An Extensive Comparison of State of Charge Estimation of Lithium Ion Battery – Towards Predictive Intelligent Battery Management System for Electric Vehicles

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***Abstract*— The electric vehicle is evolving as a futuristic technology vehicle to focus on the frequent serious energy and environment concerns. The Battery Management System (BMS) is the primary segment which has an essential job in controlling and securing the electric vehicle. The important functions of BMS include estimating battery state of charge (SoC) using various algorithms and propose features towards developing predictive intelligent BMS. Estimating SoC accurately is relevant for designing a predictive intelligent BMS. The accurate SoC estimation of a Li-ion battery is tough and involved task due to its excessive complexity, time-variant, and non-linear characteristics. This work intends to estimate and compare the SoC of thermal dependent Lithium Ion cell using different methods viz. Coulomb Counting (CC), Extended Kalman Filter (EKF) and Artificial Neural Network (ANN) algorithms.**

Keywords— Lithium-ion battery, battery management system, artificial neural network, state of charge, Coulomb counting, extended Kalman filter, PIBMS.

I. Introduction

The recent challenges in energy shortage and environment pollution demands for innovations in the development of various energy vehicles. Electric vehicles which excel as zero emission vehicles are considered as the new face of future transportation. Furthermore, due to the exponential growth within the price of these fuels, locating a secondary source for transportation has its significance inclusive of the hybrid and battery-electric vehicles (PHEV&BEV), new energy vehicles (NEVs) and fuel cell electric vehicles (FCEVs). These days, storage batteries have won significant attention in the market due to their excessive demand in battery-operated automobiles such as PHEVs, EVs and HEVs. The Li-ion battery one of the popular forms of the rechargeable battery have the characteristics like excessive reliability, high energy and power density, long lifespan, excessive power density, high performance, low rate of self-discharge and reduced memory effect.

The fundamental component of EVs includes an effective BMS which assures efficient, safe, long-lasting, and stable operation of Li-ion battery. Besides, the accurate data on its state of life, health, available power is also provided by an effective BMS. The BMS acquires the voltage, current and internal battery temperature data from the battery using which safeguards the battery from overcharging and discharging situations and may be utilized for estimating various states of battery. In this study, the different state of charge estimation methods of a lithium-ion battery is compared for implementation of a Predictive Intelligent Battery Management System to improve the overall efficiency of Electric Vehicles. The Coulomb Counting, Extended Kalman Filter and Artificial Neural Networks are the three different methods considered which come under the Book-keeping, Model-based and, Artificial Intelligence categories respectively. The measures like mean average error (MAE) and root mean square error (RMSE) are calculated to quantitatively evaluate the performance of these estimations methods.

$$MAE = \frac{1}{n}\sum_{1}^{n}(real\ value - predicted\ value) \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(real\ value - predicted\ value)^2} \tag{2}$$

Predictive Intelligent Battery Management System (PIBMS), developed by incorporating a predictive and intelligent component with the BMS optimizes the emission, travel time and energy consumption. The predictive component is realized by integrating the vehicle with Dedicated Short Range Communication (DSRC) which enables the wireless communication of charging and vehicle traffic data. The on-board optimization programming capability of PIBMS contributes to its intelligent component.

II. LITERATURE SURVEY

The main challenge in state estimation of a Li-Ion battery is the difficulty in direct estimation by sensors [1]. The SoC estimation of Li-ion batteries has turned an interesting topic for researchers. The analysis of the research papers based on SoC estimation of Li-ion battery shows a significant interest in SoC estimations in recent times. The important five categories of SoC estimation methods are classified as shown in Fig.1 [2].

In this work, the bookkeeping, model-based, and computer intelligent methods are considered. Specifically Coulomb Counting, Extended Kalman Filter and Artificial Neural Network methods are the respective subcategories. The Coulomb counting is the approach that is grounded on the battery current while charging and releasing processes [3].

