage, current and temperature of the battery cells using sensors and data acquisition system [12], [13], data can be generated to analyze the consumption pattern of electric vehicles and the prediction of battery's future status by using feature extraction and data-driven methods [14], [15].

Batteries of electric vehicles have to be protected from over-current or over-voltage during charging or discharging mode, i.e., driving on-road or connected to grid. Therefore, a battery management in these modes are important to effectively protect it and prolong its life cycle [11], [16].

Given the physical properties of battery, there is a challenge to access its internal parameters. Particularly for lithium-ion batteries, they possess nonlinear behaviors owing to some time-variant parameters. Thus, accurate models are needed in BMS to address these behaviors and to estimate the battery internal parameters and states. Many scholars have proposed various models to estimate the state of charge (SOC), state of health (SOH), remaining useful life (RUL), state of power (SOP), and state of function (SOF). However, inaccurate battery modeling is still exist [17], [18].

In EVs, series-connected battery cells are used to feed the electric motors and their accessories. The operating conditions of these cells are different meanwhile the charging and discharging modes of battery. Each cell might have different voltage and current from other cells, and can lead to overcharge or undercharge to some of the cells. These may cause early damage to some cells and sometimes internal short circuit due to deformation of the battery anode, cathode and separator. To solve such a problem, cell balancing is used to equalize the voltage levels of cells and energy distribution in EV [19], [20].

Optimizing the power consumption of electric vehicle batteries, reducing energy losses and distribution of cell energy require an effective battery power management control (PMC). Effective BMS can reduce the number of battery charge/discharge during the life cycle. The PMC provides a variety of electronic devices and patents that have been effective by addressing this challenge and are now one of the major topics in industrial research and automotive research. For PMC, it has proposed many of electronic devices and patents [21], [22] that have been effective in addressing this challenge and now it is one of the major topics in industrial research and automotive manufactures.

When the battery is in the discharging mode, it may be exposed to under-current and under-voltage. While in the charging mode, the battery may be exposed to over-current and over-voltage, and consequently, its temperature will increase rapidly [23]. Therefore, the battery protection is indispensable in BMS and plays a crucial role. In the past few years, many accidents have been witnessed and have led to life and financial losses. These issues prompted the battery manufacturers to develop solutions for temperature control and heat management that guarantee operations in the permissible and tolerable ranges of the cells and prevent from thermal runaway and internal short circuit [24], [25].

In order to implement BMS in EV, a combination of hardware and software is always needed. With the development of the wireless charging of EVs over the sparse charging stations in the smart network, communication and networking as one of the subsections of BMS will affect the overall battery performance [26].

III. Overview of Machine Learning Approaches

Machine learning (ML) is a broad topic with a large variety of applications. A comprehensive classification of ML is presented in [27], which describes the different techniques of machine learning. This paper aims to provide an appropriate classification of machine learning techniques that have been implemented in BMS applications and is shown in Fig 3. In this classification, the machine learning methods are divided into three main groups; (A) supervised learning, (B) unsupervised learning, and (C) reinforcement learning. The following is a brief description for each group that are used in regression and classification applications.

A. Supervised Learning

1) Artificial Neural Networks (ANN): The ANN concept is based on biological neural networks. In ANN, the activation functions, such as Sigmoid functions, are used to connect its nodes and to sum its weights. In general, the ANN neural nodes are trained with a stochastic gradient descent method called back-propagation. For more details, please refer to [28]. This ANN class can be divided into two subgroups:

- *Classic Neural Networks*: This subgroup includes wavelet neural network (WNN), radial basis function (RBFN), feed forward neural network (FFNN), and extreme learning machine (ELM).
- *Modern Neural Networks*: The modern neural networks are usually called deep neural networks, as a class of machine learning algorithms, that use multiple layers to progressively extract more features from the original input. Deep NNs are also attributed as deep learning approaches which mainly include Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and the expansion of RNN and CNN, such Long short-term memory network (LSTM). Note that combinations of the existing deep learning methods have recently been investigated to improve their performances [29].

2) Support Vector Machine: The Support Vector Machines (SVMs) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis [30]. The technique here is adopted from kernel regression and has been used in many linear and non-linear regression applications such as support vector regression (SVR) and relevance vector machine (RVM). For more details about SVM, please refer to [31].

B. Unsupervised Learning

The two main goals of this group that are used in different applications are clustering the data into groups by similarity and dimensionality reduction to compress the data while maintaining its structure and usefulness data [32], [33]. This group includes Gaussian process regression (GPR), kernel density, Boltzmann machine, and isometric feature mapping (ISOMAP).

