Co-estimation of state of charge, state of health, remaining useful life and state of function prediction for lithium ion battery in electrified vehicle using machine learning methods: A comprehensive review

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Abstract

A novel machine learning based co-estimation approach of Lithium ion battery (LIB) co-estimation of State of Charge (SOC), State of Health (SOH), Remaining Useful Life (RUL)and State of Function (SOF), which provides comprehensive capabilities like range knowledge, battery diagnostics and prognostics need in electrified vehicle is proposed in this work. The review introduced a methodology for state co estimation for battery health management and monitoring, challenges, benefits, and key findings. It is considered as game changing technology that can push the boundary of electric vehicle applications. Recent breakthroughs in model-based, data-driven, and hybrid techniques are highlighted to provide one point solution by introducing the first comprehensive vision of battery's health management system. A flowchart illustrates the different techniques for co-estimation process and highlight its experimental conditions. Together, it provides a powerful guide to designing experiments or models for investigating battery health management system for electric vehicles.

Keywords. Electric vehicle, co estimation, lithium ion battery, machine learning, state of battery

1. INTRODUCTION

With widespread deployment of rechargeable lithium ion batteries (LIB) because of its high energy and power densities, aging and degradation prediction for safety, diagnostics and prognostics need has emerged a challenging issue [1],[2]. This nonlinear degradation by way of various thermo- electric- chemical- mechanical factors dependents on operating and environmental conditions [3],[4]. On electrochemical side, this is due to irreversibility in following recession reasons -phase changes in electrode materials, electrode dynamics during recession, electrolyte breakdown, and production of SEI films resulting into capacity and power fade [5],[6]. This fade necessitates quantization of various states like SOC, SOH, SOF, SOT, SOP, SOL, RUL, SOL [7],[8]etc. forms part of modern day requirement. All these state parameters are intertwined in some way as a battery can have low SOC (defined as ratio of available capacity and the maximum possible capacity) at high SOH (a figure of merit of present condition and is a ratio of present capacity to capacity at fresh) or high SOC at low SOH, but is not sufficient to guarantee performance of a certain duty, The peak output power of the battery [9], which is constrained by thresholds like voltage restrictions, current constraints, and SOC limits, may be used to illustrate how the battery performs in relation to actual load demands [10]. This is referred to as SOF and considered as a functionality derived from LIB transient behaviour and RUL, an asset at a particular time of operation. All these four state fulfil the aspects of safety, diagnostics, prognostics and performance of LIB and this review is centred on prospecting and proposing a novel co-estimation methodology for these four major indirect measurable indices.

Different state estimation approach focus on single or dual parameters, whereas very few work on over two states. The strong links between the four stages make it difficult for an isolated assessment of one or even two states to accurately reflect the true status of the battery. In actuality, the battery might adapt and optimise itself to its use case and hence requires significantly less calculations provided these estimated states are made available on the battery itself [11]. The main challenge for accurate prediction of actual state and the complexities in estimation has leads towards different methodologies like electrochemical methods, electrical equivalent circuit methods, mathematical methods and data driven methods, which requires different level of domain knowledge and expertise. These parameters are fundamental to the future development of electric vehicles, energy storage devises etc. which are large-scale deployment and complex in applications.

Complexities of real LIB is much more than a single cell, which houses hundreds to few thousands of identical capacity(but often slightly different behaviour) cells with battery management system (BMS), connectors, thermal management systems, packing materials, housings [12],[13]. where each and every components are responsible for its performance. The real battery works with huge fluctuation in vital and direct measurable parameters, voltage (V), current (I), temperature (T), internal impedance (IR) on time scale, which generates huge data for further development of secondary indices like state parameters. This data leads towards development of states understanding by way of employing suitable methods which can handle voluminous data and give suitable analysis and prediction in a timely manner with least resources used. Here comes different data driven machine learning (ML) methods, which comes handy in this application. In ML methods also, selection of an appropriate method is a multidimensional problem, depending on the extent of data available, quality of results looked for and physical interpretability of model required, which itself is a need for how accurate state estimation of some battery properties is needed or life predictions[14]-[16]. In addition, all these ML methods only provide point estimation of states (which serves as a “best guess” or “best estimation” of an unknown parameter). Especially for the data-driven method, state estimation result a non-smooth curve due to the measure noise and outliers of direct measurable indices. Hence, quantifying estimation uncertainty is to enable reliability assessment of state estimate, which not only keeps away from over-conservative estimations. The steps commonly employed are data pre-processing, training and estimation.

