Validation Analysis of a Distributed Battery Management System Implementation

Invited Paper

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***Abstract*—In this work, a hardware implementation of a distributed Battery Management System was carried out. This hardware is formed by a current and voltage monitor, a SD card, and a microcontroller, in which a remaining discharge time prediction algorithm based on an extended Kalman filter was programmed. The Kalman filter estimates the state of charge and another dynamic variable that allow to use the Lambert function to find the remaining discharge time from the end-of-discharge voltage value. By using a commercial battery, the performance of the algorithm was evaluated at different discharge rates. The experimental results show that the proposal is suitable to be implemented on a embedded system or integrated into an application specific integrated circuit to be coupled in a battery pack.**

***Index Terms*—Distributed BMS, Remaining Discharge Time prediction, Reduced Order Electrochemical Model, Extended Kalman Filter, State of Charge estimation.**

I. INTRODUCTION

The BMS is used in efficient electrochemical energy storage systems to give safety and adequate response when a certain current is demanded. The main tasks of the BMS include: the estimation and prediction of internal variables of the batteries, the charge balancing, and the thermal control, [1], [2]. The principal variables used as indicators are the State of Charge (SoC), the State of Health (SoH), the Remaining Discharge Time (RDT), and the State of Energy (SoE). The strategies to obtain these variables can be classified into two groups. One of them is formed by those methods that use physical models to represent the current-voltage relation of the battery. The other group includes methods that use neuronal networks, fuzzy logic, and other similar tools to obtain the values of the variables from exhausted training results previously stored in a dynamic look-up table, [3], [4]. Generally, the computational complexity of the second approach is large in contrast with the model-based strategy that results in a suitable trade-off between the reduced parameters involved and the accuracy obtained, hence, is the mostly used in BMS on-hardware implementation, [5], [6].

Besides the selected algorithm, the implementation of the BMS system can also be a challenge, either because the precision of the measured variables can affect the accuracy of the predictions, which implies that the model has to be readjusted, or because that larger battery packs can contain up to a hundred battery cells connected to be controlled. There are many proposed IC solutions in the literature, with different applications and versatility [2]. They can provide a one-cell monitoring, so-called "fuel gauges", [7] or an entire battery pack control, [8], in which more complex functions are provided. These last ones are implemented with master-slave configurations and have the capacity to manage a fixed number of cells. Therefore, for expanding the system new Integrated Circuits (ICs) or extra modules are necessary.

In this work, an experimental implementation of a BMS algorithm is presented. An RDT prediction jointly with a SoC estimation was implemented in a microcontroller. The basis of the algorithm is the solution presented in [9] in which the reduced order electrochemical model (ECHM) [10] was used to find a direct solution to the RDT prediction. We propose an executable solution that allows us to know these variables of a battery in real-time using a discrete version of the ECHM using an Extended Kalman Filter (EKF). Furthermore, a distributed BMS implementation is introduced to scale the proposal to larger systems without hardware modifications. This would allow the inclusion of the algorithm and the necessary additional electronics systems into an on-chip integrated solution to be incorporated in commercial rack-able battery packs.

The work is organized as follows, in section II the RDT solution and EKF equations are detailed. Section III describes the distributed bms proposal and the hardware chosen. In section IV the experimental results are presented. Finally, in section V the conclusions of this work are exposed.

II. ALGORITHM DESCRIPTION

The algorithm implemented in this work involves the model state estimation and the RDT prediction. From the current and voltage measurements, the state observer estimates the two internal variables of the ECHM to finally calculate the prediction of the RDT. In section II-A the reduced order electrochemical model of [9] is presented and in section II-B the proposed state observers algorithm which estimates the internal variables of the ECHM is introduced. Finally, in section II-C the algorithm for the RDT prediction is shown.

A. Reduced Order Electrochemical Model

The ECHM is obtained by modeling the two process (charge transference and mass transport) that occurs inside the battery when the current flows through their terminals [10]. The reaction that takes place in the electrode surface produces the charge transference reaction modeled by a Butler-Volmer type equation, [11]. On the other hand, the reactive materials arrive at the surface by a mass transport process that can be modeled using the two Ficks laws. The complete model is given by the block diagram shown in Fig. 1.

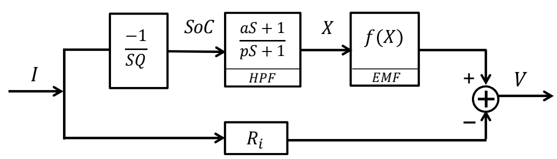

Fig. 1. Block diagram of the ECHM.

