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Review

A review on prognostics and health monitoring of Li-ion battery

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ABSTRACT

The functionality and reliability of Li-ion batteries as major energy storage devices have received more and more attention from a wide spectrum of stakeholders, including federal/state policymakers, business leaders, technical researchers, environmental groups and the general public. Failures of Li-ion battery not only result in serious inconvenience and enormous replacement/repair costs, but also risk catastrophic consequences such as explosion due to overheating and short circuiting. In order to prevent severe failures from occurring, and to optimize Li-ion battery maintenance schedules, breakthroughs in prognostics and health monitoring of Li-ion batteries, with an emphasis on fault detection, correction and remaining-useful-life prediction, must be achieved. This paper reviews various aspects of recent research and developments in Li-ion battery prognostics and health monitoring, and summarizes the techniques, algorithms and models used for state-of-charge (SOC) estimation, current/voltage estimation, capacity estimation and remaining-useful-life (RUL) prediction.

Contents

1. Introduction

With the growing awareness of climate change, anxiety of depleting fossil fuel and the interest in "electric drive", more consumers have begun to consider purchasing battery-driven hybrid vehicles for their higher MPG rating and lower individual carbon footprint. Analysis of the 2009 Year-end Hybrid Market Dashboard [1] shows that the U.S. HEV market shares have increased to 2.8% among all vehicles sold in 2009. Given the tough economic situation in the last year, the U.S. hybrid sales dropped only 7.6%, compared to 21.4% for overall vehicle sales. In California, 55,553 new HEVs were sold in 2009; in DC, every 3.7 new HEVs were purchased for every 1000 residents in the past year. The forecast for 2010 hybrid sales is still promising given the exciting introductions of PHEV and accelerating economic recovery.

The technological breakthroughs in battery life, abuse tolerance and drive range will eventually result in the development of cost-effective, long lasting Li-ion batteries. However, no matter how good the Li-ion battery is, it will degrade over time due to aging, environmental impacts and dynamic loading. Therefore,

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it is always desirable to be able to detect the underlying degradation, take countermeasures to impede the developing faults and ultimately prevent the catastrophic failures from occurring. This is how health monitoring works. Prognostics, on the other hand, deals with fault propagation/degradation and predicts how soon a system/component will fail, or reach a level that cannot guarantee satisfactory performance. Health monitoring and prognostics are two integral parts in realizing near-zero-breakdown performance. Preferably, prognostics is conducted first, with or without information extracted from health monitoring. For cases in which prognostics cannot accurately predict remaining-useful-life, health monitoring is relied on to disclose the health status of a Li-ion battery. Effective health monitoring and prognostics functionality for Li-ion batteries will adequately address customers' concerns regarding safety issues and help companies establish early leadership positions in the field.

Health monitoring and prognostics for machinery has garnered much attention in the research community in recent years. Hundreds of papers in this field, including theories and practical applications, appear every year in conference proceedings, academic journals and technical reports. The most popular models, algorithms and technologies for machinery diagnostics and prognostics can be found in a review given by Jardine et al. [2]. However, a Li-ion battery, which features electro-chemical behaviors, is fundamentally different from a mechanical system in various aspects. First of all, the electro-chemical reactions inside a Li-ion battery pack are almost inaccessible using common sensor technologies, resulting in the scarcity of data for analysis. Secondly, in comparison to waveform type machinery data, the most available monitoring data collected from Li-ion battery is value-typed such as voltage, current and temperature. Lastly, the operation profiles of Li-ion battery are much more dynamic than those of mechanical systems. For example, in a PHEV the Li-ion battery is subject to drive behaviors, electronic device usages, driving environments, etc. Other factors affecting the performance and degradation of Li-ion batteries include aging-dependent capacity loss, capacity imbalance among battery cells, self-discharge, etc. Therefore, the development of appropriate methodologies and algorithms for Li-ion battery health monitoring and prognostics must take into account the uniqueness of Li-ion battery system.

