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Smart Battery System Applied to a Hybrid Electric Vehicle

Jenie Archana. J[1], Mathivadhana. R[2], Guruprasath. R[3], Dhanish. K[4], Madhusudhanan. G[5]

[1,2,3,4]*Student, Valliammai Engineering College, Kanchipuram, Tamil Nadu*
[5]*Assistant Professor, Valliammai Engineering College, Kanchipuram, Tamil Nadu*

ABSTRACT

The use of green energy is becoming increasingly more important in today's world. Therefore, electric vehicles are currently the best choice for the environment in terms of public and personal transportation. Because of its high energy and current density, lithium-ion batteries are widely used in electric vehicles. Unfortunately, lithium-ion batteries can be dangerous if they are not operated within their Safety Operation Area (SOA). Therefore, a battery management system (BMS) must be used in every lithium ion battery, especially for those used in electric vehicles. In this work, the battery is evaluated by calculating the state of charge, state of life, charging and discharging control and by cell balancing algorithm. High precision estimation can maintain the battery cells working at a good situation and extend the service life of the battery pack, reducing the cost of use indirectly. This is meaningful for Li-ion battery's industrial application.

Keywords: *Battery Management Systems, Hybrid Vehicles, Smart Battery, Microcontroller and State of Charge.*

1. INTRODUCTION

Electric vehicles (EVs) are expected to play an important role in sustainable mobility thanks to the efficient energy utilization and zero–emission when in use. The battery has a great 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 paramount importance. From today's perspective, Li-ion chemistry is the battery technology of choice due to its good energy density, good power rating and charge/discharge efficiency in pulsed energy flow systems. Usually, a large number of cells, depending on the application, are series connected to build a battery string with the required voltage (up to 400 V). Li-ion chemistry is very sensitive to overcharge and deep discharge, which may damage the battery, shortening its lifetime, and even causing hazardous situations. This requires the adoption of a proper Battery Management System (BMS) to maintain each cell of the battery within its safe and reliable operating range. In addition to the primary function of battery protection, a BMS should estimate the battery status in order to predict the actual amount of energy that can still be delivered to the load. This is quite a challenging task, as the performance of the battery in terms of usable capacity and internal resistance, varies over time. Another important function of a BMS is to extend the battery life by facing the charge unbalancing issue that may arise in series-connected cells. This reduces the usable capacity of the battery because the least charged cell determines the end of discharge, even if there is still energy stored in the other cells of the battery.

Due to the strict voltage limits applying to Li-ion batteries, charge unbalancing cannot be self-recovered, but instead worsens with time. Indeed, when one cell reaches the upper voltage limit, the charging process must be interrupted causing some cells not to be fully recharged. Even assuming that all the cells have the same capacity (capacity mismatch is typically limited to only a few percents), charge unbalancing can be caused by cells with different self– discharge rates. This mismatch can also be determined by a temperature gradient along the battery string. A BMS should thus implement a charge equalization technique to periodically restore the balanced condition. The purpose of this paper is to describe the main issues in the design and management of a battery for an electric vehicle. The paper covers aspects ranging from Li-ion technology, to BMS requirements and architectures and techniques for battery status estimation and charge equalization. They are then applied to the design of an innovative BMS to be integrated in an electric vehicle.

2. LITHIUM-ION BATTERY

Lithium is the lightest metal with the greatest electrochemical potential and the largest energy density per weight of all metals found in nature. Using lithium as the anode, rechargeable batteries could provide high voltage, excellent capacity and a remarkably high-energy density. However, lithium is inherently unstable, especially during charging. Therefore, lithium ions have replaced lithium metals in many applications because they are safer than lithium metals with only slightly lower energy density. Nevertheless, certain precautions should be made during charging and discharging.

The lithium-ion battery requires almost no maintenance during its lifecycle, which is an advantage that other batteries do not have. No scheduled cycling is required, and there is no memory effect in the battery. Furthermore, the lithium-ion battery is well suited for electric vehicles because its self-discharge rate is less than half of the discharge rate of lead-acid and NiMH batteries.