This model uses the SoC and another extra variable, X, to describe the Rate Capacity Effect (RCE). The RCE is the phenomenon by which the capacity of the battery is reduced when the discharge rate increases. Is produced by rapid consumption of the reactive material in the electrodes surface. Therefore, the variable X represents the reactive concentration on the surface while the SoC represents the average concentration of the reactive inside the battery. Consequently, the integrator system of Fig. 1 is modeling the SoC while the high pass filter (HPF) models the RCE. It is a causal linear system that produces the surface charge concentration X from the averaged charge stored SoC. The parameters of the ECHM needed to know the evolution of the variables are: the gain of the accumulator, namely the maximum capacity of the battery (Q), the pole ($-1/p$), and the zero ($-1/a$) of the transfer function of the HPF, the internal resistance (R_i) and the EMF function ($f(X)$). In order to track in real-time the variables of the ECHM, the initial condition must to be given, therefore a state observer is used to do this.

B. Proposed State Observers Algorithm

A state observer is an algorithm that uses information of the input and output of a system to estimate its internal variables. In our case, the SoC and X are estimated from the current and voltage measurements using an EKF due to the nonlinearity of the model. The structure of the EKF assumes a "noisy" system where the variables are contaminated with additive and mutually independent signals with probability density function jointly Gaussian. It is considered that the noisy signals have zero mean and variance given by the matrix N and the scalar r_2, both positive definite. The equations of the EKF applied to the ECHM can be summarized as follows:

$$C(k) = \left[0 \quad \left.\frac{\partial f}{\partial X}\right|_{\hat{X}(k)} \right] \tag{1}$$

$$K(k) = \frac{P(k)C(k)^T}{C(k)P(k)C(k)^T + r_2^2} \tag{2}$$

$$\hat{z}(k) = \hat{z}^-(k) + K(k)\left(V(k) - \hat{V}(k)\right) \tag{3}$$

$$Q^{-1}(k) = P^{-1}(k) + \frac{C(k)^T C(k)}{r_2^2} \tag{4}$$

$$\hat{z}^-(k+1) = A\hat{z}(k) + BI(k) \tag{5}$$

$$P(k+1) = AQ(k)A^T + NN^T \tag{6}$$

The convergence condition of these equations can be seen in, [12]. Hereinafter, the integer $k \geq 0$ will be used to note the time $t = kh$, being h the sampled period and the hat ^ stands for estimated values. The initials condition needed to start the algorithm are $\hat{z}(0)$ and $P(0)$, where $\hat{z}(k) = [S\hat{o}C(k) \ \hat{X}(k)]$ is the estimated states vector and $P(k)$ is the *posteriori* error covariance matrix. Further, $I(k)$, $V(k)$ are the current and the voltage measurements respectively and $\hat{V}(k) = C(k)\hat{z}^-(k) + I(k)R_i$ is the voltage estimation. The matrix formulation of the model is obtained from the transfer function of the linear systems shown in the block diagram of Fig 1. The state-transition matrix A and the input vector B are described in terms of the parameters of the model (a, p, Q) as

$$A = \begin{bmatrix} 1 & 0 \\ 1 - e^{-h/p} & e^{-h/p} \end{bmatrix}; \tag{7}$$

$$B = \begin{bmatrix} -1 \\ (p-a)(1 - e^{-h/p}) - 1 \end{bmatrix} \frac{h}{Q}. \tag{8}$$

C. Remaining Discharge Time prediction

The RDT (Δ_t) is the period of time in which the battery is able to provide a certain current to the load until the terminal voltage reaches its admissible lower limit provided by the manufacturer, V_{min}. Using the proposed ECHM, the prediction of the RDT is obtained by solving the step response of the linear model, which is equivalent to considering a constant current discharging the battery. Using the matrix formulation 7 and 8, the RDT can be obtained by solving the two dynamic equations of the model if the current and the final value of the X are given. A solution based on this idea was published in [9], where was demonstrated that the RDT prediction can be obtained using the Lambert function. The final result is the equation (9)

$$\Delta_t = \left(\mathcal{W}\left(\theta_2 e^{\theta_1}\right) - \theta_1\right) p \tag{9}$$

$$\theta_1 = \left(X_{min} - S\hat{o}C(k)\right)\frac{Q}{p\,I} + \frac{a}{p} - 1 \tag{10}$$

$$\theta_2 = \left(\hat{X}(k) - S\hat{o}C(k)\right)\frac{Q}{p\,I} + \frac{a}{p} - 1, \tag{11}$$

where $\mathcal{W}(\cdot)$ is the Lambert function [13] and the known constant θ_1 and θ_2 are calculated in each sampled time by the EKF estimated values. The final value X_{min} is obtained from V_{min} using the equation (12), where $f^{-1}(\cdot)$ is the inverse function of the EMF.

