Estimation of SoC using SVM regression technique for an Efficient Electric Vehicle Battery Management System using c-RIO DAQ

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Abstract: Vehicle electrification can effectively mitigate oil crisis andenvironmental pollution. In an Electric Vehicle (EV), several cells connected in series/paralleltopologies, powering the EV for the maximum range of 50-500km. Consequently, BatteryManagement System (BMS) is necessary to manage the battery pack to ensure safe and proper operations of EV.With increase of cycle numbers of Li-ion batteries, the electrodematerials gradually become inactive, leading to the performance degradation of the battery. The battery State of Health (SoH) is an estimation to evaluate the battery capability status, by which the batteryrelated inner parameters including State of Charge (SoC) and remaining driving range can be accessed with higher precision. Accurate SoC estimations have always been a critical and important concern in the design of BMS. To design an efficient BMS, it is important to precisely acquire battery pack voltage, cell voltage, current and temperature of the EV battery.This paper proposed an efficient Battery Management System to estimate SoC and SoH accurately using LabVIEW based c-RIO Data Acquisition System (DAQ) with Support Vector Machine (SVM). In this work, the battery parameters have been precisely acquired through c-RIO DAQ based measurement and control system.The system swiftly process the acquired battery parameters and produced the Open Circuit Voltage (OCV), Current, Thermal parameters. These outputs of c-RIO DAQ were applied to the SVM module to estimate SoC and SoH of the battery pack precisely. The result ensured that the proposed system efficiently estimate the SoC and SoH over the coulomb counting method.
Keywords - Battery Management system (BMS), c-RIO, Electric Vehicles (EV), State of Charge(SoC), State of Health (SoH) and Support Vector Machine (SVM)

1. Introduction

Electric vehicles (EVs) are expected to improve the mobility of the future. It plays an important role in efficient energy utilization and zero–emission when in use. The battery has agreat impact on the performance of electric vehicles, basically determining the driving range. As a consequence, the choice of the battery technology and its effective utilization is of vital importance.Li-ion batteries are used in EVs is due to its good energy density, good power rating and charge/discharge efficiency. Usually, a large number of cells, depending on the application, are connected in series to build a battery string with the required voltage (up to 400V).EVs consist of four main components: an energy storage system (battery), mechanical transmissionsystem, motor, and power converter.

An efficient battery management system (BMS) is one of the primary components in EVs to guarantee the safe, reliable, efficient, and long-lasting operation of a Li-ion battery while dealing with the electric grid and challenging driving conditions (Xing et al., 2011; Lu et al., 2013; Hannan et al., 2017). Furthermore, an efficient BMS alsoprovides information on the battery states, such as the State of available Power (SoP), State of Charge (SoC), State of Life (SoL), and State of Health (SoH). The BMS can sense the battery voltage, batterycurrent, and temperature to avoid overcharge and over discharge conditions. These measuredparameters can be utilized to estimate the states of the Li-ion battery (Lu et al., 2013; Hannan et al., 2017). Accurate SoC estimations have always been a critical and important concern in the design ofBMS in EVs. Accurate and precise estimations can not only be used to evaluate the reliability of a battery, but also provide some important information, such as the remaining energy and/or remaining useable time (Zhang and Lee, 2011). In other words, the SoC shows the vehicle driving range or theremaining power of the battery in EVs. Furthermore, it prevents the Li-ion battery from overcharge/discharge. The Li-ion battery is a highly complex, time varying and nonlinear electrochemicalsystem; its performance changes due to different factors, such as the charge-discharge current, aging,and temperature variations. Therefore, accurate SoC estimation of Li-ion battery is a tricky taskbecause it cannot be directly assessed using any physical sensor. Currently, the Li-ion battery SoC and SoH estimation is a hot topic for researchers. In this paper, an efficient Battery Management System is proposed to precisely estimate SoC and SoH using LabVIEW Based c-RIO Data Acquisition System (DAQ) with Support Vector Machine to improve the life of battery and avoid occurrence of safety hazard.

2. Review of Literature

Estimating and controlling the SoC is vitally important in various power system applications such as Battery Energy Storage Systems (BESS) and Electric Vehicles (EVs).The Battery Management System is the brain of the battery pack, taking information from the various sensors within the pack as well as external data from the vehicle, running control algorithms using that data, and issuing control commands to actuators within the pack and performance data back to the vehicle. Battery Management System (BMS) is an Electronic Control Unit comprising of Hardware and Firmware controlling different functions of the Battery system.

The main functions of a BMS are Controlled charging/discharging to protect the battery from overcharging and deep discharging; to estimate the battery's states (SoC and SoH); to monitor the battery's temperature and cell balancing. The SoC is the most important index in aBMS to regulate charge/discharge decisions and to ensure the battery's safety,efficiency, and longevity. The researchers are emphasizing on the task of estimating the battery's states in the BMS.This section is going to elaborate the various existing techniques related to the estimation of SoC and SoH. Finally the section summarizes the gaps found in the existing SoC estimation techniques.