This review summarizes different methods to predict the state of charge, voltage, current and capacity, as well as techniques and methods for predicting remaining useful life, of Li-ion batteries. Note that since Li-ion batteries have come into popular use in only the past 5 or 6 years, the literature that directly addresses diagnostics and prognostics aspects are limited in terms of quantity and relevance. For the purpose of establishing a broader perspective some traditional diagnostic techniques for other types of batteries such as lead-acid batteries and nickel metal hydride batteries are also covered in this review. It should also be noted that terms such as "degradation", "health" and "failure" are used interchangeably when discussing health monitoring. The reason is that "failure" has multiple definitions in various situations and both "degradation" and "health" are related to "failure" in one way or another. One description of failure assumes that failure only depends on the condition variables. Once the condition variable exceeds a predetermined threshold, a failure has occurred. Other definitions of failure are judged by criteria such as performance (performing at unsatisfactory level), functionality (incapable of conducting specific function) and availability (machine breaks down) [2]. The necessity of studying the mechanisms of specific failure modes, such as over-heating, over-charging, chemical and metal contamination, has attracted more and more attention. Due to the complexity of experiment design and critical safety issues, few reports are available in the literature up to now. The progress of various projects can be found in [3]. Some published papers related to this topic with emphasis on electro-chemical analysis are [4–6].

The subsequent sections of this paper are arranged as follows: Sections 2–5 explain the techniques, algorithms and methods applied in SOC estimation, current/voltage estimation, capacity estimation and remaining-useful-life prediction, including the pros and cons of each method; and the final section contains conclusions drawn based on this review.

2. State of charge (SOC) estimation

State of charge estimation has always been a big concern for all battery driven devices. An accurate SOC estimation not only assesses the reliability of products, but also provides critical information such as the remaining useful energy and/or the remaining usable time. Moreover, an efficient and accurate SOC estimation will guide the design of charging/discharging strategies (cell-level balancing) which is of great importance in high current application where individual cells are likely to have different capacities due to manufacture variation, natural aging, degradation, etc. In this case, an optimal charging/discharging strategy will effectively prevent the occurrence of abnormities such as overcharging, overheating and over-discharge from happening. As a result, the reliability of the energy storage device will be enhanced and the product life extended.

A multitude of SOC estimation methods has been introduced since the 1980s, the adoption of which has been gradual in various academic research and industrial applications. However, the definition of SOC has yet to be agreed upon by all of the relevant stakeholders—this ambiguity has resulted in much confusion in understanding the meaning and usefulness of SOC and its involvement in further analytical tasks, such as capacity estimation and remaining-useful-life prediction. To address this confusion, this section starts with itemizing and explaining some common definitions of SOC, which hopefully will give readers a broader perspective of the issues. The SOC estimation methods introduced will focus mainly on models, algorithms and technologies without emphasizing the definition of SOC.

Charge counting or current integration shown in (2.1) is probably the most classical SOC calculation method.

$$\mathrm{SOC} = 1 - \frac{\int i \cdot dt}{C_n} \tag{2.1}$$

where i is the current; C_n is the nominal capacity; t is the time. This approach requires dynamic measurement of the cell/battery current, the time integral of which is considered to provide a direct indication of available capacity. The nominal capacity, however, is measured at a constant discharge rate under controlled temperature. These conditions seldom occur in real-world applications. Therefore, the use of nominal capacity as the total capacity remains controversial [7]. Besides, due to its reliance on integration, errors in terminal measurements accumulate and large SOC errors may occur, thus requiring a recalibration at regular intervals [8]. Another version of SOC calculation considers the effect of coulombic efficiency and is given as follows:

$$\mathrm{SOC} = 1 - \frac{\int i \cdot \eta \cdot dt}{C_n} \tag{2.2}$$

where η is the coulombic efficiency defined as the ratio between charging energy and discharging energy required to restore original capacity. η is equal or less than 1. Still another version of SOC was simply in a linear relationship with a preset voltage level. For example, when minimum discharge voltage was reached during discharge cycle, the battery was considered fully discharged at 0% SOC [9].

Making extensive and costly tables comparing SOC and OCV (open circuit voltage) under different temperatures has long been the common practice of battery manufacturers for preparing manufacturer's recommended datasheets. Once sufficient tables were made and stored appropriately, the inference of SOC from OCV became very straightforward. Guiheen et al. disclosed another similar SOC estimation method which looked for recording relationships of the magnitude of ramp-peak current and SOC [9]. This method, however, requires extensive testing and table making as well and is taken more as a supplemental means to assure the accuracy and effectiveness of traditional SOC–OCV tables. One major drawback of these table-making efforts is that the real-world conditions seldom match exactly those recorded, resulting in significant discrepancies between the estimated SOC and true SOC [10].