$$X_{min} = f^{-1}(V_{min} + IR_i) \tag{12}$$

III. Experimental Setup

The final purpose of the electronic device presented in this work is the design of a distributed BMS formed by master-slave devices. Each battery, coupled with the electronic board developed, forms a smart cell (SC) which is a battery that knows its own internal variables. In this way, each SC can share the information with other SC by using a communication bus. Fig. 2 shows the proposal schematic setup of the complete system. The difference between the slaves and the master cells is the inclusion of an SD card. The master device program includes the ability to periodically request the variables calculated by the slaves and store them. In this work we present the development of a single electronic board correspondent to the master device, as a proof of concept, leaving the rest of the design to future work.

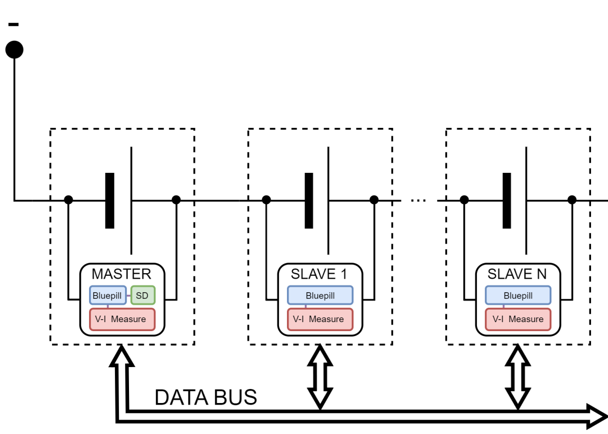

Fig. 2. Distributed BMS proposed.

Fig. 3 shows the experimental setup mounted. As central processing unit, a *Bluepill* board was chosen. This board has embedded a 32 bits STM32F103C8 microcontroller with 72 MHz of clock speed, which brings enough calculus power to accomplish with the algorithm requirements. For acquiring the voltage and the current from the battery, an instrumentation amplifier INA219 was selected. The algorithm's results are stored in a SD module to a posterior analysis. The voltage is sourced by an step up/down regulator based on LM2577S and LM2596 integrated circuits.

The *Bluepill* is programmed with a state machine with four states, each of them used to carry out the fundamental tasks of the algorithm: i) acquiring the voltage and current measurement, ii) calculus of the mean of the values, iii) implementation of the EKF and RDT equations and iv) store the results into the SD card. A representation of the state machine is shown in Fig. 4. The detailed tasks of each state are:

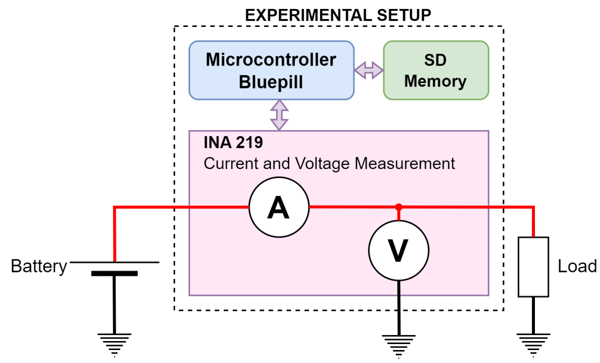

Fig. 3. Experimental diagram scheme.

- **Acquiring:** Repeatedly, the *Bluepill* communicates with the INA219 to acquire the voltage and the current measurement from the battery.
- **Average:** Using a sampled period previously configured in the internal Real Time Clock (RTC), the average of the measurement is calculated in order to get a smooth value of the current and voltage.
- **Estimation and prediction:** The EKF equations are executed using the matrix formulation approach to estimate the model variables. Subsequently, the RDT is predicted using the Lambert-function-based algorithm.
- **Datalog:** The estimation and prediction results obtained are written in a new line of a text document created on the SD card.

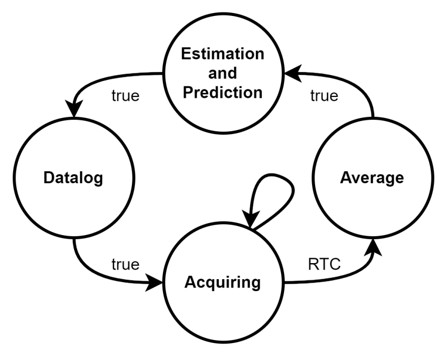

Fig. 4. Diagrama del programa de la bluepill.

