Estimation of VRLA Battery States and Parameters using Sigma-point Kalman Filter

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Abstract - This paper describes a hybrid electrical model of valve-regulated lead-acid battery (VRLA) and its application in Matlab/Simulink environment. Based on the charge/discharge test characteristics of the telecommunication battery stack, all parameters of the hybrid electrical models are derived. After implementing the charge/discharge simulations of hybrid electrical model and comparisons with actual tests of battery stack, joint estimation of model states and parameters is carried out using Sigma-point Kalman filter (SPKF). Results of performed joint estimation correspond to model simulations and it is shown that the SPKF algorithm is good for estimation of model states and parameters. After validation of the hybrid electrical model and validation of SPKF algorithm, joint estimation of battery states and parameters is performed to charge/discharge test of VRLA battery stack using Unscented Kalman Filter (UKF) method.

Keywords—valve-regulated lead-acid battery, state of charge; open-circuit voltage; hybrid battery model, Sigma-point Kalman filter, state and parameter estimation

I. INTRODUCTION

Battery is a component that converts chemical energy contained in its active materials into electricity using a single electrochemical oxidation-reduction reaction. Electrochemical batteries are distinguished as primary and secondary, depending on their ability of being electrically recharged. Thus, the primary batteries are non-rechargeable, while the secondary ones can be recharged. The primary batteries generally have a potential to obtain higher energy and power densities due to a limitation on materials that can be practically recharged in case of secondary batteries. VRLA batteries are the most convenient choice of all secondary batteries for telecommunications. Many attempts have been reported with the aim of modeling secondary batteries. The essential distinction between them is the way of representing the underlying processes. To that extent, three main groups of models can be distinguished: electrochemical models, mathematical models and electrical models. The electrical battery models are the most practical ones for circuit analyses. There are three main groups of electrical models: Thevenin-based models, Impedance-based models and Runtime-based (R-B) models [1] and [4]. Hybrid electrical model is a comprehensive electrical model that includes the best characteristics of each mentioned models and it is presented in [1], [2] and [3]. For these models it has been shown that they are able to accurately describe the behaviour of lithium-ion and VRLA batteries.

Operational use of these models requires to determine model parameters, as well as the model state, with respect to the measurements acquired on the modelling object – a real battery system. Nonlinear Kalman filter or SPKF is an alternate approach to generalizing the Kalman filter to state and parameter estimation for nonlinear systems. The general approach is to use system inputs and measurable system outputs estimate the current state and parameters. SPKF as other Kalman filters can be used to concurrently estimate both state and the slowly time-varying battery parameters by combining the battery model state vector with the model parameters. This method is called joint estimation.

Dual estimation of hybrid electrical model states and parameters is performed in [4] using Extended Kalman filter (EKF). Authors in [5] demonstrate joint estimation of model states and parameters using Central Difference Kalman filter (CDKF) as a method of SPKF. Additionally, the comparison of simulations with actual charge/discharge tests of VRLA battery are given. Researchers around the world have applied successfully rapid method for determining model states and parameters of lithium-ion batteries [6]. This method is successfully applied for determining model states and parameters of VRLA batteries as well. Author in [7], [8], [9] and [10] has described several Kalman filters that can be used for estimation of battery states and parameters. It has been shown that SPKF more accurately performed estimation of battery states and parameters compared to EKF. Two methods of SPKF algorithm have been described: UKF method and CDKF method. The essential distinction between them is the way of calculating the weight constants.

This paper is organized as follows: Section II describes hybrid battery electrical model. Experimental charge/discharge tests of VRLA 48 V battery stack of nominal capacity 150 Ah are performed. Battery states and parameters are determined using rapid method. Section III presents the implementation of hybrid electrical model in Matlab/Simulink environment. In addition, verification results are presented after comparison of model simulations with actual charge/discharge tests and joint estimation of model states and parameters using UKF method of SPKF algorithm. In Section
IV joint estimation of battery actual states and parameters using UKF method is performed. Implemented estimations are the first step towards an automated battery management system (BMS) in which the battery will be effectively included.

II. BATTERY PARAMETERS DETERMINATION

A. Hybrid electrical model of a battery

Hybrid electrical model of a battery (Fig. 1.) can be presented by a full-capacity capacitor $C_{\text{capacity}}$, a self-discharge resistor $R_{\text{self}}$, and an equivalent series resistor (the sum of $R_{\text{serial}}$, $R_{\text{fast}}$ and $R_{\text{slow}}$). It incorporates the best characteristics from Thevenin and R-B electrical model [1], [2].