Instead of relying exclusively on SOC–OCV tables, more advanced SOC estimation methods based on fuzzy logic, autoregressive moving average, artificial neural network, extended Kalman filter and support vector machine have been proposed in academic journals, conference proceedings and filed patents. To better evaluate and explain the advantage and disadvantage of these approaches in SOC estimation, brief descriptions of these algorithms are given first. The detailed approaches in tackling SOC estimation follow. Finally, the pros and cons of these approaches are discussed.

2.1. Fuzzy logic

Instead of pursuing only absolutely clean and precise information, fuzzy logic methods allow a certain level of uncertainty and ambiguity in processing incomplete and noisy data. The implementation of fuzzy logic method consists of 4 parts: rule-based input–output relationship, membership function for inputs and outputs, reasoning and defuzzification of outputs.

Salkind et al. [11] applied the fuzzy logic methodology to estimate SOC using EIS (electro-chemical impedance spectroscopy) data both from Li/SO_2 battery and NiMH (nickel metal hydride) battery. In the Li/SO_2 battery case, the model had 3 inputs and 1 output. The three inputs were imaginary impedances measured at 3 different frequencies—the output was SOC. In the NiMH battery case, the model had 2 inputs and 1 output. The two inputs were capacitance (an element in assumed battery circuit) and cycle number. Again, the Output was SOC. The empirical relationship between capacitance and imaginary impedance was established to facilitate capacitance estimation. The reported accuracy was within a 10% margin of error. In [4], only a subset of electro-chemical model parameters (3–4) were found to be very important and therefore served as inputs for the Fuzzy logic model in order to speed up EIS testing and reduce redundancy in data collection. However, the size and high instrument cost for EIS is likely to inhibit the extension of these approaches to on-line application.

2.2. Autoregressive moving average (ARMA)

Autoregressive moving average (ARMA) model is a popular statistics model applied to time series and index-based data to study the underlying patterns of a system and/or predict near-future values in a series. ARMA models are composed of two parts: an autoregressive (AR) part and a moving average (MA) part. An ARMA model, denoted as ARMA (p, q) is expressed as follows:

$$x_t a + \varepsilon_t \sum_{i=1}^{p} \varphi_i x_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{2.3}$$

where x is time series or index-based data; a is constant; ε is white noise; p is AR order; q is MA order; φ and θ are model coefficients.

In order to infer the SOC from impedance measurement, Kozlowski [4] developed a two-electrode electro-chemical model and used measured impedance data for validation. The inputs of this model, such as electrolyte resistance, charge transfer resistance and double-layer capacitance, were extracted and fed into a second-order ARMA model to compute the SOC. ARMA is basically a regression model with noise added. The accuracy of an ARMA model depends on completeness and representativeness of the historical data used in training. In real world applications, it is more likely that the historical data is incomplete and recursive model training and updating is required to make a reasonable estimation and one-step-ahead prediction.

2.3. Artificial neural network (ANN)

An ANN, which consists of various nodes and layers, is a simple imitation of human brain. It requires little expert knowledge in modeling complex systems and adopts a "black box" approach to various sources of data. Due to its simplicity in handling data from, and structure of, complex or even unknown systems, ANN has become one of the most widely used methods in complex system modeling. A typical simple neural network consists of 3 layers: an input layer, a hidden layer and an output layer. Depending on the specific needs, such as number of inputs and outputs, the number of nodes within different layers can be defined, for convenience or out of necessity. The lines connecting each pair of nodes are denoted as weights, which are literally mapping functions from one space to another space.

In [4], battery internal parameters, such as charge transfer resistance and electrolyte resistance, were used as inputs to ANN to estimate the SOC. Other approaches avoided the need for impedance measurement and utilized much less resource intensive external measurements as the inputs to the neural network. In [12], two neural networks were used to adaptively predict when a predetermined voltage level would be reached. The first NN predicted the remaining useful energy and remaining usage time in the current discharge cycle. The inputs of this NN included a preset discharge voltage and the temperature measured. The second NN assigned weights on the first neural network in order to compensate for manufacturing variation, aging effects and specific usage patterns under testing conditions. The inputs of this NN were all acquired from external measurements, including initial voltage, initial number of cycles, the beginning of discharge period, and the instant at which the initial measurements are available. However, this method was proposed specifically for lead-acid battery monitoring. One assumption made was that the discharge current was low for the most of the time.