Despite the advantages of lithium-ion batteries, they also have certain drawbacks. Lithium ions are brittle. To maintain the safe operation of these batteries, they require a protective device to be built into each pack. This device, also referred to as the battery management system (BMS), limits the peak voltage of each cell during charging and prevents the cell voltage from dropping below a threshold during discharging. The BMS also controls the maximum charging and discharging currents and monitors the cell temperature.

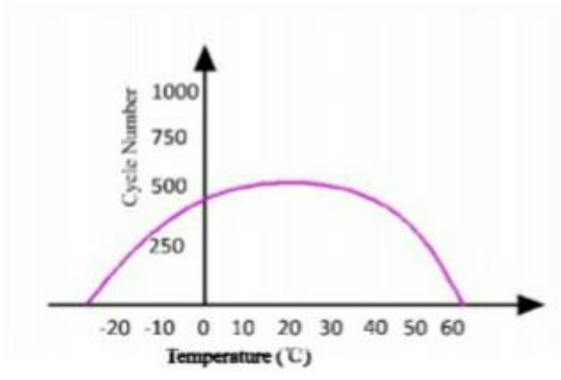
3. LITHIUM BATTERY CHALLENGES

The operating temperature and voltage are the most important parameters that determine the performance of lithium-ion cells.The cell could be permanently damaged if it is operated outside the safety zone. The batteries could be charged above its rated voltage or be discharged under the recommended voltage. If the recommended upper limit of 4.2 V was exceeded during charging, excessive current would flow and result in lithium plating and overheating.

On the other hand, overly discharging the cells or storing the cells for extended periods of time would cause the cell voltage to fall below its lower limit, typically 2.5 V. This could progressively break down the electrode.

The operating temperature of lithium-ion cells should be carefully controlled because excessively high or low temperatures could damage the cell. Temperature-related damages could be grouped into three types: low-temperature operational impact, high temperature operational impact and thermal runaway.

While the effects of voltage and temperature on cell failures are immediately apparent, their effects on the lifecycle of the cells are not as obvious. However, the cumulative effects of these digressions may affect the lifetime of the cells. Figure shows that the lifecycles of the cell would be reduced if its operating temperature falls below approximately 10 °C. Similarly, their lifecycles would be reduced if the cells were operated above 40 °C. Furthermore, thermal runaway would occur when the temperature reached 60 °C. The thermal management system, which is part of the BMS, must be designed to keep the cells operating within its limitation at all times.



It is clear from the discussion above that the goal of the BMS is to keep the cells operating within their safety zone; this could be achieved using safety devices such as protection circuits and thermal management systems.

4. PROPOSED SYSTEM

BATTERY MANAGEMENT SYSTEMS (BMS):

There are different types of BMSs that are used to avoid battery failures. The most common type is a battery monitoring system that records the key operational parameters such as voltage, current and the internal temperature of the battery along with the ambient temperature during charging and discharging. The system provides inputs to the protection devices so that the monitoring circuits could generate alarms and even disconnect the battery from the load or charger if any of the parameters exceed the values set by the safety zone. The battery is the only power source in pure electric vehicles. Therefore, the BMS in this type of application should include battery monitoring and protection systems, a system that keeps the battery ready to deliver full power when necessary and a system that can extend the life of the battery. The BMS should include systems that control the charging regime and those that manage thermal issues.

In a vehicle, the BMS is part of a complex and fast-acting power management system. In addition, it must interface with other on-board systems such as the motor controller, the climate controller, the communications bus, the safety system and the vehicle controller.

DEFINITION OF THE BMS:

While the definition of a BMS could differ depending on the application, the basic task of the BMS could be defined in the following manner, according to:

- It should ensure that the energy of the battery is optimized to power the product;
- It should ensure that the risk of damaging the battery is minimal;
- It should monitor and control the charging and discharging process of the battery.