The most popular SoC estimation Techniques are shown in Fig.1

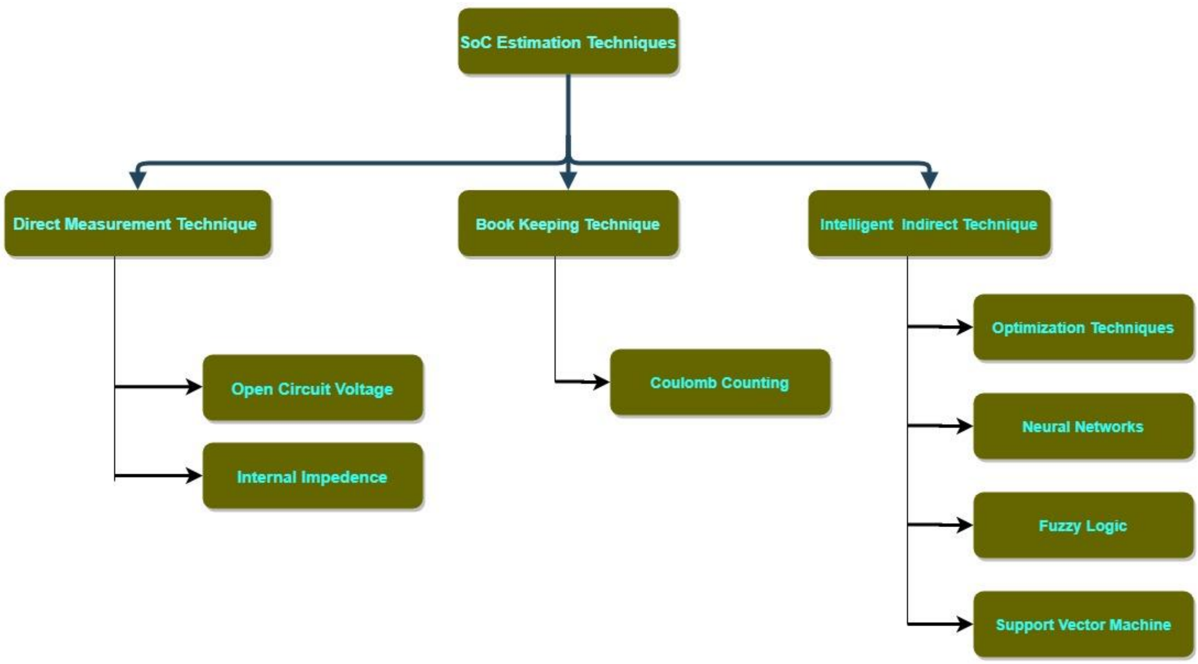

Fig.1 SoC Estimation Techniques

Precise SoC estimation reflects some significant information such as battery performance, remaining life of battery Ng et al., 2008) that ultimately lead to an effective management and utilization of the battery power and energy (Chang, 2013; Xiong et al., 2018). Furthermore SoC estimation can be used to regulate over-discharging andover-charging of the battery, which lead to a reduction in battery life, explosion or flame, accelerating aging and permanent damage to the cell structure of batteries (Ren et al., 2019) Accurate SoC indication is thus important for the user convenience and to ensurethe battery's efficiency, safety, and longevity. An accurate estimation of SoC is a fundamental consideration to eliminate failures due to thermal runaways and to regulate cell balancing (Gundogdu et al., 2018). Major clusters of SoC estimation techniques are Direct measurement technique, Book keeping Technique and Intelligent Indirect Technique.The details of various SoC and SoH estimation techniques are discussed in this section.

- **Direct Measurement Technique**

The foremost SoC estimation technique is Direct measurement technique. In this technique SoC value is estimated using physical measurements such as voltage and the impedance of the battery. A direct measurement SoC estimation technique can be classified into the Open Circuit Voltage (OCV) method and Internal Impedance (II) method.

The OCV method can be utilized to measure the SoC after an adequate pause to allow the battery to reach the equilibrium state. Open circuit voltage (OCV) is the battery thermodynamic potential under no load condition that has a nonlinear relationship with SoC for a Li-ion battery (Chang, 2013; Barai et al., 2015). The OCV is usually obtained through offline OCV test at definite ambient temperatures and aging stages (Xiong et al., 2017). Even though the open-circuit voltage (OCV) method is very accurate, it requires arest time to estimate the SoC and hence difficulty to be utilized in real world applications.OCV is present in Electrical Equivalent Circuit models (ECM) as an ideal but variable voltage source to which over-potential is added by the remaining resistor and capacitor elements of the ECM. The relationship between the SoC and OCV vary from battery to battery (Hussein, 2014). This method is very simple and highly accurate,but it needs long resting time to reach the equilibrium state. The resting time also depends on the environmental conditions. Moreover, careful measurements of the voltages are required due to the hysteresis characteristics of the battery.

In order to calculate the SoC using the impedance method, both voltage and current measurement are recorded at different excitation frequencies since the battery impedance depends on the frequency. The principle consists of injecting current in a certain range of frequencies to find impedance. The change of impedance is negligible for higher values of the SoC but when the SoC reaches a certain low SoC level, the impedance increases swiftly (Chang 2013). Recently, a direct current short pulse (DCSP) method has been proposed to determine the Internal Resistance (Bao et al., 2018). The value of the resistance is very low which is challenging to measure (Lu et al., 2013). Therefore,this method is not a good choice for SoC estimation. Impedance Spectroscopy was applied to measure the SoC of a Li-ion battery. In the IS method, currentfrequencies are applied across the Li-ion battery to determine the impedance (Barcellona et al., 2016; Westerhoff et al., 2016; Xu et al., 2013; Wu et al., 2018). Once theinternal impedance is known, it can be plotted easily against the SoC using Nyquist plot. The Nyquist plot impedance spectra is parted into three section: low frequency section, mid frequency section and high frequency section. The parameter identification is simplified due to thispartition process and the SoC can be estimated using ECM model-based methods. IS method can also be used for online SoC estimation. Even though there are many methods of estimating SoC based on IS, the complexity of using IS directly is considerable high.