Table 1. State co estimation by different researchers

Reference	**Battery**	**Cell**	**CAP**	**SOC**	**SOH**	**SOF**	**SOE**	**SOT**	**SOP**	**RUL**	**SOB/SOS**
[1]	✓			✓				✓			
[2]	✓			✓	✓	✓					
[6][7]		✓	✓	✓							
[9]		✓		✓							
[10]		✓		✓	✓						
[11][12]	✓			✓					✓		
[15]		✓		✓	✓						
[5]		✓	✓	✓							
[18]		✓	✓	✓							
[19]		✓	✓	✓							
[20]		✓	✓	✓							
[21]		✓		✓	✓				✓		
[4][9]		✓		✓	✓						
[5][21]		✓		✓	✓						
[6][24]		✓		✓	✓						
[7][15]		✓	✓	✓							
[18][23]		✓		✓							

[[1][14]		✓		✓				
[20][24]		✓	✓	✓				
[5][10]	✓			✓	✓		✓	
[6][22]		✓		✓				
[9][24]		✓	✓			✓		
[7][13]		✓			✓			✓
[16][21]	✓	✓	✓	✓				

ML based different state estimation are available in literature, however very few studies are carried out for co estimation of different states using ML methods. [17] carried out SOC, SOH, RUL co estimation using DL method, [18],[19] used multi-stage model fusion method for estimating capacity-SOC. [20] used forgetting factor dual particle filter algorithm for estimation of SOC- SOH. Similar exercise and research is been carried out selectively [21]. To the best of our knowledge, there is, however, a lack of studies on ML based co-estimation of SOC, SOH, SOF and RUL prediction, Hence, it is a clear advantages of ML based estimation were insufficiently harnessed in the area of battery state monitoring, where handling the coupling of different states is a key challenge. Considering this research gap, we are strongly innervate to devise an innovative data-driven DL based co- estimation scheme of different states for improving battery monitoring and BMS accuracy and robustness. Figure 1 represents the interlinking relationship of SOC, SOH, RUL and SOF.

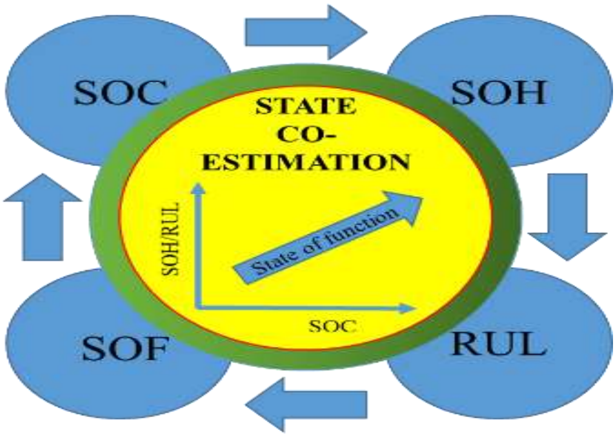

Figure 1. Interlinking relationship of SOC-SOH-RUL-SOF in LIB

The motivation of the review work covers state co estimation of lithium ion battery used in electric vehicle technology covers, Most of the research work for LIB state co-estimation is still in laboratory stage with predefined duty cycle and at controlled environment where as in reality operating and environmental condition in real world scenario is totally different, where actual battery works with several inconsistent cells. Limited works has focused on effective state co-estimation where accuracy of one state prediction is associated with the variation of another, which influences the result of other. Simultaneously, computational competency shall also increase to BMS in this scenario. Poor generality of model among family of LIB with different operating and environmental conditions.

2. PROPOSED METHODOLOGY

It is established that SOC and SOH are fully coupled in a nonlinear fashion; RUL has a linear relationship with SOH, SOF is dependence on discharge load on SOC and SOH at a given temperature. In model-based method the prediction results are universal and estimation accuracy does not depend on historical data, however it requires higher domain knowledge and is not practically applicable to the applications of EV[19]. In the proposed methodologies, we proposed ML based methodology which don’t requires much domain knowledge, fast, capable of unified co estimation of different states and can be integral part of BMS[12],[13],[20],[21].

SOH is a metric to appraise the aging level, which includes capacity fade and/or power fade on time scale and the common used indicators are capacity decrease, DC resistance increase and AC impedance increase. The non-empirical lab data is handy to test and validate the result and trend can be conserved for a specific cell electrochemistry. The decrease in SOH has an impact on SOC and hence it is proposed that continuous SOH status shall be used as input for SOC estimation even it is a slowly time-varying state, which is also supported by research conducted earlier[9],[16]. The actual vehicle status data is continuously fetched and analyzed through BMS, which in conjunction to online SOH data is used for estimation of SOC. RUL is directly related to SOH data and is predicted from the results of SOH. The whole input of lab data & actual EV battery data is been processed for prediction in a suitable ML method based framework for determine the degradation physiognomies of batteries. This SOC & SOH data is proposed to be used for determining SOF with cell level temperature data using limiting algorithm, as SOF is the ability estimation and is dependent on SOC, SOH with temperature.