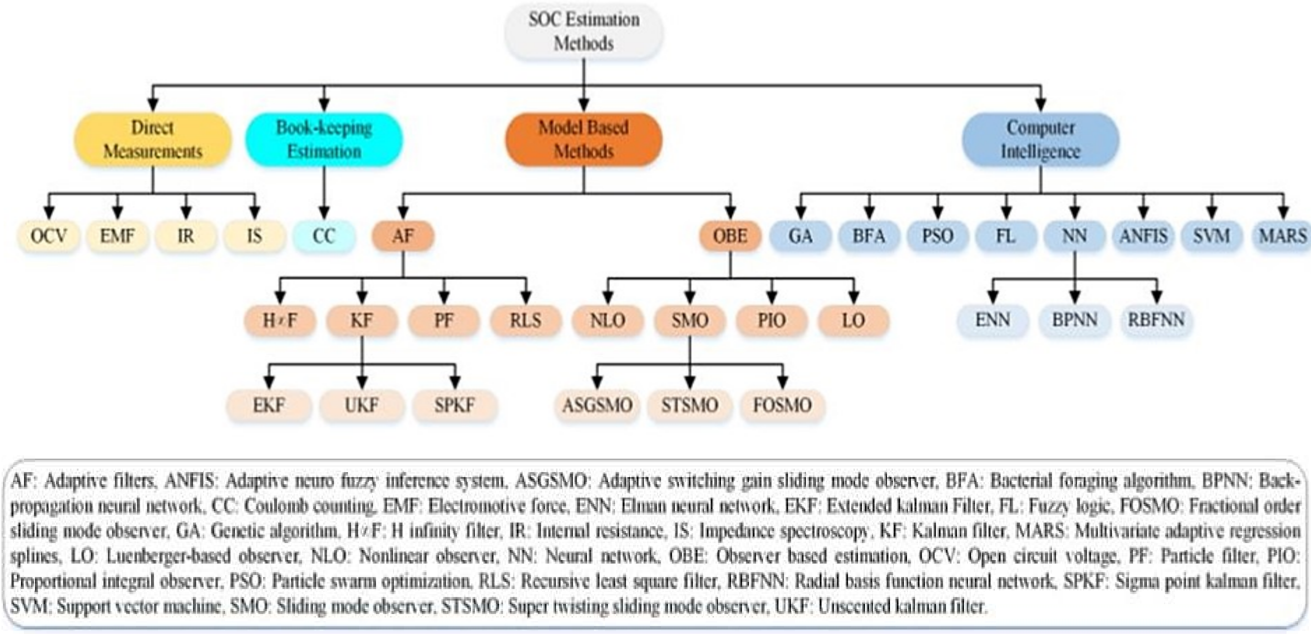

Fig. 1. State of Charge estimation of Lithium-ion batteries.

The conventional estimations methods have some concerns related to their accuracy and efficiency considering the real-time applications. Model-based SoC estimation methods have various features that get the better of the imperfections in the traditional methods. Model-based methods utilize certain battery parameters to employ its equivalent model and then battery state is estimated with advanced algorithms like EKF, H infinity filter (H ∞ F) and Nonlinear observer (NLO). The most regularly utilized models are Electrochemical Model (EChM) describes the chemical kinetics inside the battery and the Equivalent Circuit Model (ECM) representing the electrical circuit elements of Li-ion battery [4]- [5]. Kalman Filter is a model based technique for the state estimation of dynamic systems which most commonly used in various fields of transportation planning, process control, and battery management system design of electric vehicles [6].

The complexity of model-based SoC estimations is to model the battery. The process of calculating the battery parameters need various tests and is a tedious task. This issue is overcome by the computer intelligence methods of state estimation. The Artificial Neural Network (ANN) is a computer intelligent framework that is created from the motivation of the biological neural system of the human brain. Many different machine learning algorithms such as Linear Regression, Support Vector Machine (SVM) and Random Forest utilize basic ANN framework to execute various tasks [7]. The ANN has learning abilities and self-adaptability to utilize huge database to establish a highly complicated and non-linear systems like Li-ion battery.

III. SYSTEM OVERVIEW

The overall block diagram of the state of charge estimation using CC, EKF, and ANN methods are shown in Fig. 2. The system consists of a Lithium-ion battery, a measuring unit, a battery model, an integrator for coulomb counting algorithm, an EKF algorithm block, a trained ANN model. The battery is modelled in Simscape language incorporating thermal effects. The battery has a nominal capacity of 30 Ah and undergoes discharge/charge cycles at an average current amplitude of 15A.