- **Book keeping Technique**

The second method of estimating SoC is Book keeping Technique. Coulomb Counting (CC) technique is a kind of book keeping Technique.The CC method is based purely on the battery charging or discharging current. This method integrates the battery charging or discharging current over time to find SoC (Rivera-Barrera et al, 2017). The mathematicalform of the CC method is expressed in Eqn. 1

$$SoC(t) = SoC_0 - \frac{1}{C_{rated}} \int i(t)\, dt \tag{1}$$

Where SoC_0 is the initial SoC value and i(t) is the current of the battery with a negative value at charge, Crated is the rated capacity. The initial SoC value (SoC_0) can be obtained by OCV method. Even though the method is simple and inexpensive, since the coulomb counter is an open loop estimator, errors in the current sensor is added by the estimator. The cumulative error becomes larger, when the SoC estimator operates through a longer time period. Also, an incorrect result can be generated faster, when the current sensor has massive errors. When the battery ages in real time, the battery capacity varies, but the coulomb counter cannot detect or take measures for the issue. As a result, SoC estimation will not be accurate,if the real pattern of the battery estimation deviates from the expected pattern. The initial SoC should be measured by the terminal voltage of the battery pack. So any error contained in the initial estimation method will be carried throughout the process and this method cannot detect or repair the initial error. The Coulomb Counting method can be improved by considering the Coulombic efficiency (Ah) at different temperature and charge rates. The estimation of SoC using the modified CC Technique is given in Eqn. 2

$$SoC(t) = SoC_0 - \frac{1}{C_a} \int \eta_{eq} i(t) dt \tag{2}$$

η_{eq} and C_a representing the Equivalent Coulombic Efficiency (ECE); Among the different battery chemistries, Li-ion batteries offer the highest Coulombic efficiency in the normal SoC_{region} (exceeds 99%) (Chang et al., 2013; Tudoroiu et al., 2018). But the estimation of Coulomb efficiency is difficult task as it requires highly accurate equipment.

- **Intelligent Indirect Technique**

Intelligent Indirect Techniques are the popular artificial Intelligence based measurement techniques which use adaptive system to deal with the nonlinearities of battery systems and show considerably excellent accuracy. Some of the Intelligent Indirect Techniques are Genetic Algorithm, Neural network, Fuzzy Logic and Support Vector Machine measurement Techniques.

The genetic algorithm (GA) is a biologically inspired optimization method to find the unknown model parameters of a nonlinear system, such as a Li-ion battery. The GA generates a string of chromosomes randomly and uses biological operators, such as crossover, selection, and mutation, to find the optimal values. The voltage-capacity rate curve was used in (Zheng et al., 2013) and implemented a GA to model the battery pack. They used four cell series-connected Li-ion batteries and determined the capacities of the entire pack and individual cells.The GA was also implemented to find the second order ECM parameters of a battery (Chen. et al., 2013) The formula using identified diffusion capacitance was derived to determine the SoH of a Li-ion battery. The GA fused with some other model-based estimation methods was used to estimate the SoC.

Neural Network is a mathematical model (subfield of artificial intelligence) that consists of interconnected artificial neurons stimulated by biological neural networks and to predict the output of a nonlinear system past data of that system is used. Neural Network consists of inputs and outputs and is made of a number of processing units called neurons interconnected with each other. The accuracy of Neural Network method depends on how far the network is trained and the training process is the most important phase.The most two common network architectures to estimate the SoC are the nonlinear input-output (NIO) feed-forward network and nonlinear autoregressive with exogenous input(NARX) feed-back network.In regarding to the SoC estimation, the neural network method determines the SoC direct from the voltage and current without OCV-SoC look-up tables. Since the current, terminal voltage and temperature have the greatest influence on the SoC of the battery, these three parameters are chosen as the input of the network, the battery SoC value is chosen as the output, and the number of nodes in the hidden layer is set according to the experience.

Fuzzy logic method can be used to model, non-linear and time-varying systems without the need for mathematical models or ECMs of a battery (Ma et al., 2018). For the estimation of SoC using Fuzzy logic method, environmental temperature, applied current and battery terminal voltage are considered as the input variable balancing the complexity and accuracy well. The higher the number of input variables (dimensions of fuzzy controller), more accurate are the results. But when the dimension is higher, the rules of fuzzy control will be much complex to implement. The working principle of FL can be divided into the following stages: fuzzification, fuzzy rule base, inference engine, and defuzzification. In most fuzzy logic methods, the SoC value of the battery is predicted without the rated capacity or previous knowledge of the discharge history of the cell and only by measuring the imaginary component of the impedance at a few specific frequencies. The fuzzy logic approach considers the battery as a black box and simply maps Battery Management System,the input characteristics of the battery to its output characteristics. It does not include any physical description of the fundamental physicochemical processes (Singh et al., 2006; Malkhandi et al., 2006). This technique's usage can help in using entire information about battery performance to derive its more accurate state of health estimation. The authors (Li et al., 2006; Yan et al., 2013), applied the fuzzy logic methodology to Li-ion battery with EIS data. This data was pre-processed to bring out parameters that were used to develop precise fuzzy logic models for predicting SoH of the battery pack. The disadvantage of this approach is that it is not realistic for EVs and HEVs because the EIS data collection is not possible in a realistic environment.

An ANFIS is an advanced form of the artificial NN, which is based mainly on the Takagi–Sugeno fuzzy inference system. The ANFIS has the benefits of FL and NN in a single framework. ANFIS is an extraordinary tool for modeling, optimization, and nonlinear mapping. In (Chau et al., 2004), capacity and temperature distributions were taken into account to estimate the SoC.

Kumar Bijender (2017) presented SoC and SoH indication algorithms is to select an accurate algorithm and to design an advanced BMS capable of providing an accurate indication of battery state. Further, this research paper describes the Neuro-Fuzzy & statistical controllers to be incorporated in Advanced BMS for accurate monitoring of battery's SoC and SoH respectively. In Neuro-Fuzzy approach, a neural network is used to model a nonlinear electrochemical behavior of the Lead-acid battery. In statistical model, a regression method is employed to predict the SoH. This paper also describes MATLAB simulation of artificial neural network (ANN) model selected for Advanced BMS design & the Field Programmable Gate Array (FPGA) design scheme for BMS implementation.

In recent years, support vector machine (SVM) techniques have attracted considerable attention.The SVM is becoming a powerful tool to solve regression problems in nonlinear systems. The SVM uses different kernel functions and regression algorithms to transmute a nonlinear model into a linear model. SVM is a managed machine learning algorithm which can be used forboth classification and regression tasks.It performs classification tasks by constructing hyper planes in a multidimensional space.