The main contributions of this study are as follows. Initially the authors proposed a suitable method for online co-estimation for SOC, SOH, RUL & SOF using machine learning. Second, SOH estimation is done through ML model and used as additional input for estimation of SOC with continuous updation. Third, SOC and SOH parameters are estimated simultaneously, and the proposed method can yield accurate SOC estimation results using the current state information of SOH. RUL is directly derivable from online SOH as being a linear functionality. Fourth, SOF is online estimated using the online input of SOC, SOF along with cell temperature data. Finally, a ML model bank is proposed to be developed to study degradation and nonlinear characteristics [22]-[26]. This study proposes the following improvements over previous studies. SOH estimation method is considerably different as it uses joint online input of EV LIB data and complete non-empirical cell level data to analysis and updation and not a single discharge cycle was used to estimate SOH, and SOH was estimated after one discharge cycle was complete.

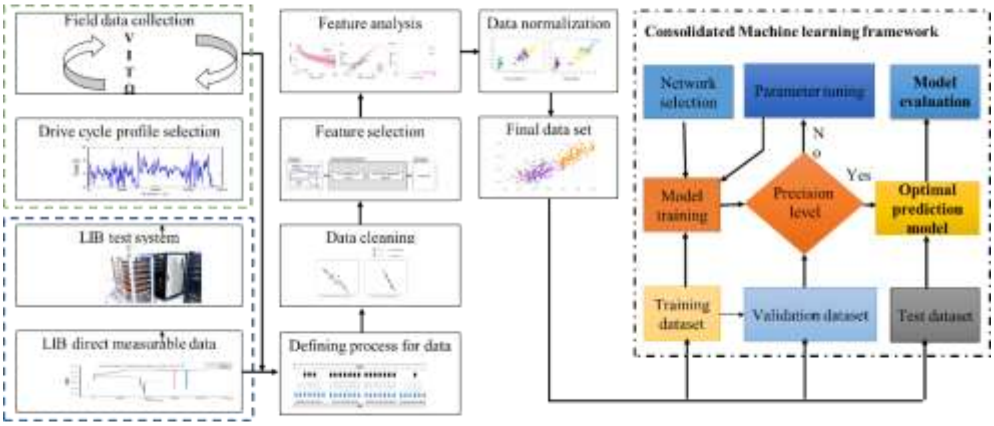

Figure 2. Online and offline data processing and consolidated machine learning framework

3. EVALUATION AND PROPOSAL OF SUITABLE ML METHOD

Existing literature has studied extensively different ML methods singularly or in hybridization with other ML methods or filter based methods. State estimation are defined as time- series processing problem [9]and it is well established that LSTM NN are effective and scalable models for handling time sequential data[4]. Other researchers had used different methods like supervised, semi supervised, unsupervised & reinforcement learning methods with different error estimation like MAE, RSME, R^2 etc [4],[16]. Temporal convolutional network (TCN), rather new concept, is found to have higher performance accuracy and thus improves considerably with increase in quantum of data where as other simple statistical learning, traditional ML, shallow ML degrades and is found suitable in typical LIB datasets which are aperiodic and nonlinearity among variables, which is incapable by models to capture and have self-adaption of the complex data features. The need for co-estimation via TCN is actually a framework employing casual convolutions and dilations so that it is adaptive for sequential data with its temporality and large receptive fields. The strong robustness and high accuracy of TCN for high fidelity and multivariate voluminous data needed to be handled for co-estimation is highly attractive and is already used selectively for individual RUL, SOH, SOC estimation.

4. CONCLUSION & FUTURE WORK

Co-estimation algorithm utilizes the relationships among these four states appropriately, and is thus more prudent and precise than traditional discrete state estimation methodology with the following advantages:

1) Impact of aging and degradation on state estimation is taken into account. The capacity used in SOC estimation is updated online for SOH estimation & RUL prediction; therefore, accuracy of SOC estimation after battery aging is improved.

2) Impact of SOC on available energy and power is taken into account for the first time, which shall give accurate SOF. As battery OCV varies with SOC, and consequently maximum available energy and power is influenced by SOC, the SOC estimation result is used to obtain OCV in SOF estimation. Therefore, with an updated on SOC and correlated OCV, the accuracy of SOF estimation can be significantly improved.

3) TCN improves the prediction accuracy and minimize multivariate time series data dependence for aperiodic data and thus eliminates extra filters and estimate methods like KFs used in previous studies, TCN can support in readily transfer necessary data from BMS, such as cell temperature, I, V, Ω etc. flowing straight to SOH/SOC estimation.

4) Using learning methods like as gradient descent, the TCN may self-learn. This is in stark contrast to existing researches such as lumped parameter models and analogous electrochemical models, which take a long time with low accuracy and tough to implement.

5) It will be demonstrated that a single TCN can learn to state estimate at various environmental temperatures. This is advantageous since typical estimating procedures require separate models or look up tables for varied atmospheric temperatures.

In future the authors intended to test and validate the proposed TCN methods with the help of publically available LIB degradation datasets (NASA, Sandia National Laboratories, Oxford Battery Degradation Dataset etc) with actual EV LIB data at different operating(both actual and standard drive cycle like DST, UDDS etc) and with different environmental conditions.

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