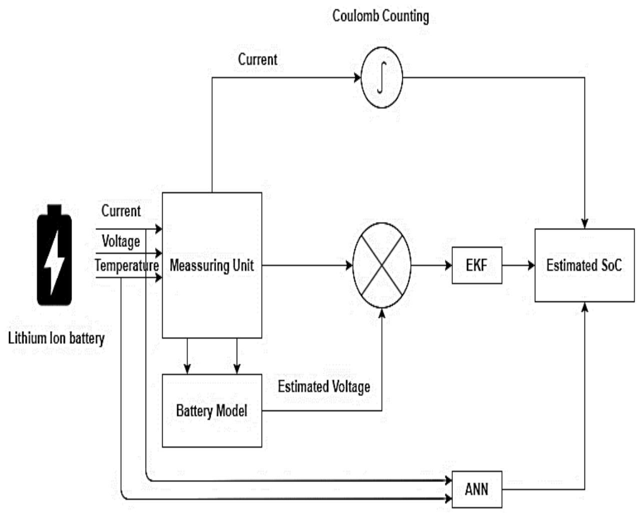

Fig. 2. General Outline diagram of SoC estimation methods.

To enable the estimation, SimscapeTMECM and a simple circuit model (containing an ideal current source and a voltage sensor) are interconnected. The automation of the estimation procedure is done using parameter estimation at the command line. The battery model obtained in [8] has been used in this work. Coulomb counting algorithm block estimates the SoC of the battery by performing the integration of battery output current upon operating time duration. The state is obtained by combining the measured voltage and estimated voltage using the EKF algorithm block. The dataset (Voltage and Battery

Temperature) along with the real SoC is collected from the Simulink model and trained the ANN model

IV. METHODOLOGY

A. Battery Modelling

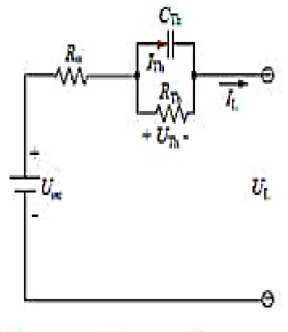

Fig. 3. Battery Thevenin Equivalent Circuit-1RC

The electrical equivalent circuit model comprising of voltage sources, resistors, and capacitors represented the dynamic response of the battery in real-time. The parameters marked in the equivalent circuit are R_o the internal resistance, R_{Th} the polarization resistance, C_{Th} the equivalent capacitance, U_{Th} the voltages across C_{Th} , I_L the outflow current of C_{Th} and U_{oc} the open-circuit voltage. In this model SoC and U_{Th} are considered as the two states. The state and measurement equations are obtained to substitute in the algorithm.

The battery model can be expressed as:

$$s(x,u) = \begin{bmatrix} \frac{I}{aCb} \\ \frac{I}{C_{Th}} - \frac{U_{Th}}{R_{Th}C_{Th}} \end{bmatrix} \tag{3}$$

$$m(x,u) = aSoC + b + U_{Th} + I_L R_o \tag{4}$$

B. Coulomb Counting Method

This is the most generally executed and least complex approach to calculate the battery's SoC. The battery state is calculated using (5).

$$SoC_t = SoC_0 + \int_0^t \frac{I_t}{C_{batt}} \tag{5}$$

Where SoC_t and SoC_0 indicates the state of charge at time = t and 0 respectively, I_t is the charging/discharging current and C_{batt} is the standard battery capacity. In Coulomb counting method, the change in SoC is calculated using battery's current by integrating it over the total time and dividing by its total capacity. The issue in estimating the accurate initial SoC is the main drawback of this method. Due to the additive behaviour of this algorithm while the integration of current, even the minor errors in current sensor value cause for the major drift in SoC estimation over time.

C. Extended Kalman Filter

Kalman Filter is a linear state estimator that overcomes the state estimation errors by appropriate choice of error covariance. The complex nonlinear systems like Lithium-ion battery use Extended Kalman filter algorithm for estimating its state.