2.4. Electrochemical impedance spectroscopy (EIS)

EIS has been widely used to provide insight into electrochemical reactions happened within chemical batteries which are usually inaccessible to common sensory technology. Before implementing EIS, an appropriate electrochemical model (e.g. imaginary battery circuit) should be proposed first. EIS can then trigger AC signals at certain frequencies and calculate the numerical values of modeled components such as resistors, capacitors and inductors, which will form the foundation for further analysis. However, EIS is not easy to use, and results from EIS are hard to reproduce mainly due to the fact that systems being measured must maintain steady state throughout testing. In [13], Blanke et al. emphasized the importance of adopting appropriate methods in using EIS. For SOC estimation, it was determined that there is a close relationship between battery SOC and a specific frequency range at which capacitive impedance equaled inductive impedance. Moreover, this frequency range ($f_\pm$) varied monotonically and reproducibly as a function of battery SOC. Therefore, SOC could be found by determining the desired frequency range $f_\pm$.

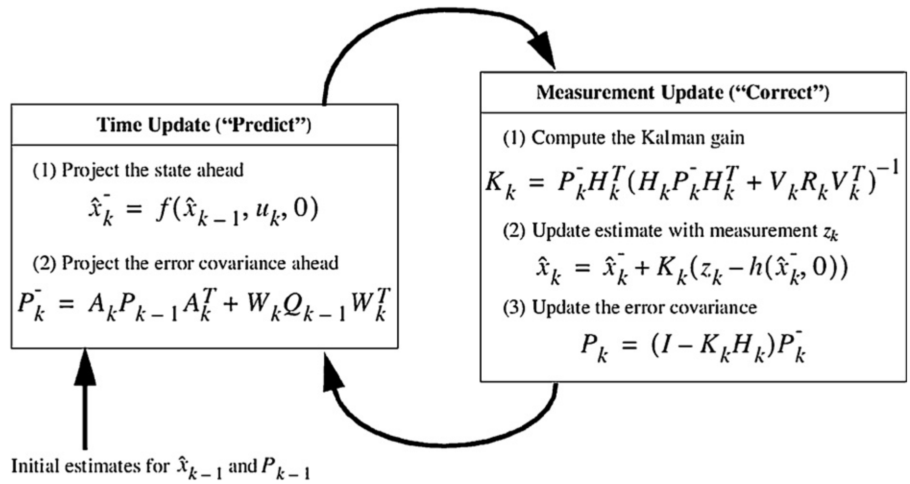

Fig. 1. A complete picture of operation of extended Kalman filter [14].

2.5. Extended Kalman filter (EKF)

Extended Kalman filter (EKF) is an extension of Kalman filter (KF) for a non-linear application. By using partial derivatives and Taylor series expansion, EKF linearizes the "Predict" and "Update" functions for current estimates. After linearization, the remaining process resembles that when using a traditional Kalman filter. A computation diagram is illustrated in Fig. 1 [14]. EKF, however, cannot deal with systems with highly non-linear characteristics since first order Taylor series approximation cannot give enough accuracy in a highly non-linear case.

Plett [15] reviewed various SOC estimation methods including Coulomb counting, chemistry-dependent, OCV measurement, molecule-scale electro-chemical model and impedance spectroscopy. The disadvantages of these methods were pointed out such as impracticality for HEV applications, inaccuracy in dynamic SOC estimation and extensive expertise required in micro-scale modeling. To enable dynamic SOC estimation with enhanced accuracy, a physics-based circuit model named "enhanced self-correcting (ESC) model" was proposed with emphasis on the treatment of hysteresis effect, temperature effect and relaxation effect. EKF was implemented based the proposed model and model state vector including SOC (as discussed in [16]) was predicted and updated recursively. The "enhanced self-correcting model" was formulated as follows:

$$y_k = \mathrm{OCV}(z_k) + h_k + \mathit{fil}(i_k) = R \cdot i_k \tag{2.4}$$

where y_k is the estimated voltage; k is index; z is SOC; h is electrochemical hysteresis; $\mathit{fil}(\cdot)$ is some dynamic operation filtering its operand; R is battery resistance; i is current. The main drawback of this approach is the use of OCV–SOC tables, which are costly and laborious to obtain, and are inaccurate to some extent when used in real-world applications. In [17], a modified OCV–SOC relationship was proposed with enhanced accuracy and consistency among batteries of the same type. A simple battery circuit was employed, and the use of dual EKFs for SOC and capacity estimation was discussed. The circuit model is shown in Fig. 2 the voltage estimation equation referenced in (2.5). The calculation of the OCV in the equation relied on the modified OCV–SOC relationship, which was generic enough for cells with comparable variations in initial capacities. In order to improve the robustness of the EKF framework under highly non-linear conditions, the measurement noise model was reformulated to function as a countermeasure for large voltage errors induced by the extreme operating conditions and inherent variations between a simple model and the true system. However, the accuracy of capacity estimation seems highly dependent on the selection of initial values, and inappropriate initialization could result in significant delay in the convergence for estimated values and true values.