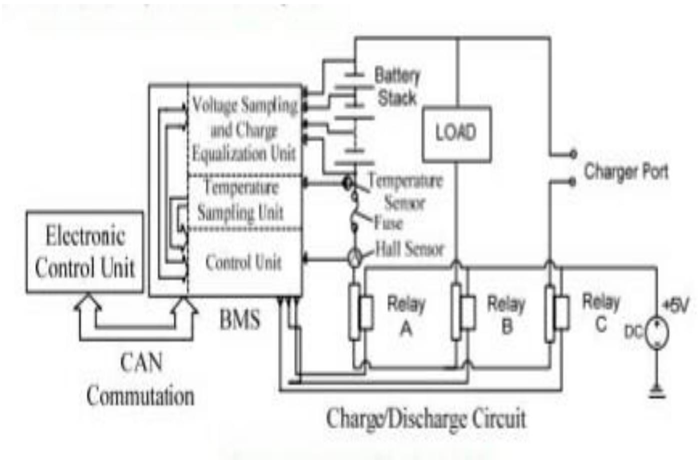
OBJECTIVES OF THE BMS:

According to the definition, the basic tasks of the BMS are identical to its objectives. Although different types of BMS have different objectives, the typical BMS follows three objectives:

- It protects the battery cells from abuse and damage;
- It extends the battery life as long as possible;
- It makes sure the battery is always ready to be used.

HARDWARE STRUCTURE OF THE BMS:

The main function of the BMS is to monitor and maintain the energy system of the electric mobile. The structure of the BMS is shown.



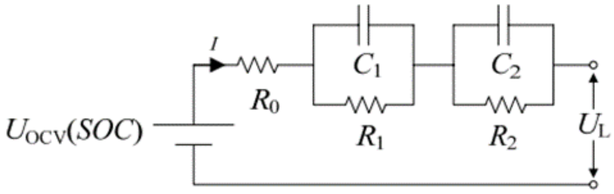
In Figure, the power system of the electric vehicle is composed of BMS, charge/discharge circuit and a battery stack. BMS is the control centre of the whole system, controlling the charge/discharge circuit through relay A, B, and C, monitoring voltage, current, the temperature of the battery stack through measurement units, and communicating with the electronic control unit (ECU) through CAN communication. When the relay A and B connect, the battery stack supply power for the electric vehicle, and when the relay A and C connects, the charger charges the battery stack. The BMS has many measurement units. Temperature sampling unit monitors the battery stack's temperature through a temperature sensor, and if the battery stack's temperature is out of the safety range resulting from overcurrent or other faults of the system, BMS would shut down the whole circuit to avoid permanent damage of the battery stack or even explosion accidents. Voltage sampling unit measures each cell's voltage and the battery stack's total voltage, and BMS implements over-charge/over-discharge protect and charge equalization through the voltage information. Current sampling unit measures the current through the Hall sensor allocated in the charge/discharge circuit. Current information is the most important signal to estimate the battery stack's SOC. In the positive pole, a fuse is allocated to shut down the circuit in case that the current surges because of a short circuit or other faults.

METHODOLOGIES FOR BATTERY EVALUATION IN BMS:

Based on the analysis above, it can be seen that the evaluation of battery status is one of the weakest links in BMS and yet it has a large impact on BMS performance. The top concern for EV users is the safety and reliability of the power system in a vehicle. The most important question is whether they will run out of battery power on the road. These issues refer to the estimation and prediction of SOC, SOH, and SOL of the EV battery. Thus, an accurate quantification of the battery status has become one of the most critical tasks for BMSs. In this section, the latest methodologies for battery state estimation and prediction are reviewed.

5. SOC ESTIMATION BASED ON EKF

SOC estimation of the battery stack is one of the most important functions of BMS, the base to maintain the battery stack working within a reasonable range, and also one of the most difficult parts in BMS design. The most widely used SOC estimation method is ampere-hour integration approach. Its principle is computing out the change of the charge by integrating current, adding the changed change to the initial charge and the whole charge can be computed out. This method is easy to implement, however, its estimation precision is often not satisfying and will divergence with time. In this article, we apply EKF in the SOC estimation, which is a nonlinear estimation method with high precision. In this method, the SOC of the battery stack is a state variable, and the state equalization is set up upon the battery model and the basic principle of ampere-hour integration approach.