In (Hussein, 2015), literature applied the method to build a battery health estimation model for EVs and HEVs. The literature in (Xu et al., 2014) proposed another method of weighted least squares support vector machine (WLS-SVM) to create the relationship of the state of charge with the cell potential, current and temperature. In (Tong et al., 2016) literature applied SVM to estimate remaining useful life (RUL) of a battery. One of the major limitations of SVM is the inadequacy of probabilistic outputs.In order to estimate SoC using SVM regression model temperature, current measurement and voltage are considered nonlinear input variables (Anton et al., 2013). Using a kernel function in the SoC estimation process, a training data set of the above input variable which covers the expectedrange of operation should be selected (Hansen and Wang, 2005; Guo et al., 2014).

Most of the SoC estimation techniques using Direct and Book keeping require very accurate measurements of either thebattery chemical content (type of electrolyte), its operating conditions or cell variables (voltage, current) and thus are only suitable for laboratory rather than real world applications. Literature related to intelligent indirect techniques choose optimization techniques, Neural network and Fuzzy Logic which are time consuming because of training the network and tuning the parameters. Support Vector Machines (SVM) is appropriate for any multi-variable function to a higher accuracy level. Also it can be applied effectively in highly nonlinear systems.

Hence the paper is proposing an efficient Battery Management System to estimate SoC and SoH accurately using LabVIEW based c-RIO DAQ with support Vector Machine to improve the lifetime of the battery. The following session will detail the architecture of the proposed system, estimation of SoC and SoH using SVM regression technique and results and discussion.

3. Proposed System

An efficient battery management system is developed using LabVIEW c-RIO based data acquisition measurement and control system integrating with Support Vector Machine (SVM). The components of the proposed system are Power Module, Li-ion battery pack, battery monitoring module comprising of c-RIO measurement and control system, SVM block, Electrical control, CAN bus communication and user interface.