$$V_k = \mathrm{OCV}(\mathrm{SOC}_k, C_{n,k}) - V_{d,k} - R_i \cdot i_k \tag{2.5}$$

2.6. Support vector machine (SVM)

Support vector machine (SVM) is a state-of-the-art classification and regression algorithm widely used in signal processing tasks such as text recognition and bioinformatics. As a kernel based method, SVM projects the original low-dimension data space to high-dimension feature space. This projection is equivalent to transforming non-linear problems in lower dimension to linear problem in higher dimension. Regulated by the well-defined constraint conditions (Karush–Kuhn–Tucker conditions), only a small subset of training data referred to as support vectors will remain and be used in formulating classification and regression equations.

In [18], Hansen and Wang used SVM to build an empirical SOC estimation model. No battery circuit was needed. The input vector included current, voltage, SOC calculated from the previous step and voltage change in the last 1 s. The output was SOC in current step. The SOC estimation model was trained using steady state data (constant current pulse) only. The evaluation of results was carried out in both the steady state SOC test and dynamic state SOC test. The reported RMS errors were around 5% and 5.76% respectively. However, information about the asserted "true SOC" was not given. There is a possibility that the "true SOC" was de facto calculated

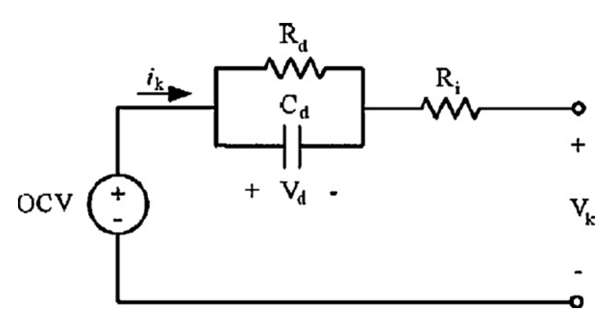

Fig. 2. Simple battery circuit. OCV represents open circuit voltage, also called equilibrium potential. R_d and R_i are internal resistances. C_d is equivalent double layer capacitance.

using Coulomb counter, as is the case for the "true SOC" in a similar dynamic test (5th urban dynamometer driving schedule) discussed in [16]. Since Coulomb counting was dismissed by the author in the first place, it could be questionable to take results from Coulomb counter as the "true SOC". Besides, a good SVM regression model requires fine tuning of some empirical parameters, such as constant C and error tube ε, among others. This trial and error process is likely to be time-consuming.

3. Voltage estimation

The effort of voltage estimation is to establish a sound battery model, which addresses chemical, electrical and physical properties of a battery to some extent and is adequate enough to simulate battery performances under different conditions. A sound battery energy estimation method not only guarantees consistent power supply to any electrical devices, but also supports near-zero downtime performance for safety critical applications such as the installation of cardiac pacemaker powered by Li-ion battery, and the adoption of a Li-ion battery as emergency energy source, due to its low self-discharge rate. There are 2 areas of focus in voltage estimation. One area is to propose efficient OCV (open circuit voltage) estimation. The other one is to improve the effectiveness of voltage monitoring in protection circuit so that severe failures such as overcharging and overheating can be prevented. A few estimation methods [19–23] that have long been adopted by industries are receiving more and more criticisms and suspicions mainly because these methods required numerous expensive tests for purpose of extensive table-makings and unsatisfactory accuracies were reported frequently under specific conditions. More advanced methods and technologies are needed to tackle the challenges.

In [24], Gao et al. built an empirical Li-ion battery model which is capable of estimating OCV (open circuit voltage) under a range of discharge rates and ambient temperatures. The proposed battery circuit is similar to that in Fig. 2, some ideas of model reference adaptive control (MRAC) [25] were embodied in the modeling process. A reference discharge model with arbitrarily chosen discharge rate and ambient temperatures was set first. This reference model was then adapted by introducing a rate factor, temperature factor and potential correction terms to fit in discharge scenarios under varying discharge rates and temperatures. The accuracy of this model relies greatly on the fine-tuning of various empirical parameters, such as the rate factor, the temperature factor, and the model resistances. Other concerns include the effect of battery deterioration against the accordance between experimental data and simulation data, as well as the applicability of this model to discharge scenarios in which discharge rates and temperatures are different from those used in modeling (in this case, rate factor and temperature factor are unknown).