Li-ion Battery Model

R0 is the internal resistance of a cell, R1C1, R2C2 is two RC loops to simulate the polarity effect of a cell. UOCV(SOC) is the open circuit voltage of a cell, which is the function of the battery SOC. The parameters of a cell above can be measured through hybrid pulse

$SOC(k+1)=Q(k+1)/Q_0=(Q(k)+I\Delta t)/Q_0=SOC(k)+\Delta Ti/Q_0$

Where k denotes sampling time.Any nonlinear system state equation can be written as

X(k)=AX(k-1)+BU(k-1)+W(k)

Z(k)=g(X(k),U(k))+V(k)

Set the voltages of R1C1, R2C2 separately is U1, U2, and the current is I, the relationship between voltage and current of the RC loop is

$Du_1/dt=(-1/R_1C_1)U_1+I/C_1$

$Du_2/dt=(-1/R_2C_2)U_2+I/C_2$

Defining time constant $t1=R_1C_1$,$t2=R2C_2$,then

$$U_{OCV}(SOC)=IR_0+U_1+U_2$$
$$U_1=U_1(0)e^{-\frac{t}{\tau_1}}+IR_1(1-e^{-\frac{t}{\tau_1}})$$
$$U_2=U_2(0)e^{-\frac{t}{\tau_2}}+IR_2(1-e^{-\frac{t}{\tau_2}})$$

Where U1(0), U2(0) is the initial voltage of capacitance C1, C2. Most SOC estimation methods based on EKF adopt 3-rank polynomial to match OCV-SOC curve, which has a big error. In this article, we adopt 6-rank polynomial and an exponential function to match OCVSOC curve, which improves the matching precision remarkably.

$$U_{OCV}(SOC)=a_0+a_1SOC+\cdots+a_6SOC^6+b_0e^{b_1SOC}$$

The parameters a0, a1…a6, b0, b1 only relate to the battery character. According to reference, the open circuit voltage (OCV) can be measured quickly, and the parameters can be estimated by the least squared method according to the OCV-SOC curve. The sampling time is denoted Δt, and the electric quantity denoted Q0, then the relation

$$\begin{bmatrix} SOC(k+1) \\ U_1(k+1) \\ U_2(k+1) \end{bmatrix}=\begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\Delta t/\tau_1} & 0 \\ 0 & 0 & e^{-\Delta t/\tau_2} \end{bmatrix}\begin{bmatrix} SOC(k) \\ U_1(k) \\ U_2(k) \end{bmatrix}+\begin{bmatrix} \Delta t/Q_0 \\ R_1(1-e^{-\Delta t/\tau_1}) \\ R_2(1-e^{-\Delta t/\tau_2}) \end{bmatrix}I(k)+W(k)$$
$$U_L(k)=U_{OCV}(SOC(k))+I(k)R_0+U_1(k)+U_2(k)+V(k)$$

$Z(k)=U_L(k)$, and the matrix $A=\begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\Delta t/\tau_1} & 0 \\ 0 & 0 & e^{-\Delta t/\tau_2} \end{bmatrix}$

Where X denotes state variable, U denotes input signal, Z denotes measured output signal, W and V separately denotes driving noise and measured noise, which are not uncorrelated white noises, whose variance matrix is separately denoted Q and R.Where the state variable is X(k)=[SOC(k), U 1(k), U2(k)]T, and the input signal is U(k)=I(k), measured output Z(k)=UL(k).

$$C(k) = \frac{\partial g(X(k),U(k))}{\partial X(k)} = [\frac{dU_{OCV}(SOC(k))}{dSOC(k)},$$

Basing on the recursive algorithm of EKF, the SOC of the battery stack can be estimated with the following process:

Step1: The prediction of the system state at time k is X(k|k-1)=AX(k-1|k-1)+BU(k-1)

Step2: The prediction of the covariance matrix of the state error is P(k|k-1)=AP(k-1)AT+Q