C. Reinforcement Learning

Reinforcement learning (RL) is an important type of machine learning in which an agent learns how to behave in the environment by taking actions and discovering their results [34]. The main tasks of RL are policy, reward function, value function, and optionally a model of the environment that can be effective for decision making of a problem. In recent years, numerous improvements have been made in this area by researches [35], [36] which includes Monte Carlo and Q-Learning methods.

IV. Machine Learning Approaches in BMS Applications

Due to the complex internal dynamic behavior of the battery and uncertain external operating conditions, is usually difficult to accurately model the battery by equivalent circuit and physical-based models that are associated with estimating the model parameters using model-based approaches. Machine learning methods which are based on mathematical and statistical concepts are considered as reliable and convenient techniques to be used in BMS. An alternative, they have been widely used in SOC, SOH, RUL estimation, and prediction of battery aging and degradation. The battery modeling using the machine learning approach does not need an exact chemical process of the system. Machine learning techniques use the battery SOH data, which can be measured by advanced sensor technology. Such methods extract appropriate feature information and build the degradation model to predict RUL and end of life (EOL). These techniques are able to represent degradation-intrinsic relationships and trends based on history data [37]. Although a huge number of data are needed during the training phase and the predictive model is non-transparent [38].

So far, there are many different literature surveys on the classification of battery management systems such as remaining useful life, fault diagnosis and prognosis, and other issues. These survey papers have briefly presented the model-based, data-driven based, and ANN-based methods. However, they did not focus on the machine learning approaches. In this section, the most important parts of the BMS are discussed, particularly that using machine learning techniques.

A. Remaining Useful Life

In Li-ion battery, some irreversible reactions occur during the operating process, such as the deposition of lithium, decomposition of electrolytes, and so on, which will lead to capacity degradation and prolong the useful life of the battery. The remaining useful life has an effect on the system's reliability. Prognosis of remaining useful life is an important way to guarantee the battery reliability. As we know the battery capacity changes during the time. Once the capacity passes the threshold of failure, it may lead to an explosion. So, the reliability and safety of the lithium-ion battery will be enhanced through this operation. It is therefore critical to making an accurate prediction of the RUL battery [8], [39], [40].

Two types of ANNs, including feed-forward neural network (FFNN) and recurrent neural network (RNN), have been successfully applied to predict battery RUL [41]. Among the neural network methods, RNN is considered to perform well in predicting the RUL due to capturing and updating the information from the degradation data [42]. On the other hand, the ability of SVM to handle small training data sets is appealing, the number of support vectors decreases accordingly when the size of the training dataset increases [43]. In order to enhance SVR's robustness and stability with large-scale training samples, decremental and incremental strategies have been introduced to integrate the relevant SVR training data sample and to dismiss the irrelevant part [44]. Nevertheless, this method also increases the computational cost [45]–[47].

Comparing with SVM, RVM provides comparable performance when using extremely sparsely defined kernel functions as well as probabilistic predictions [48], [49]. Therefore, RVM is an effective approach in the RUL prediction due to uncertainty representation. Moreover, to improve the RVM's long-term predictive performance and accuracy, an incremental online learning strategy is proposed in [48].

It has to be noted that GPR is another kernel-based ML approach which can discover prognostics combined with prior knowledge based on Bayesian model and can provide variance to explain the associated uncertainty around its mean prediction [50], [51].

Recently, deep neural networks have been used for predicting RUL owing to their high predictive abilities [39], [52]–[54]. In [39], the long-short-term memory (LSTM) recurrent neural network (RNN) is established to learn the long-term dependencies related to the degraded lithium-ion battery capacity. The LSTM-RNN is adaptively optimized by using the resilient mean square back-propagation method and the over fitting problem issue is addressed by applying the dropout technique. The optimized LSTM-RNN is capable of capturing the underlying long-term dependencies between the degraded capacities and creating a specifically capacity-oriented RUL predictor whose long-term learning efficiency is compared with the support vector machine, the particle filter, and the original RNN.

B. Fault Diagnosis and Prognosis

There are some critical issues in the battery management system, including protection of over/under voltage and over current, which are a common fault type of battery systems [55]. In charge/discharge mode, the battery undergoes irreversible chemical reactions that can affect the lithium plating and dendrite formation, especially in low temperature. In addition, the formation of dendrite due to the intercalation between anode and cathode can lead to an internal short circuit, which can affect the battery performance and safety. Ignoring this critical issue can cause catastrophic faults owing to thermal runaway. Therefore, a lot of efforts have been done on the fault diagnosis and safety management using model-based and machine learning methods for the battery protection [56].