To compensate for the effects of aging and varying discharge rates, Hirsch et al. [19] established a universal normalized discharge voltage curve for lead-acid batteries. The comparison of the normalized measurement to the universal normalized discharge voltage curve would lead to the determination of percent of the discharge level and reserve time (an equivalent entity to total capacity as claimed). One beneficial consequence of this normalization method is that the relationship between discharge voltage and time becomes almost linear for the most parts of the normalized time scope (close to 90%). This feature definitely benefits the accuracy of reserve time estimation. However, since this empirical normalization method was proposed purely based on the observations under certain specific conditions, it is hard to assess its usability to more dynamic operating profiles. In addition, careful validation must be made to apply this approach to Li-ion battery case.

In [26], Puglia et al. designed a high power Li-ion battery device (300 V and 1.2 MW h) for the US navy's Advanced SEAL Delivery Systems. To ensure the reliability and safety of this large battery pack, failure prevention measures were employed with an emphasis on voltage monitoring. The first of these measures involves adding load on the cell when cell voltage rises beyond a preset voltage level. The second measure, to be employed if the first measure fails, alerts the operator or automatically reduces charging current. If these two measures fail, the final measure is employed and the charging process is terminated. However, the challenge lies in the fact that the propagation rate of failures under extreme cases, such as crashes and circuit shorts, is likely to be much faster than the monitoring rate. In such scenarios, the generation of excessive heat will not stop even if the circuit is switched off.

4. Capacity estimation

Capacity is rated in ampere-hours (A h), which quantifies the available energy stored in a battery. The loss of capacity, as a result of increased impedance, mainly on a battery's cathode, will cause reduced performance when electrical devices cannot operate at a satisfactory level and functional failure when the battery fails to supply the required energy and power. The rate of capacity loss is highly dependent on the charging/discharging conditions such as maximum charge voltage, depth of discharge, magnitude of current, load profiles, and temperature. Specific to traditional Li-ion batteries, the Li-ion battery also suffers permanent capacity loss over time. For example, a typical laptop Li-ion battery stored at 100% SOC in 25 °C will irreversibly lose 20% of total capacity every year [27]. Thus, there is a need to accurately estimate the available capacity for reliability and better management of energy use. Furthermore, accurate battery capacity estimation will benefit the design of innovative materials for battery fabrication and protection circuits that balance battery longevity and energy needs.

Estimation of battery capacity is closely related to that of state-of-charge (SOC), as SOC is usually defined as the ratio between available capacity and rated capacity. Manufacturers, however, determine the rated capacity, or nominal capacity, for a battery by conducting measurements under a constant discharge rate and in a controlled environment. Therefore, the use of rated capacity as the reference point often becomes inappropriate for real-world applications. As mentioned previously, SOC may have different meanings and definitions for specific applications and goals. In contrast, battery capacity is more well-defined, the estimation of which has become a standalone research field.

There are a few battery capacity estimation models that are widely cited in the literature, including linear model [28], rate-dependent model [28–31] and relaxation model [28–30,32]. These models are based on different assumptions and have a unique balance of simplicity, accuracy, computational cost etc. Park et al. [28] reviewed the pros and cons of the aforementioned models, and challenged their effectiveness and accuracy in varying operating profiles. In this review it was determined that the DC/DC converter plays an important role in capacity estimation since a DC/DC converter can change a load profile, based on its own characteristics. Therefore, it was decided that experimentation and measurement is the most reliable way to estimate true capacity. They further advocated that the improved battery capacity model should take into account the effect of the DC/DC converter.

In [33], Chan et al applied artificial neural network (ANN) to build a correlation between discharge current and capacity for lead-acid batteries. This is a single input and single output neural network with 4 nodes in the hidden layer. The training process involved one set of current–capacity pairs within one cycle and another set of data from the same cycle in the testing process. The results were compared with capacity measurements with an average error rate below 1%. However, since too little data was used to train the neural network, the model could be subjected to "over-fitting" of training data. As well, the modeling approach assumed that aging and degradation of the battery would not play a major role in capacity estimation, which could be the case in lead-acid batteries, but unfortunately not for Li-ion batteries.