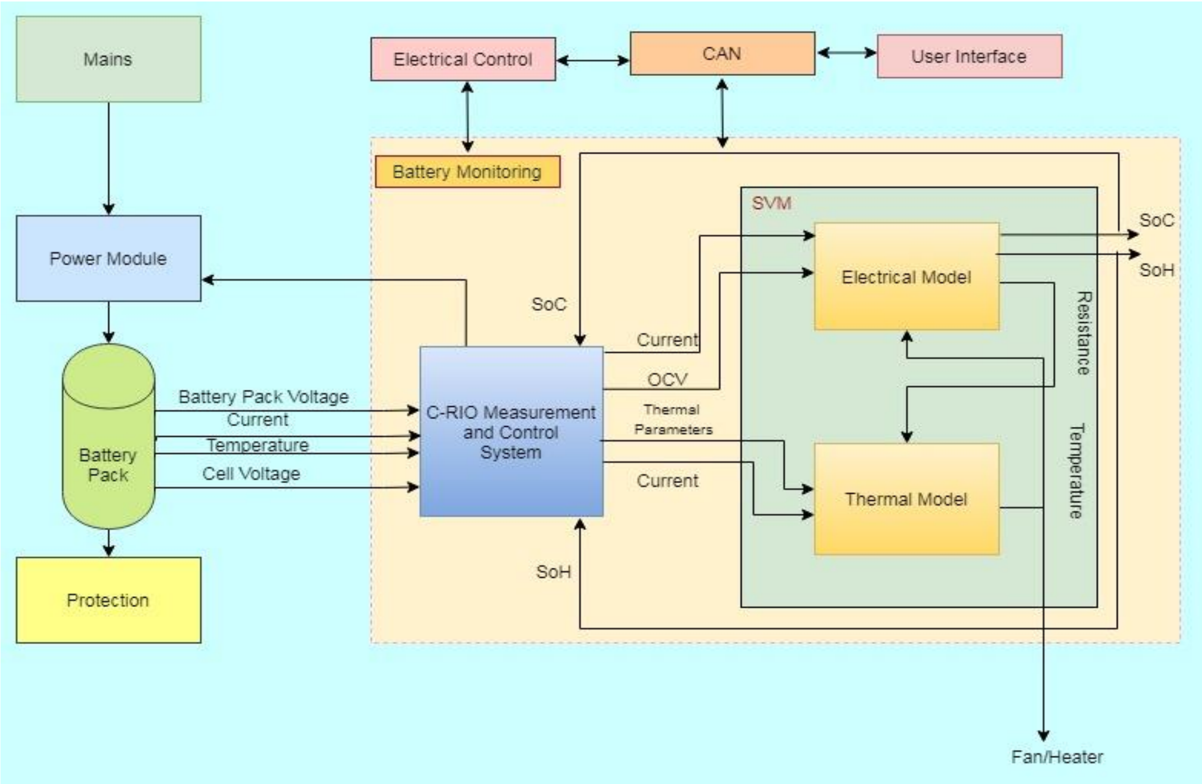

Fig 2. Proposed Battery Management system

The architecture of the Proposed Battery Management system is shown inFig.2. The Li-ion Battery is charged from the mains through the power module which is a power electronics converter circuit designed with compatibility to charge and maintain the health of the battery pack. Li-ion batteries exhibits high power capabilities, high energy density, low self-discharge, long life cycle and high number of charge discharge cycles, low operational and maintenance requirements, satisfactory operating temperature ranges, high reliability, technological diversity as compared to other standard battery types such as lead-acid and nickel cadmium (Awadallah and Venkatesh, 2016; Chun et al., 2015; Larsson et al., 2015; Zubi et al., 2018). However, over charging or over discharging of Li-ion batteries can cause permanent damage to the battery cells which may cause fire or even exploding batteries (He et al., 2011). So an accurate estimation of SoC can conserve the lifetime of batteries by preventing frequent charge and discharge. To estimate the SoC and SoH of the battery pack it is important toacquire the battery parameters, battery pack voltage,cellvoltage, current and temperature from the Li-ion battery packprecisely. The acquisition of these battery parameters are achieved using LabVIEW based c-RIO data acquisition system.c-RIO Controller is basically a Controller with Real-Time Processor and Reconfigurable FPGA. LabVIEW software (Rathy et al., 2019) is used to provide the user Interface and processing the acquired information from c-RIO DAQ. c-RIO is not only precisely acquiring the battery parameters but also processes the acquired parameters through FPGA module accurately with increased speed and communication with the user interfaces (Syaifuddin Mohd et al., 2013). The c-RIO DAQ measurement system swiftly process the acquired battery parameters and produces the OCV, current, Thermal parameters at the output. These output of c-RIO DAQ are applied to the SVM module which comprises of Electrical and thermal model block to estimate SoC and SoH of the battery pack . The acquired OCV and current obtained from the c-RIO is applied to the electrical model to estimate the internal resistance of the battery pack. Similarly the thermal parameters and current acquired from the c-RIO DAQ is applied to thermal model to determine the temperature of the battery pack. The determined temperature will control the fan/heater to maintain the ambient temperature of battery pack. Fig. 3 shows the flowchart of the proposed BMS.

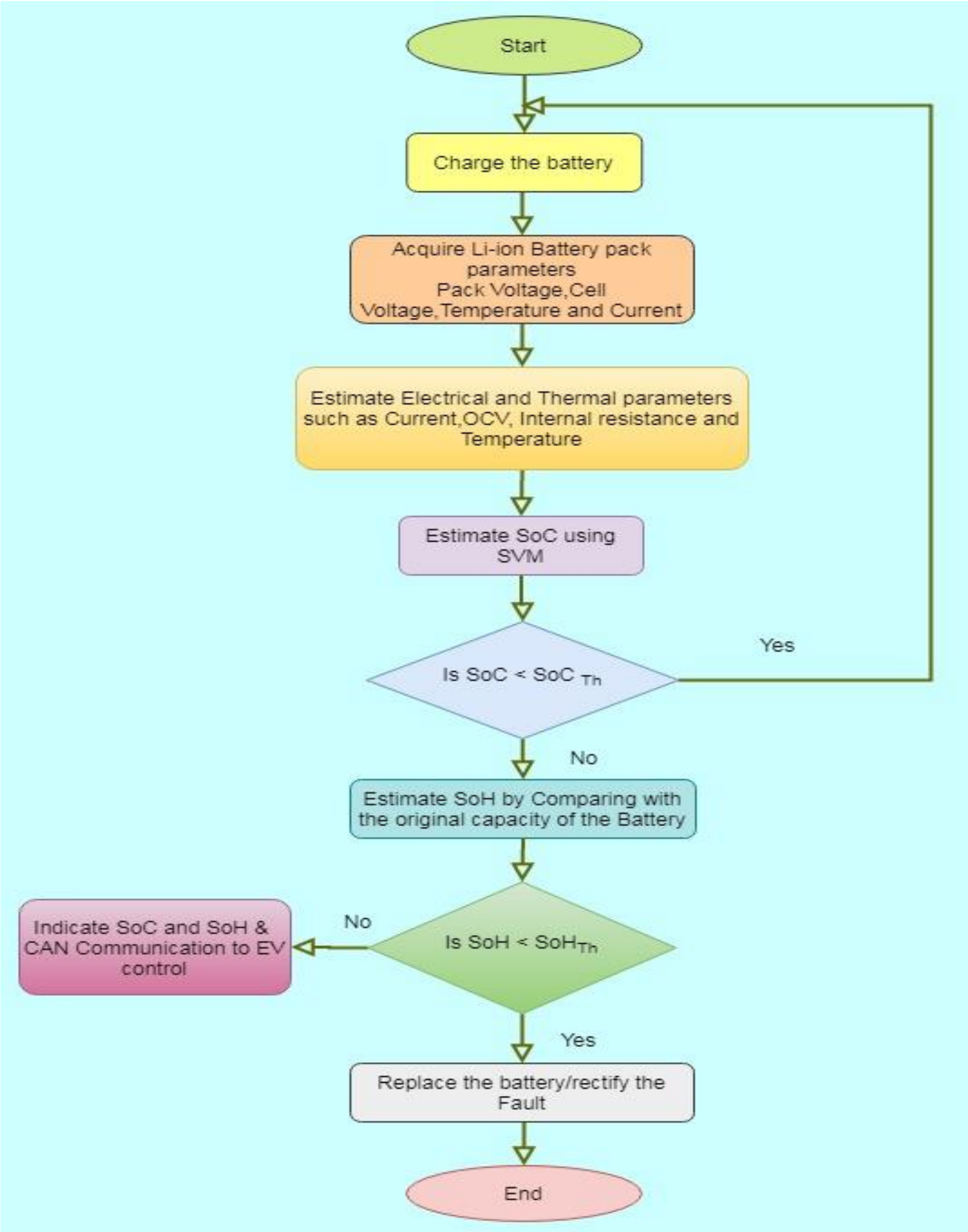

Fig 3.Flowchart of the Proposed Battery Management system

The SVM model uses the estimated temperature, internal resistance current and Voltage as nonlinear input variables to estimate SoC and SoH. Using a kernel function in the SoC estimation process, a training data set of the above input variable which covers the expected range of operation should be selected. The estimated SoC is again fed back to the c-RIO measurement and control system to generate the control inputs to the power module. The power Electronics circuit in the power module will be controlled according to the estimated SoC value to charge and maintain the health of the battery pack.

Similarly the estimated SoC and SoH can be effectively communicated to the external user interfaces of the EV through CAN BUS communication for monitoring Electrical Controls and operation. Front panel user interface application are developed using LabVIEW software. The implementation of the proposed system is detailed in the following section.