In recent years, numerous efforts on diagnosis and prognosis were developed by means of model-based methods. On the other hand, only a little studies were proposed that use machine learning approaches such as ANN [38], [57], SVR [58], GPR [59]. In [60], a data-driven approach is proposed for embedding diagnosis and prognostics of battery health using a support vector machine. Hong and et. al. developed a new deep learning approach to accurately predict multi-forward-step voltage for battery systems using RNN-LSTM. The analysis showed that the proposed method has a strong predictive capacity for battery voltage. The accuracy and robustness of this method are both verified by comparisons between different hyper-parameters [56]. In [61] an accurate and robust algorithm for on-board diagnosis of short-circuit (SC) battery anomaly is presented. Note that the likelihood algorithm uses the battery terminal voltage and current information that are measured by logged by the power management integrated circuit (PMIC).

In [62], the classification efficiency of machine learning approaches is investigated by using supervised learning methods. The algorithms, that are evaluated for the diagnosis of battery cells, are k-nearest neighbors (k-NN), logistic regression (LR), Gaussian naive Bayes (GNB), kernel space vector machine (KSVM), and neural network (NN). These linear and nonlinear techniques are proven to classify Ni-MH battery cells that are unbalanced and damaged. In this paper, it has been proven that LR algorithm is the easiest algorithm to be set up and has a good performance. K-NN algorithm has weak classification efficiency as its classification curve edge is not smooth. KSVM methods have a greater classification performance because the function of the radial base kernel can be better adapted to the operation of the battery cells. Based on the occurrence probability of events, GNB produces a non-linear smooth curve classifier that operates with high efficiency. It has to be noted that NN provides a high evaluation score with correctly classified data. However, in its classification regions, there are some zones that do not fit the data trend. Thus this technique requires a lot of training data to improve its efficiency.

V. Conclusion and Recommendations

In this paper, machine learning approaches for estimation, monitoring, and control of the battery management systems including the state of charge, state of health, and remaining useful life are reviewed with the focus on their weaknesses and strengths.

Firstly, the parts of the battery management systems, which can affect the performance, have been investigated and their weaknesses as well as the associated challenges are briefly explained. Secondly, since achieving an accurate model of the battery is almost impossible with physical phenomena such as hysteresis, identification of the battery internal parameters, state of charge and state of health estimation, and prediction of battery status by means of model-based methods are not sufficient.

Therefore, this paper is provided a comprehensive investigation on the use of machine learning methods in battery management systems. By comparing the existing methods, the advantages and disadvantages of these methods in RUL prediction and fault diagnosis and prognosis are discussed.

It has to be noted that due to the variety of the available applications in terms of the classification and regression in the BMS, each method can work well for a particular application. Thus a brief comparison is made by discussing the the advantages and disadvantages of each method along with their principles as listed in Table I. Moreover, this review paper provides some recommendations for improving the robustness and accuracy of the RUL prediction and fault detection in solving the existing problems. The authors do believe that these recommendations will make a significant contribution

TABLE I

COMPARISON OF THE MACHINE LEARNING METHODS VS MODEL-BASED METHODS

Methods	Principle	Advantages	Disadvantages
Classic NN	Non-linear and self-adaptive information processing system formed	High accuracy Easy transplant to hardware after offline training Temperature effect is taken as an input Capable of working in battery non-linear conditions	Time consuming Large set of data set is required for the training process Hard to generalize to different working conditions
Modern NN	The same structure with NNs but with deep multi-layer	Higher accuracy Suitable for high complex non-linear fitting via ML-NNs	Time consuming Need large memory storage to store the trained data
SVM	Supervised learning model in high dimensional feature space	High accuracy The size of training data set is small vs NNs method Performs well in non-linear and high dimension models Prediction is quickly and accurately by using suitable data	Not easy to select a good kernel function High complex computation
RVM	Identical to SVM, with a probabilistic method and Bayesian framework	Good accuracy High learning ability Sparsity Easy training process	Large data-sets are required fort training High time and memory demands High complex computation
GPR	kernel-based and deriving from the Bayesian framework	Provide covariance to generate uncertainty level Non-parametric; Being flexible	Performance is highly affected by kernel functions High computational cost
Model-based	Including different methods for estimation	Insensitive to initial SOC; Good robust High accuracy (IF accurate model be available)	High computational cost Depend on modeling accuracy

towards the improvement of machine learning methods for BMS in the future which are listed as follows:

- Given that the Li-ion battery maybe exposed to different environmental conditions in real-word that not able to be simulated in laboratories, it is better to take into account the different uncertainties including noise effect, different temperature conditions during the data acquisition.
- Further studies are needed to reduce the computational complexity of machine learning approaches by means of different optimization techniques.
- In the real-time systems of the realistic world, the algorithms need to be processed at high speeds which utilises less data-based techniques to fasten the training process. Moreover, parallel computing techniques can also be used to speed up the computation and learning processes.

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