A framework based on big data for intelligent monitoring of battery packs

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Abstract
Existing literature focus on the prediction of states of batteries are scattered and are individually studied based on several battery aspects such as: 1) Chemical (ionic concentration measurement or diffusion coefficient evaluation), 2) Electrochemical (capacity), 3) Electrical (internal resistance), 4) Thermal (temperature), 5) Mechanical (stack/enclosure stress) and 6) In-situ/ex-situ (characterization methods to measure porosity and grain size). Unfortunately, these studies have been done by experts of different fields and are yet to be combined in a common platform to predict the states of batteries in a comprehensive way. In this paper, the aim of this research is to propose a framework so as to establish a big database (from sources of literature, by performing real-time experiments and uncertainty studies) for batteries at all operating conditions by incorporating all aforesaid aspects. Once the data base is established, a suitable artificial intelligence approach such as artificial neural network will be applied to train and build the model for state of health prediction and physical evaluation that subsequently have the prime advantage of accurately predicting the battery capacity at system level as well as cell level based on all existing design parameters (diffusion coefficient, grain size, temperature, internal resistance, etc.) from the big database. Data collection will be processed on brand new batteries by repeating cycles of charge and discharge modes under dynamic current profiles at different temperatures for accuracy. The proposed battery model can be then integrated to the battery management system in the electric vehicle without any additional integration complexity.

Keywords: electric vehicles; big data; intelligent monitoring; SOH/SOC

1. Introduction
Due to the pollution problems caused by automobiles and the growing shortage of resources, countries around the world have stepped up their research efforts on electric vehicles (EVs). As the most important part of the EV power system, and its health status directly affects the performance and safety of the EV. A battery that is safe, high-performance, environmentally friendly can improve power performance, driving range, and battery life [1].

However, the battery on the EV still has a series of problems during use. The most difficult problem is that the battery cannot monitor and predict its status in time, and the battery often appears over-discharged. Charging, overheating, and battery charging and discharging characteristics are greatly affected by environmental conditions. These conditions will not only increase the cost of using EVs, but also directly
damage the life of the battery itself, and even cause extreme damage such as vehicle damage or even explosion [2].

Due to the complex external environment, power batteries often have many faults throughout the whole life cycle: insufficient capacity, increased internal resistance, abnormal temperature, and short or open circuit. To minimize the impact of these problems, the battery needs to be intelligently monitored.

Battery modeling is primarily intended to accurately predict state of health (SOH), state of charge (SOC), and remaining useful life (RUL) thereby preventing unpredictable accidents that threaten drivers, vehicles, and road safety with the help of battery management systems (BMSs). There have been some in-depth research results on the degradation mechanism and prediction methods of lithium-ion batteries. The estimation of RUL can improve the safety and cost savings of EVs [3, 4]. With the actual needs of engineering, handful of studies have been found for modeling batteries over a wide range of operating conditions to estimate the SOC [5]. Several methods are also available in literature for SOH and SOC assessment in EV batteries. Electrochemical models are highly accurate for battery modeling as they have the capability to emulate macroscopic quantities like cell concentration, potential, current etc. Most widely used EMs are one-dimensional [6] and two-dimensional EMs [7]. However, one common disadvantage of both these models is that, they are complex and computationally in-efficient to emulate the cycling behavior of batteries. Therefore, to improve its prediction accuracy over the entire cycle, EM is applied in conjunction with advanced filter techniques (Kalman and Particle filter) in [8, 9]. Though these techniques are well efficient to predict the battery characteristics based on current, voltage and temperature, complex calculation-intensive algorithms are required for simulation and therefore, limits its applicability to EV applications. On the other hand, ECM techniques rely on electrical equivalent circuits predominantly developed by using several resistor-capacitor circuits to approximate the battery performance. Therefore, to replicate the dynamic chemical behaviors involved, large networks are required. For instance, some researches have reported ECMs for SOC estimation and unfortunately all these techniques require facilitate the use of complicated equations for estimation [10-12]. Most of these models are only applicable to research laboratory conditions and test environment rather than the practical application. Moreover, these techniques cannot accurately represent the interrelated physics and electrochemical phenomena associated with batteries. In contrary, electro-chemical impedance based models are more accurate since battery impedance is an effective indicator to the health of the battery [13]. Such models usually predict the battery performance by comparing the variation in impedance value with respect to its nominal value. Though satisfactory results are obtained using electro chemical impedance models developed in [14, 15], EIM cannot be applied for real time monitoring as the battery has to be disconnected from EV for measurement. Additionally, these techniques have been implemented only at cell level and not for the entire battery back used in an EV. In contrast to all above techniques, Spec-based models (SMs) try to approximate the battery health without experimentations. Mathematical relations/equations are derived from the manufacturer’s data sheet parameters for estimation. An efficient approach based on SM is recently proposed by Fiodar et al., in [16]. Nonetheless, like EIM techniques, spec-based models cannot be realized for an entire battery back and also, need different models according to the battery make. In summary, these techniques cannot be applied globally and hence, not suitable for EV applications.