There are numerous algorithms for the classification of faults for machine tool diagnostics such as Bayesian classifier, Discriminant analysis, SVM and Artificial Neural Networks. SVM belong to the family of kernel methods, this method is highly popular in the field of supervised machine learning. It has several benefits when compared with other statistical classifiers like MLPs (Multi-Layer perceptron). MLP and RBF networks don't care about the quality of classification i.e, they stop converging in ending the hyper plane that correctly classifies the training data. Hyper plane is the classifier which separates two distinct classes. If the number of hidden neurons in Neural Network is big, the training error becomes small and this increases the generalisation error, computational complexity and this makes the usage intractable. The most significant benefit of SVM is higher efficiency in high dimensional nonlinear classification problems while the other statistical classifiers often fail in achieving it. In the condition monitoring and fault diagnosis problem, SVM is employed for recognizing special patterns from acquired signal, and then these patterns are classified according to the fault occurrence in the machine (MIT Electric Vehicle Team, 2008). After signal acquisition, a feature representation method can be performed to define the features, e.g., statistical feature of signal for classification purposes. These features can be considered as patterns that should be recognized using SVM. SVM is designed in achieving better minimization generalization error. SVM is more efficient in handling very large datasets, the dimensions of classified vectors does not effect the performance of SVM.

- **Estimating SoC using SVM Regression Technique**

The fastest growing area of artificial intelligence is statistical machine learning algorithms which enable to draw conclusions and make generalizations from the learning sets and the sample real time observation sets.The Support Vector (SV) method is the most important method which leans on a statistical base. The Support Vector group is made up from different variants of Support Vector Machine. The main task of the SVM method is to find the optimal solution but at the current level of development it can still be used for approximating functions and classifications as well. The SVM is applicable for real time applications thanks to its ability to make and implement decisions very quickly

One of the important characteristic feature of Support Vector Machine Regression is that instead of focusing on training error minimisation, it attempts to minimise the generalised error region so as to achieve a generalised response.In this work SVM regression technique is used to minimize the error in the estimation of SoC and SoH.

Considering a data training set, T, represented by Eqn.3

$$T = (x_{1,}y_1), (x_{2,}y_2), \dots, (x_{m,}y_m) \quad (3)$$

wherex are training inputs vector and y are training outputs or targets vector $\in R^n$.

In the proposed system, OCV, current, Temperature and internal resistance parameters will be the training input to the SVM. The Li-ion battery parameters are nonlinear in general. The nonlinear function used in the SVM to map the training input vector with the target output vector is given by Eqn.4

$$f(x) = W^T \emptyset(x_i) + b \quad (4)$$

where w ∈ R is the weight vector, b ∈ R is the bias, and $\emptyset(x_i)$ is the high dimensional feature space, which is linearly mapped from the input space x. Assume further that the goal is to fit the data T by finding a function f(x) that has a largest deviation from the actual targets for all the training data T, and at the same time is as small as possible.

The computation of SVM can be simplified by using Eqn. 5

$$p(x) = sgn(\sum_{j=1}^{n} \alpha_j y_j K(x_i, x_j) + b \quad (5)$$

Where α_j is the Lagrange multiplier of observation , and $K(x_i, x_j)$ is called the kernel function.A kernel methods works on data only through dot product, so that the orientation of original input space is not lost or changed and it is given in Eqn.6.

$$K(x, y) = K(x).K(y) \quad (6)$$

K(x) and K(y) are some kernel functions that is symmetric and satisfies Mercer's rules. When the functions follow the rules they are then considered to be valid Kernel functions capable of projecting x and y into higher dimension space. The selection of the kernel function of the model is very important when SVM is used to predict the Remaining Useful Life (RUL) of Li-ion battery. The use of SVM with different kernel functions will form different prediction models, which will produce different prediction accuracies and efficiencies. The four types of kernel functions commonly used in SVM are Linear, polynomial, Hyperbolic and Radial Basis Function. Radial basis function (RBF) kernel is a typical local kernel andPolynomial kernel is a typical global kernel. RBF kernel has local characteristics and has better learning capability. Moreover, the polynomial kernel function has global characteristics and has strong generalization performance. The performance and complexity of the RUL prediction model of the Li-ion battery are determined by the kernel function

The proposed work estimates SoC of the Li ion battery using RBF local kernel function because of its better learning capability which is given in Eqn.7 .

$$K(x_i, x_j) = e^{-\gamma \| (\gamma(x_i - x_j) \|^2)}, \gamma > 0 \quad (7)$$

$\gamma$is a parameter that adjusts the spread of kernel, or the deviation mainly used for nonlinear kernels.

Feature set refers to the final input data that is provided to the training algorithms. Feature selection is crucial for the development of good regression model. Proper feature selection can help us to simplify the design of battery model with important influencing details. On the other hand, improper feature selection will deteriorate the performance of the model. The proposed work suggest suggests that changing the sensor data will directly reflect on selected features i.e. different sensor measurements will have different features which are good for regression. In the presence of any categorical data, like in classification feature selection becomes a crucial issue.

Unlike classification, regression involves estimation of real value data. Therefore it is logical to consider the major input parameters affecting the output target value. It might be necessary to include additional parameters like, deviation of output measurements as an input, sample time intervals and also in some case product of input parameters. In the work the data-set is prepared in range from -1 to 1 for normalisation. From the trained data set and SoC is estimated using Eqn. (8)

$$SoC(\%) = a.V + b.\left(\frac{1}{V'}\right) + c \quad (8)$$

where a, b, and c are regression coefficients.

$$V' = \frac{\Delta V}{\Delta t}$$

ΔV is the voltage drop in the discharging process

A battery's SoH normally ranges from 0–100% and it is 100% when the battery is new. The end of life of a Li-ion battery is commonly defined by the maximum cycles when the SOH drops to 80%. SoH is a key indicator of safe operation because it provides a timely warning that replacement is required.