Step3: The measuring-state transfer matrix is

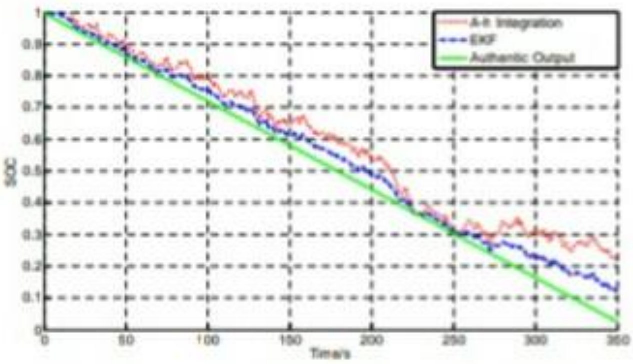
$$C(k) = \frac{\partial g(X(k),U(k))}{\partial X(k)}$$

Step4: The gain matrix Kg is K g(k)=P(k|k1)C(k)[C(k)P(k|k-1)C(k)T+R]-1

Step5:The optimal estimation of the system state at time k isX(k|k)=X(k|k-1)+Kg(k)[Z(k)-g(X(k),U(k))]

Step6: The covariance matrix of the state error at time k isP(k|k)=[1-Kg(k)C(k)T]P(k|k-1)

Discharging a Li-ion cell with a nominal voltage of 3V, and estimating its SOC utilizing ampere-hour integration approach and EKF separately according the current and voltage information, the estimation error of ampere-hour integration approach is 15.48%, and the EKF method is 7.27%. The SOC curve is shown in Figure



It is showed clearly that by utilizing EKF method, the SOC estimation precision is improved remarkably comparing with ampere-hour integration approach.

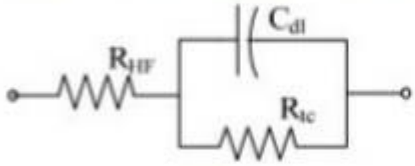
6. STATE OF HEALTH (SOH)

SOH describes the physical condition of a battery, ranging from internal behavior, such as loss of rated capacity, to external behavior, such as severe conditions. Unlike SOC, there is no clear-cut definition of SOH. A general definition of SOH is that it reflects the health condition of a battery and its ability to deliver specified performance compared to a fresh battery.The SOH in EV applications is used to characterize the ability to drive a specific distance or range. SOH in HEV applications is a characteristic of the specified power, such as the cranking power from regenerative braking.

Scholars and manufacturers use the percentage of nominal capacity as the health threshold of the battery. When the capacity reduces to 80% of the beginning of life capacity after charge-discharge cycling, it is defined as battery failure. However, studies have defined different rules or indicators to quantify the SOH in terms of battery characteristics, test equipment, and different applications.When combining capacity fade and power fade as health characteristics, Capacity fade indicates the decrease in the driving range with a fully charged battery pack, and power fade indicates the reduced acceleration capability.

Both of these features were input into an auto-regressive Support Vector Regression (SVR) model to estimate SOH. Here, the power fade was due to an increase in cell impedance during aging. The total resistance ($R = R_{HF}+R_{tc}$) was obtained from EIS data using nonlinear least squares, where RHF and Rtc are the high-frequency resistance and the transfer resistance.

A sample entropy (SampEn) could be taken as input data to predict SOH for target vectors of an intelligent system. SVM and its Bayesian version, relevance vector machine (RVM) were used to compare the predictive performance. Randles circuit model for a lithium-ion battery.



$$P = \frac{V^2}{R}$$

$$\text{Power Fade} = 1 - \left(\frac{\text{Power}(k)}{\text{Power}(0)}\right) = 1 - \frac{R(0)}{R(k)}$$

$$\text{Capicity Fade}(\%) = 1 - \left(1 - \frac{\text{Capacity}(k)}{\text{Capacity}(0)}\right) \times 100\%$$

The results also demonstrated that SampEn could serve as an indicator of SOH. SampEn is expressed as

$$\text{SampEn}(m, r, N) = -In\left[\frac{A^m(r)}{B^m(r)}\right]$$

where N is the total number of data points, m is the length of sequences to be compared, r is the tolerance parameters, B^m (r) is the mean value of two similar signal segments that are composed of input vectors with m points, and A^m r()is similar to B^m (r) and will match for m+1 points.