From the previous works, some research gaps draw immediate attention to be addressed to improve the reliability of BMSs. Battery modeling techniques developed till date have only paid emphasis to a cell level approach. However, sophisticated approach combining battery (cell level) and battery pack (system level) is found missing. Most of the existing techniques have been formulated in offline laboratory conditions and their applicability in a practical scenario is questionable. Most of the existing techniques require off-line measurements to estimate the battery health and therefore, real time monitoring is not possible. Integrating existing battery modeling techniques to EVs require numerous sensors and measurements that make the system highly complex, bulky and expensive. For accurate and reliable battery health prediction at all operating conditions, physical, electrical, chemical and mechanical aspects/properties need to be evaluated. To against these research gaps, this paper develops a framework based on big data for intelligent monitoring of battery packs. The objective of this paper is to propose framework so as to establish a big database (from sources of literature, by performing real-time experiments and uncertainty studies) for batteries at all
operating conditions by incorporating all aforesaid aspects. Once the data base is established, a suitable artificial intelligence (AI) approach such as artificial neural network will be applied to train and build the model for state of health prediction.

2. Methodology background
The SOC can tell the driver how much power is left, and how much mileage the vehicle can currently travel. The SOH of the battery indicates the aging degree of the battery, which can tell the driver the current life of the battery, wherein the aging of the battery is: an increase in the ohmic internal resistance of the battery, a decrease in the power density and energy density of the battery. The Remaining Useful Life (RUL) is usually expressed as the length of service available from the current time to end of Life (EOL). Artificial Neural Networks (ANNs) is one of class of Artificial intelligence approach (AI) for formulation of the mathematical models for complex systems. ANN can continuously learn and train the weights of the network by processing the sample information, so as to output the calculation results of the sample. The cross-integration of artificial neural network technology and other disciplines has played an important role in many engineering fields, and the integration of ANN technology and pattern recognition technology has also been more in-depth excavation and research in the field of mechanical equipment detection and fault diagnosis. After the basic functions of the artificial neuron are determined, the work of the neural network system mainly depends on the network topology and the corresponding learning mechanism.

3. Research Statement
Traditional methods of relying on manual experience to repair and maintain battery packs have not met current needs. To feedback the real-time parameters of the battery to the vehicle controller, a BMS design is needed to protect the driver's safety, ensure the normal operation of the battery pack and extend the battery pack. Intelligent monitoring of the battery pack is the main content of the BMS. The performance of the monitoring capability will affect the battery safety and the implementation of the vehicle control strategy. Therefore, an intelligent monitoring system with higher efficiency and higher precision needs to be developed to improve the driving safety and power of the vehicle. In this paper, all type of EVs predominantly uses Li-ion batteries as a primary or secondary power source owing to its high power density, energy efficiency and less maintenance requirements. Though having set an ambitious target to achieve 22% of the global vehicle share by 2030, EV sector still leaves a lot to be desired to emerge as an interesting proposition for consumers. The reasons being: 1) non-availability of charge stations, 2) low power range, 3) battery recycling issues and 4) power overload. With all global countries investing constantly to increase the overall accessibility to EV charge stations, the above challenges 2-4 perceives colossal research attention to improve the reliability of EVs. As the factors governing these challenges are highly interrelated, properly designed Battery Management Systems (BMS) are inevitable in EVs that in turn supports the overall vehicle management system to ensure optimal performance. An ideal BMS must accurately monitor the following crucial variables to perform a series of BMS tasks like charging, discharge, cell balancing and fault detection: 1) SOC that indicates the battery capacity available, 2) SOH that quantifies battery aging, life and health and 3) Battery parameters such as current, voltage, power and impedance. Unfortunately, neither of these variables can be obtained/sensed from the battery by direct measurement and therefore, needs to be estimated based on the available battery parameters. Also, such techniques are expected to have low complexity and high computational efficiency. Therefore, development of accurate, reliable and robust battery modeling techniques is decisive for prognosis and estimation of battery performance parameters in EVs.