Extended Kalman filter has also been used in capacity estimation, usually together with SOC estimation. In [16], a dual extended Kalman filters framework was proposed for state estimation (fast changing variables such as SOC) and parameter estimation (slowly changing variables such as capacity). The main justifications for using two separate EKFs instead of one were to circumvent the need of tackling large matrix and to provide flexibility for specific needs and interests (e.g. one may be only interested in tracking capacity fade and SOC; in this case, other variable estimations, though not desired, will inevitably utilize valuable computational power and result in reduced overall computation speed). Based on the specific state/parameter models involved, some interactions between two EKFs may exist.

In [34], a multivariate linear model was disclosed to establish the relationship between capacity and a multitude of inputs including internal DC resistance, open circuit voltage (OCV), temperature, V_{up} and I_{up} (voltage and current measured at the transition from normal charge to over-charge), V_{dn} and I_{dn} (voltage and current measured at the transition from overcharge to normal charge). The magnitudes of V_{up}, I_{up}, V_{dn} and I_{dn} were derived from an internal resistance measurement process in which controlled current pulses were applied to the battery. There are several concerns regarding this approach. Firstly, OCV can be measured directly but the process is very time-consuming. Secondly, capacitive resistance was ignored in resistance measurement (though this practice may be applicable for lead-acid batteries). Thirdly, for such data-driven modeling, over-fitting or under-fitting is always a big challenge. In addition, if this approach were to be applied to Li-ion battery applications, care must be taken in calculating resistive impedance since the relationship between the current and the voltage is regarded as highly non-linear [35].

External measurements such as voltage, current and surface temperature, though easy to access, are subject to a multitude of influential factors, such as charging rate, discharging rate, and ambient temperature, and therefore do not well represent the inherent properties of Li-ion batteries. In investigating the root causes of degradation mechanisms and their effect on capacity loss, changes in the electrical, chemical and physical properties of anode, cathode and electrolyte during controlled cycling test must be studied.

In [5], Li-ion pouch cells ($LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$/graphite) were cycled over 100% DOD (depth of discharge) at 25 °C and 60 °C to study the adverse affects of temperature extremes on Li-ion battery capacity. Advanced inspection methods such as electrochemical impedance spectroscopy (EIS), X-ray diffraction (XRD), Raman spectroscopy and current-sensing atomic force microscopy (CSAFM) were used to investigate the changes in the electrochemical properties and the physical properties of anode and cathode. There are two conclusions of this research. First, the capacity loss at the cathode accounted for the majority of overall capacity fade. Second, the root cause of capacity loss at the cathode is the accumulation of a low-conductivity SEI (solid electrolyte interface) layer on the cathode. Zhang et al. [6] studied the effects of various operating conditions such as ambient temperatures, variations in SOC and cycling profiles, on a baseline cell chemistry. The focus of this study was on characterizing the shifting electrical, chemical and physical properties of the anode (carbon), cathode ($LiNi_{0.8}Co_{0.2}O_2$), electrolyte (diethyl carbonate–ethylene carbonate $LiPF_6$) and current collectors. Four factors that contribute to Li-ion battery degradation mechanisms were identified: dissolution and non-uniformity of the SEI layer on the anode; morphology changes, phase separation and capacity loss on the cathode; current collector corrosion on the cathode; and chemical contamination of the electrolyte.

5. Remaining-useful-life (RUL) prediction

Remaining-useful-life (RUL), also called remaining service life and residue life, refers to the available service time left before a system degrades to an unacceptable level. Successful RUL prediction for batteries is highly desired; it enables failure prevention in a more controllable manner in that effective maintenance can be administered in appropriate time to correct impending faults without permanently damaging battery as traditional protection circuits do. In addition, accurate RUL prediction for batteries can enable the development of new innovative service models dedicated to exploring new opportunities and markets. An example of such a service model will be introduced in Section 6: "Smart Battery Mobility Service System". Successful RUL prediction for Li-ion batteries must take into account current health status of battery, history data/information, failure mechanisms, failure propagation, etc. Although RUL prediction for Li-ion batteries has not been the focus in the literature up to now, an increasing number of research efforts are being developed, as can be seen in the numerous projects that have been recently sponsored, or led directly, by federal agencies such as DOE and NASA.