The SoH of the lithium-ion battery is described by the loss of rated capacity, which is given in Eqn. (9)

$$SoH = \frac{C_{bat}}{C_{nom}} \times 100\% \quad (9)$$

Where C_{nom} and C_{bat} denote the nominal and actual battery capacity, respectively.
C_{bat} gradually decreases with battery aging. Now SoH is determined by Eqn. (10)

$$\mathrm{SoH}(\%) = \alpha(\mathrm{SoC}).[\mathrm{A}.\left(\frac{1}{\mathrm{V}'}\right) + \mathrm{B}] \quad (10)$$

Where A and B are regression coefficients.

The algorithm for the Estimation of SoC using SVM regression technique for an Efficient Electric Vehicle Battery Management System using c-RIO DAQ is as follows:

Step 1: Initialise the proposed system by charging the Li-ion battery.

Step 2: Acquire the Li-ion battery pack parameters such as pack voltage, cell voltage, temperature and current using LabVIEW based c-RIO measurement and control system.

Step3: Obtain Electrical and Thermal parameters such as current,OCV,internal resistance and temperature of the Li-ion battery pack.

Step 4: Apply the obtained real time electrical and thermal parameters as the training input vector to the SVM $and\ T = (x_{1,}y_1), (x_{2,}y_2), \dots, (x_{m,}y_m)$where x are training inputs vector and y are training outputs or targets vector ∈ R^n. Use the nonlinear function $f(x) = W^T \emptyset(x_i) + b$ to map the training input vector with the target output vector.

Step5: Achieve linear decision using SVM regression function

$p(x) = sgn(\sum_{j=1}^{n} \alpha_j y_j K(x_i, x_j) + b$, where $K(x_i, x_j)$ is called the kernel function and $K(x_i, x_j) = e^{-\gamma \| (\gamma(x_i - x_j) \|^2)}$,$\gamma > 0$,γis a parameter that adjusts the spread of kernel

Step 6: Estimate SoC using $SoC(\%) = a.V + b.\left(\frac{1}{V'}\right) + c$

Step 7: If the estimated $SoC<SoC_{TH}$ go to step 1 else go to step 8

Step 8: Estimate SoH by comparing with the original capacity of the Battery and obtained using $\mathrm{SoH}(\%) = \alpha(\mathrm{SoC}).[\mathrm{A}.\left(\frac{1}{\mathrm{V}}\right) + \mathrm{B}]$

Step 9: If $SoH<SoH_{TH}$ then go to step 10 else indicate SoC and SoH using LabVIEW based user interface and communicate the same to the EV control through CAN bus communication

Step 10: Replace the battery/ rectify the fault

4. Results and Discussion

This section is going to present the performance analysis of the proposed work. In the proposed work the experiments are carried out using Li ion batteries. The Li-ion batteries operate at room temperature in three different operating conditions, namely, charge, discharge, and full impedance. Charge mode: Charging was implemented in a constant current mode of 1.5 A until the battery voltage reached 4.2 V, and then maintained a constant voltage mode until the charge current is reduced to 20 mA. Discharge mode: Discharging was conducted at a constant current level of 2 A until the battery voltage dropped to 2.8V. Repeated charge and discharge cycles are the main causes of the accelerated fading of a battery. When Li-ion batteries reached up to 30% rated capacity aging (this experiment is from 2 Ah to 1.4 Ah), the experiments were stopped and the Li-ion batteries were considered to have reached their end of life.

The battery parameters such aspack voltage, cell voltage, temperature and current are acquired using LabVIEW based c-RIO DAQ measurement and control system. SoC and SoH are estimated using SVM regression technique. The size ofdataset used is 3072x4, hence the random split covered wide. The experiments were carried out using LabVIEW software and the results are monitored using LabVIEW based user interfaces and applied for EV control.

The proposed system is RBF kernel function and the SVM regression model is trained by applying different kernel spread, no of support vector and weights for the data set of 3072x4. Rsq and MSE with training and prediction time are obtained for different RBF function and tabulated in table 1.From the table it is observed that the proposed SVM regression model is showing better performance such as Rsq value of 0.9982 and the MSE value of 3.174e-05 with the training time of 58.31 and prediction time of 0.062 over the RBF input functions. Rsq is measured using Eqn. (11).

$$R_{square} = 1 - \frac{Sum\ of\ Squares\ of\ Error}{Square\ of\ Sum\ of\ Error} \quad (9)$$

Table 1.Computation of Rsq and mse for the RBF kernel function with different input parameters

Kernel	RBF	RBF	RBF
γ	0.5	1.0	5.0
No of support vectors	128x4	256x4	512x4

Weights	128	256	512
Training time	82.71	74.89	58.31
Prediction time	0.81	0.34	0.062
Rsq	using 0.9741	0.9832	0.9982
Mean square error(MSE)	0.00064	0.000087	3.174e-05

Fig 4. Cycles Vs SoH compares the SoH performance of estimated by the proposed system with the SoH value computed through experimental results for the different cycles from 0 to 1200. The SoH performance varies from 100% - 80% for the cycles 0-600. Then the SoH performance drastically reduced to 28% for the cycles 1200. From the fig 5 it is observed that the estimated and experimental results are almost similar.