7. STATE OF LIFE (SOL)

SOL is also known as the remaining useful life (RUL) of a battery. Accurate SOL predictions will facilitate failure prevention and maintenance to prolong the service life of batteries. The increasing requirements for battery reliability, especially in military products, have promoted the development of state-of-the-art algorithms.

$$RUL(k) = h(\{P(i), C(i)\}_{i=1}^{k})$$

The RUL of a battery could be predicted using a moving average SVR for different thresholds of capacity fade C i( ) and power fade P i( ), where k is the k th week. The RUL for an end-of-life criterion is approximately 23% power fade and 30% capacity fade. RVM can provide the probabilistic interpretation of its outputs.RVM regression can be used to predict SOH in the capacity fade. The results suggested that RVM produced a more accurate prediction than the SVM model. The likelihood of a data set can be written as Equation.

$$p\left(\mathbf{t}|\boldsymbol{\omega}, \sigma^2\right) = \left(2\pi\sigma^2\right)^{N-2} \exp\left\{-\frac{1}{2\sigma^2} \|\mathbf{t} - \Phi\boldsymbol{\omega}\|^2\right\}$$

where Φ is the N ×N + (1) design matrix with $\Phi_{nm} = \{1, K(x_i, x_1), K(x_i, x_2), \cdots, K(x_i, x_N)\}^T$ N is the number of input vectors; ω ={ω1 ,ω2 ,.. ,ωN } is the regression coefficient vector; ω0 is the bias; and K xx (, i) is the kernel function.

RVM regression model, could also be used which was built using internal battery parameters from EIS data. This methodology combined the parameters of an offline model with an online state process. RVM regression was used to fit the related parameters of the exponential models with a probabilistic output. The exponential model is:

$$\bar{x} = C_x \exp(\lambda_x t)$$

where x is the model's predicted value. In this case, x includes charge transfer resistance, RCT , and electrolyte resistance, RE . The fitted parameters (λ RCT , λRE) were input into the online particle filter (PF) process. Based on the combination of PF and RVM, the end of life point can be determined with a narrower probability density function (pdf).

8. DISCHARGING CONTROL

The primary goal of a BMS is to keep the battery from operating out of its safety zone. The BMS must protect the cell from any eventuality during discharging. Otherwise, the cell could operate outside of its limitations.

9. CHARGING CONTROL

Batteries are more frequently damaged by inappropriate charging than by any other cause. Therefore, charging control is an essential feature of the BMS. For lithium-ion batteries, a 2-stage charging method called the constant current-constant voltage (CC-CV) charging method is used. During the first charging stage (the constant current stage), the charger produces a constant current that increases the battery voltage. When the battery voltage reaches a constant value, and the battery becomes nearly full, it enters the constant voltage (CV) stage. At this stage, the charger maintains the constant voltage as the battery current decays exponentially until the battery finishes charging.

10. CELL BALANCING

Cell balancing is a method of compensating weaker cells by equalizing the charge on all cells in the chain to extend the overall battery life. In chains of multi-cell batteries, small differences between the cells due to production tolerances or operating conditions tend to be magnified with each charge-discharge cycle. During charging, weak cells may be overstressed and become even weaker until they eventually fail, causing the battery to fail prematurely.

To provide a dynamic solution to this problem while taking into account the age and operating conditions of the cells, the BMS may incorporate one of the three cell balancing schemes to equalize the cells and prevent individual cells from becoming overstressed: the active balancing scheme, the passive balancing scheme, and the charge shunting scheme.

In active cell balancing, the charge from the stronger cells is removed and delivered to the weaker cells.

In passive balancing, dissipative techniques are used to find the cells with the highest charge in the pack, as indicated by higher cell voltages. Then, the excess energy is removed through a bypass resistor until the voltage or charge matches the voltage on the weaker cells.n charge shunting, the voltage on all cells would be leveled upward to the rated voltage of a good cell. Once the rated voltage of the cell is reached, the current would bypass the fully charged cells to charge the weaker cells until they reach full voltage.

11. CONCLUSION

In this article, a BMS designed can monitor voltage, current, and temperature of the battery stack and protect it from overcharge/over-discharge, over current, high-temperature faults according to the measured signals, and it also can estimate the SOC of the battery stack with a high precision with the improved algorithm basing on EKF. The system has been tested that it can maintain the battery stacks in a good state and improve the reliability and security of the electric vehicle.

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