5.1. Relevance vector machine (RVM)

RVM is a machine learning technique for solving regression and classification problems. RVM has nearly identical function form to support vector machines (SVM), however, the ways that they are formulated and used are dramatically different. Compared to SVM, RVM is constructed under Bayesian framework and thus has probabilistic outputs. Also, RVM models are sparser than SVM models, while maintaining comparable accuracy in results. A more detailed discussion of RVM and SVM can be found in [36]. When used for regression problems, the most distinguished merit of RVM is its capability to control "under-fitting" and "over-fitting"—Essentially "Ockham's Razor" at work [37]. A regression problem in RVM is reformulated as follows:

$$p(t_n|x_n, w, \sigma^2) = N(y(x_n; w), \sigma^2) \tag{5.1}$$

where t_n is the regression target (output) which follows normal distribution with mean y and variance σ^2; x is the input; y is the regression model without noise; and w is the regression coefficient. Further analysis and derivation can be found in [36–38].

In [39], an RVM regression model was built using battery internal parameters inferred from an electro-chemical model. The underlying assumption was that the internal parameters, such as charge transfer resistance and electrolyte resistance, would change gradually as battery degradation proceeded. And RVM model was used to accurately track the degradation trend. To predict remaining-useful-life, particle filter (PF) was used to adaptively choose appropriate coefficients for the RVM model and extrapolation was applied from the latest degradation model to find the end-of-life point, which determined the length of the RUL.

5.2. Particle filter (PF)

Particle filter is a sequential Monte Carlo method, which estimates the state PDF (probability distribution function) from a set of "particles" and their associated weights. The benefit of using state PDF is that it enables appropriate management of inherent estimation uncertainty. The use of weight, on the other hand, adjusts the state PDF to its most likely form. The particles are inferred recursively by two alternate phases: a prediction phase and a update phase. In the prediction phase, the value of each particle for the next step is estimated by previous step information. No measurement or observation is involved in this step. In the update phase, the value of each particle estimated in the prediction phase is compared with measurements and updated accordingly.

Saha et al. [39] applied particle filter to estimate the coefficients of an exponential growth model for electrolyte resistance and charge transfer resistance. The relationship among electrolyte resistance, charge transfer resistance and capacity was established to infer future capacity from the predicted electrolyte resistance and charge transfer resistance. Finally, RUL was calculated as the interval between the current cycle and the end-of-life (denoted by preset capacity value) cycle. However, the reliance on impedance measurement inhibits this prediction methodology's use in real-world applications, mainly due to the cost of equipment, stringent measurement requirements and space constraints. Without using EIS equipment, Saha and Goebel [40] again built an empirical capacity model which took coulombic efficiency factor and relaxation effect into account. Particle filter was used to estimate the values of battery model components; the future capacity value was extrapolated to give RUL estimation. Compared to the previous paper [39], internal battery parameters were not inferred from EIS measurement. Instead, a combination of empirical models was explored to represent energy losses incurred by IR drop, activation polarization and concentration polarization.

6. Conclusion

The Li-ion battery has been widely regarded as the most promising energy storage solution to electrify the U.S. transportation sector and reduce the consumption of gasoline. However, the reliability of Li-ion battery in high current application has long been a concern since large Li-ion batteries tend to have lower thermal stability, and the phenomenon of capacity loss becomes very severe in high current application. Li-ion technology will of course continue to evolve and the reliability of such batteries will improve. No matter how good a Li-ion battery is, however, the system will degrade over time, and the rate of degradation is affected by environmental impacts and operation profiles. Therefore, it is desirable to be able to detect the underlying degradation and to predict how soon the Li-ion battery will fail or reach a level that cannot guarantee satisfactory performance. This paper reviews recent research and development in health monitoring and prognostics of Li-ion batteries. Various algorithms, models and approaches are discussed for SOC estimation, voltage estimation, capacity estimation and RUL prediction. It is our hope that these summarizations and discussions will give readers a broad perspective on both progress in, and challenges of Li-ion battery health monitoring and prognostics.

Though not discussed in this review, it is also worthwhile to point out the importance of establishing innovative business models and designing unique managerial strategies in promoting the market penetration of hybrid or battery electric vehicles. More and more governments, automotive manufacturers, charging service providers and energy companies are reaching agreements of collaboration and committed to deploy electric vehicles in mass scale. The latest advances include Better Place and Renault launching Fluence Z.E, an electric car featuring a fixed-priced package of "unlimited mileage" and utilizing wind energy (with DONG Energy) [41]; Coulomb Technologies installing ChargePoint stations at Missouri-based Novus International, Inc that deliver benefits such as access control, data collection and Smart Grid compatibility [42]; Toyota, Electricite de France (EDF) and the city of Strasbourg launching large scale PHEV demonstration in Strasbourg that highlights installing charging stations at private homes and various public sites [43].

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