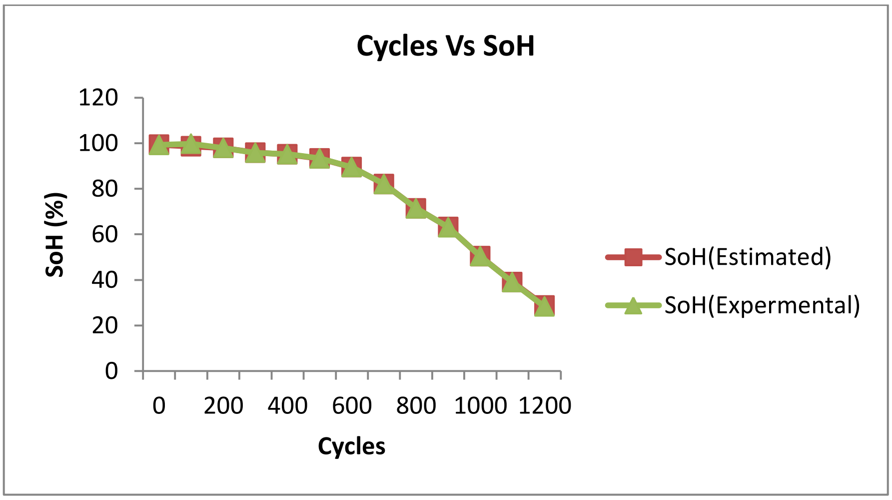

Fig 4. Cycles Vs SoH

Fig. 5 compares the SoH performance of the proposed system with the existing conventional coulomb counting technique. From the graph it is inferred that the proposed SVM based technique improves the SoH performance considerably over the existing. For 1200 cycles the proposed system achieved 28.76% of SoH and the existing system achieved 18.11%. The SoC performance comparison of the proposed SVM based technique with the couloumb counting technique in respect of battery voltage is shown in Fig 6. From the figure it is observed that the proposed system performs better in retaining the battery voltage for a longer time over the existing technique.The improvement is due to the precise acquisition of Li-ion battery parameters using c-RIO DAQ measurement and control system and the estimation through SVM regression technique. In the existing techniques the data acquisition is carried out using the conventional controllers. Also the estimation is performed using LabVIEW programming tool which is specifically designed for measurement and automation.

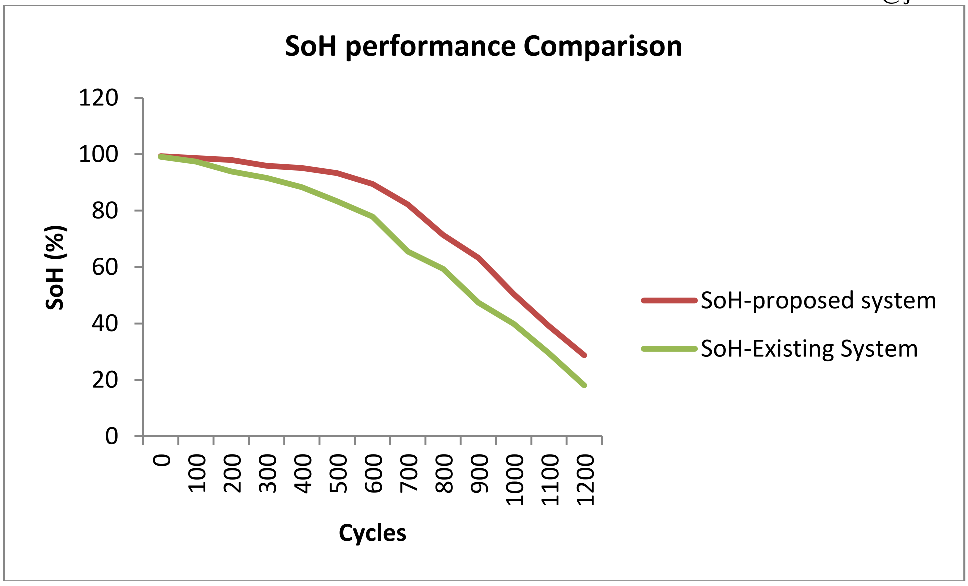

Fig 5.SoH performance comparison

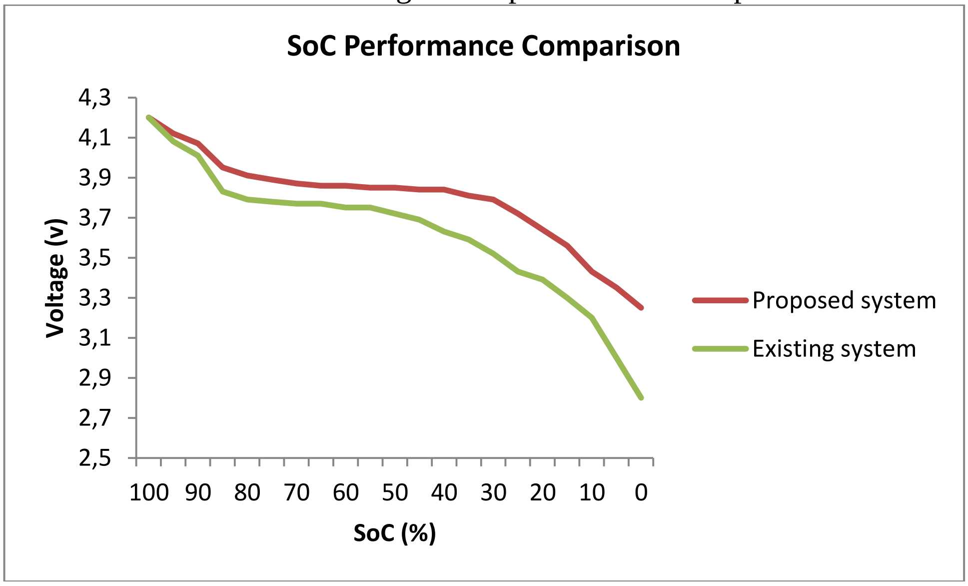

Fig 6.SoC performance comparison

5. Conclusion

An efficient Battery Management System was proposed to precisely estimate SoC and SoH using LabVIEW based c-RIO DAQ with SVM. In the proposed work, the battery parameters such as battery pack voltage, cell voltage, current and temperature of the EV battery have been precisely acquired through LabVIEW based c-RIO DAQ measurement and control system.The c-RIO DAQ measurement and control system swiftly process the acquired battery parameters and produced the Open Circuit Voltage (OCV), Current, Thermal parameters as output. These outputs of c-RIO DAQ were applied to the SVM module which comprises of electrical and thermal model block to estimate SoC and SoH of the battery pack precisely. The RBF kernel function is used in the SVM regression model to estimate SoC accurately. The result ensured that the proposed system efficiently estimated the SoC and SoH over the coulomb counting method and improved the life time of the battery.

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