4. Proposed Methodology
Research has been done for development of models based on the temperature, the voltage and the current to estimate SOH, most these models are formulated offline and under controlled laboratory conditions. The proposed methodology, in contrary, intends to develop a globally applicable system level approach for battery modeling and health prediction that completely eliminates the use of complex computational
algorithms in real-time monitoring. The proposed work intends to design, develop and implement a new big data driven approach to estimate SOC, SOH and RUL of batteries (preferably Li-ion) used in EVs. Past studies focus on the prediction of SOH or study of SOH are scattered and are individually based on several battery aspects like: 1) Chemical (ionic concentration measurement or diffusion coefficient evaluation), 2) Electrochemical (capacity), 3) Electrical (internal resistance/ AC or DC impedance), 4) Thermal (temperature), 5) Mechanical (stack/enclosure stress) and 6) In-situ/ex-situ (characterization methods XRD, EDS to measure porosity and grain size). Unfortunately, these works have been done by experts of different fields and are yet to be combined in a common platform to predict the SOH/SOC/RUL of EV batteries in a comprehensive way. Therefore, the aim of this research is to establish a big database (from sources of literature, by performing real-time experiments and uncertainty studies) for EV batteries at all operating conditions by incorporating all aforesaid aspects. Once the database is established, a suitable Artificial Intelligence (AI) algorithm, preferably Artificial Neural Network (ANN) will be applied to train and build the model for SOH prediction and physical evaluation that subsequently have the prime advantage of accurately predicting the battery capacity (or SOH/SOC) at system level as well as cell level based on all existing design parameters (diffusion coefficient, grain size, temperature, internal resistance, etc.) from the big database. Data collection will be processed on brand new batteries by repeating cycles of charge and discharge modes under dynamic current profiles at different temperatures for accuracy. In addition, different neural networks architectures, such as feed-forward, recurrent and radial basis function will be investigated to provide accurate estimation. Multiple configurations, based on the number of inputs, delays, hidden layers, neurons, activation functions, and training methods will be analyzed to find the most accurate estimation model. It is also important to note that, to improve the adaptation ANN and thereby improving the prediction accuracy, dedicated optimization techniques are intended to be integrated with the neural networks. Furthermore, the computational complexity of each configuration will be analyzed for comparison and selection of accurate solutions. The collected data will be divided into two sets: training set to be used to train the neural network and testing set, not used in the training process, to validate the neural network performance. Also, as the data set size and computational time are interrelated, the data size will be correlated with the size of the battery. The proposed battery model can be then integrated to the BMS in the electric vehicle without any additional integration complexity. Another additional feature of the proposed technique is that the established data base can be extended and efficiently used for further applications such as: 1) battery damage characterization, 2) battery pack design, 3) battery enclosure design and 4) recycling of batteries. For a better understanding, the methodology is graphically represented in Fig. 1.

Figure 1 Proposed Battery modelling approach.
5. Conclusions

Previous studies have been done by experts of different fields and are yet to be combined in a common platform to predict the states of EV batteries in a comprehensive way. In this paper, a big database (from sources of literature, by performing real-time experiments and uncertainty studies) is established for EV batteries at all operating conditions by incorporating all aforesaid aspects. A suitable AI algorithm is used to train and build the estimation model for states prediction at system level as well as cell level based on all existing design parameters (diffusion coefficient, grain size, temperature, internal resistance, etc.) from the big database. The proposed battery model can be then integrated to the battery management system in the EV without any additional integration complexity.

In comparison to the existing techniques available for battery modeling, the following scientific contributions are overlaid in this work:

1. To the best of authors understanding, the proposed approach is first of its kind. A big data based AI model combining multiple scenario aspects like chemical, electrochemical, electrical, mechanical and thermal behavior of the existing techniques will be conceptualized.

2. The proposed method has its inherent capability to attribute to system level as well as cell level approach for battery modeling.

3. Substantial enhancement in prediction accuracy due to large dataset collection from different possible aspects and improved adaptation of AI algorithm.

4. A modeling technology compatible for all EVs irrespective of the type, size and make of vehicle is proposed.

5. The proposed concept can be extended for other battery performance characterization techniques as well.

Future work for authors is to work on sophisticated surrogates-assisted evolutionary algorithms, deep learning [17-18] and support vector machines [19-20] to realize the true potential of AI for an efficient power battery management system design.

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