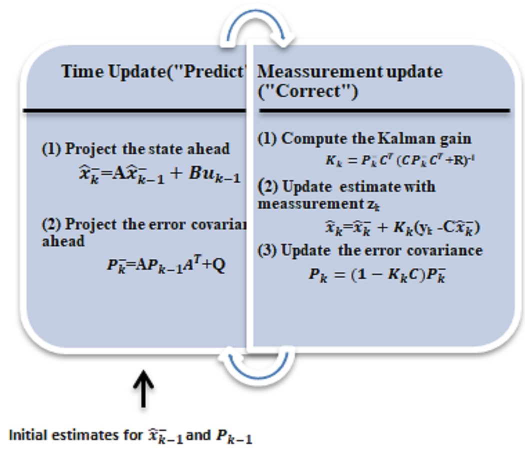

Fig. 4. Block diagram of Kalman filter algorithm.

In EKF the discretization of state and measurement equations are done before Kalman filter algorithm. The two steps in KF computation are prediction step and update step. In the prediction step, the error covariance predicted from the assigned values of process noise, measurement noise, and initial state. Once the predictions are determined, the Kalman gain is calculated and updated the states of the system and error covariance in the update step. Fig. 4 explain the flow of KF algorithm. The battery model equation should be discretized in after linearization. Taylor series expansion of the battery model equations is taken at operating points, for linearization.

Let the states of the system be SoC (denoted as x_1),U_{Th} (denoted asx_2) and the input be I (denoted as u). Then the equations (3) and (4) can be rewritten as:

$$s(x,u) = \begin{bmatrix} S_1 \\ S_2 \end{bmatrix} = \begin{bmatrix} \frac{u}{aCb} \\ \frac{u}{C_{Th}} - \frac{x_2}{R_{Th}C_{Th}} \end{bmatrix} \tag{6}$$

$$m(x,u) = ax_1 + x_2 + uR_o + b \tag{7}$$

After linearization and discretization the battery model changes to:

$$\dot{x} = A_k x + B_k u$$

$$y = C_k x + D_k u$$

D. Artificial Neural Network

Artificial Neural Network (ANN) is an intelligent machine learning tool having characteristics such as flexibility in fitting any complex non-linear system, adaptive and self-learning capabilities never which demands any physical knowledge of the system to be modelled.

Considering the battery state estimation several algorithms of ANN are developed with its advancement. Fig.5 [9] shows a feed-forward ANN contains several units called neurons where non-linear activation functions are operated. Interconnections of adjacent layers are done by connecting these units using weights (links). Feed-forward networks employ static mapping by spreading the data from input to output through hidden layers in a forward direction.

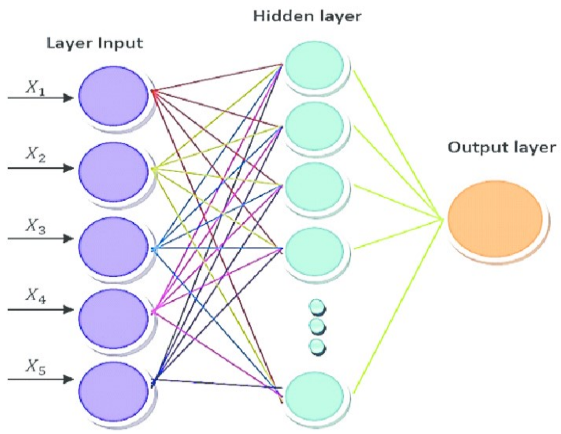

Fig. 5. Schematic diagram of ANN Model.

In this work, the NN tool of deep learning toolbox on Math Works Matlab® is used. This GUI helps the user to implement different types of neural networks for the applications such as classification, clustering and regression using different methods and helps to import, create, use, and export neural networks and data.Neural network fitting tool with different inputs as battery terminal voltage, the temperature was used for SoC estimation as part of this work. Whereas, pattern recognition and clustering tools are not a good choice for SoC estimation of the battery.

The training algorithm requires trial and error method depending upon the fitting problem. The selection of training algorithm is a difficult task that requires trial and error method depending upon the fitting problem. There are advantages and disadvantages to each method. The MATLAB documentation proposes LM back propagation is one among the fastest though requires more memory.

V. SIMULATION AND RESULTS

The three SoC estimations methods Coulomb Counting, EKF and ANN are implemented in MATLAB/Simulink. The Coulomb Counting and EKF Simulink model is shown in Fig.6.The dataset including battery voltage, internal temperature and SoC to train the ANN model is collected from Simulink EKF battery model.