IV. Experimental results

In order to evaluate the performance of the proposed implementation, several charge/discharge tests were completed. These tests consist on charge and discharge a lithium-ion (Li-ion) cell, using a constant current with random amplitude. The current is kept charging the cell until the maximum voltage limit (given by the manufacturer) is reached, and subsequently it is discharged to V_{min} using different current amplitudes. In this experiment, a $1.3Ah$ commercial Li-ion Nickel Manganese Cobalt (NMC) cell was used, and the charge/discharge procedure was repeated several times using rates in the interval $[\pm C/3,\ 1C]$, where the C-rate is a dimensionless unit used to measure the velocity at which the battery is fully charged or discharged: $1C$ means that the battery is charged/discharged with a current amplitude that needs one hour to completely charge/discharge it.

The state machine was set with the previously identified model parameter values and the sampled period chosen was $h = 1\mathrm{s}$. The RDT algorithm performance was evaluated by comparing the prediction ($\hat{\Delta}_t$) with the *a posteriori* RDT calculation (Δ_t). Fig. 5 shows the results of two representative discharge processes versus the RDT prediction; the blue solid line is the calculated RDT, stored in the SD card, and the black dashed line is the true RDT.

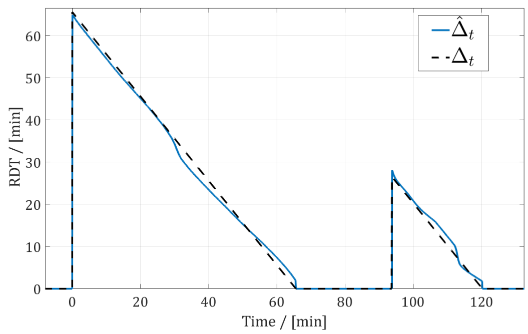

Fig. 5. Blue solid: RDT prediction using the proposed algorithm. Black dash: True RDT.

It can be noted from the figure that the difference between the true and the RDT prediction does not keep constant during the discharge, due to the correction action executed by EKF. Therefore, in order to quantify the accuracy of the prediction, the Root Mean Squared Error (RMSE) was used, being

$$RMSE \quad = \quad \sqrt{\sum_k \left(\frac{\Delta_t(k) - \hat{\Delta}_t(k)}{\Delta_T} \right)^2}, \tag{13}$$

where Δ_T is the entire true RDT of the whole discharge considered, used in order to obtain the relative RDT prediction error.

Fig. 6 shows the RMSE obtained as a function of the discharge rate, for 29 different cases. It can be seen that the RMSE increases with the current discharge rate. This can be explained by the reduced order model used, that may not capture the entire transient dynamics. Moreover, the observer algorithm gets a feasible estimation of the variables only after the convergence time. Therefore, the RDT prediction accomplishes more accuracy when the time of the discharge is larger than the transient and convergence time.

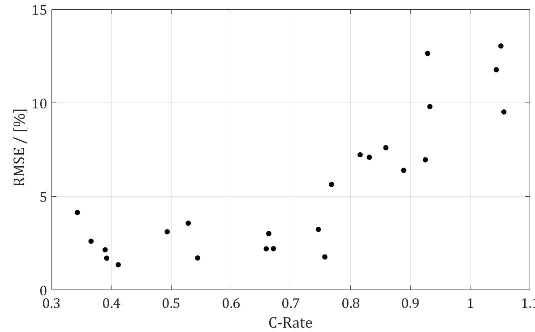

Fig. 6. RMSE obtained at different discharge rate.

V. Conclusion

In this work, the implementation of an algorithm that performs BMS tasks was presented. The development includes hardware selection and software design. The implemented algorithm predicts the remaining discharge time of a reduced-order electrochemical model from its two internal variables. The equations of an extended Kalman filter were implemented in order to estimate these variables from the current and the voltage measurement.

The entire system was implemented using commercial components and a state-machine-based controller, obtaining averaged RDT errors lower than 13%, when the battery was discharged with rates between $C/3$ and $1C$. The results indicate that the proposal could be implemented with good accuracy in small electronic embedded systems, or integrated on an application-specific integrated circuit coupled in a battery pack. Furthermore, the distributed approach makes this technique versatile to add as many new slave cells as needed, without the necessity of change or expand the existing hardware.

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