Fig.7 shows simulation result of Coulomb Counting and EKF in comparison with real SoC.

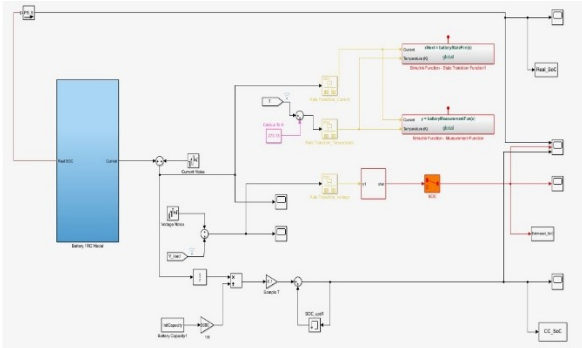

Fig. 6. Simulink model of Coulomb Counting and EKF.

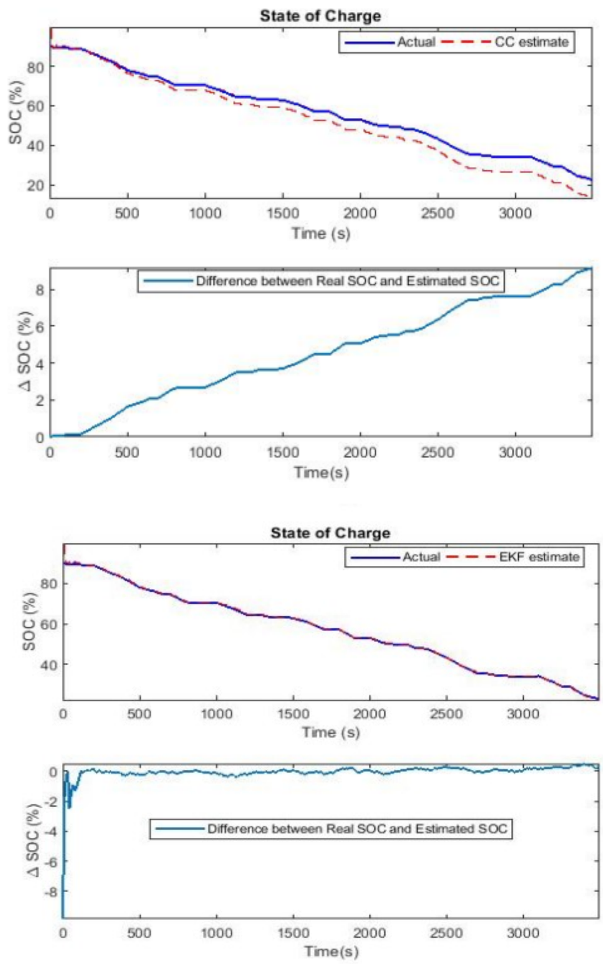

Fig. 7. Simulation Results of CC amd EKF models.

Table I compares the mean average error (MAE) and root mean square error (RMSE) values of the three methods. The parameters MAE and RMSE values have wide variations.

TABLE I. MAE AND RMSE VALUES

Method	Parameters	
	MAE	***RMSE***
CC	-0.49627	0.01820
EKF	-0.00474	0.00190
ANN	-0.00138	0.00076

The CC has the least accuracy, whereas ANN is the most accurate of the three methods. The accumulated error of CC resulted in high values of errors, whereas a well-trained ANN battery model with a dataset considering all the possible values showed low error values.

VI. CONCLUSION

The SoC estimation of a thermal dependent Lithium-Ion battery cell was modelled. The estimation techniques were Coulomb Counting, Extended Kalman Filter and Artificial Neural Network Methods respectively. A first-order Thevenin equivalent circuit model (ECM) of the cell was utilized for implementing CC and EKF methods. The dataset consisted of the cell voltage, the internal temperature as inputs and the SoC as output. The battery cell model helped to collect the dataset required for training the ANN model. The resultant SoC obtained using the ANN technique showed better accuracy than the CC and the EKF algorithms. The battery modelling for EKF method is a complicated task whereas ANN does not require any physical knowledge of the system. The results obtained using the ANN algorithm can be further improved by using a proper data set of the battery under various operating conditions.

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