![Fig. 1. Hybrid electrical model of a battery](image)

Full-capacity capacitor $C_{\text{capacity}}$ represents the whole charge stored in the battery, i.e. state of charge (SOC), by converting nominal battery capacity in Ahr to charge in coulomb and its value is defined as [2], [4]:

$$C_{\text{capacity}} = 3600 \times K_{\text{nom}} \times k_1(\text{cycle}) \times k_2(\text{temp})$$  (1)

where $K_{\text{nom}}$ is nominal capacity in Ahr, $k_1(\text{cycle})$ is a correction factor for number of charge-discharge cycles the battery experienced, $k_2(\text{temp})$ is a temperature-dependent correction factor. Correction factor that defines capacity dependence of current value is not expressed in (1). Performed charge/discharge tests are in operating area of small current values and that factor can be neglected. By setting the initial voltage across $C_{\text{capacity}}$ ($V_{\text{SOC}}$) equal to 1 or 0 V, the battery is initialized to its fully charged (i.e., SOC is 100%) or fully discharged (i.e., SOC is 0%) state. In other words, $V_{\text{SOC}}$ represents the SOC of the battery quantitatively.

The resistance $R_{\text{self}}$ represents leakage when the battery is stored over a long period. $R_{\text{self}}$ is a function of SOC, temperature, and frequently, number of experienced charge/discharge cycles.

B. Test system and procedure

Fig. 2 shows a principal scheme of the test system with Fiamm 48 V VRLA battery stack, with nominal capacity of 150 Ah. This battery stack consists of four 12 V batteries connected in series and before the tests it was not used. This battery type is chosen due to its wide use as a backup power supply in telecommunication base stations of company JP Hrvatske Telekomunikacije d.d. Mostar. The experiment was carried out firstly by discharging a fully charged battery stack with current of 15 A. Discharge period of 60 minutes was altered with the resting period of 20 minutes. Similar pulse current strategy was applied for charging of the battery stack, whereas charging current was 14 A. Manufacturer threshold voltage levels are 43.2 V and 54.48 V, and these are chosen for stopping discharging and charging processes.

VRLA battery stack 48 V, 150 Ah
DC power supply 48 V, Delta

![Fig. 2. Experimental test system](image)

Figures 3-5 show: battery voltage, discharge current, battery temperature and 12 V battery voltage of each battery during discharge test. Fig. 5 shows decreasing trend of one 12 V battery voltage after 11 hours of discharge, which leads to conclusion that its factory performance is worse and has capacity less than 150 Ahr.

![Fig. 3. Battery discharge voltage](image)

![Fig. 4. Battery discharge current](image)
After fully discharge state was reached, charge test was applied with similar strategy (charge period of 60 minutes and resting period of 20 minutes), until the battery voltage reached upper voltage limit (54.48 V). Figures 6-8 show all battery measurements during charge test.

C. Model state and parameter determination

There are several methods for determining open-circuit voltage (Voc) at different SOC values. Battery voltage tends to its open-circuit voltage after charge/discharge current decrease to near-zero value. The open-circuit voltage is normally measured as a steady-state battery open-circuit voltage at various SOC points. However, for each SOC point this measurement can take days [1]. Authors in [6] proposed rapid method for determining open-circuit voltage using simple approximation where open-circuit voltage is determined by curve fitting method between peaks during resting periods, as shown in Fig. 9.

Battery voltage in Laplace s-domain according to the hybrid electrical model is defined as:

$$U_{batt}(s) = V_{OC}(SOC, s) - I_{batt}(s) \cdot Z(s)$$  \hspace{1cm} (2)

where $V_{OC}(SOC, s)$ is open-circuit voltage as a function of SOC, $I_{batt}(s)$ is battery current and $Z(s)$ is battery impedance that can be expressed as:

$$Z(s) = R_{serial} + \frac{R_{fast}}{1 + s \cdot \tau_{fast}} + \frac{R_{slow}}{1 + s \cdot \tau_{slow}}$$  \hspace{1cm} (3)

where $\tau_{fast}$ and $\tau_{slow}$ are voltage transient time constants:

$$\tau_{fast} = R_{fast} \cdot C_{fast}; \quad \tau_{slow} = R_{slow} \cdot C_{slow}$$  \hspace{1cm} (4)

Battery parameters ($R_{serial}$, $R_{fast}$, $R_{slow}$, $C_{fast}$ and $C_{slow}$) according to the equivalent model is analytically calculated from voltage-time curve of each resting period that lasts 20 minutes. Fig. 10 shows one resting period during discharge with all values. Battery resistances are calculated using the following equations [5]:

$$R_{serial} = \frac{\Delta V_1}{I_{batt}}, \quad R_{fast} = \frac{\Delta V_2}{I_{batt}}, \quad R_{slow} = \frac{\Delta V_3}{I_{batt}}$$  \hspace{1cm} (5)

where $I_{batt}(s)$ is battery current change that caused battery voltage transient response, $\Delta V_1$, $\Delta V_2$ and $\Delta V_3$ are voltage changes.
drops at series resistor, fast and slow transient RC network. Voltage drop $\Delta V_3$ is defined by the following expression:

$$\Delta V_3 = [V_{oc} (SOC) - V_3]$$  \hspace{1cm} (6)

where $V_3$ is battery voltage at the end of fast transient response.

Fig. 10. Resting period - discharge

Calculated values of electrical resistances, using (4) as a function of SOC, during charge and discharge are shown in Fig. 11.

III. ESTIMATION OF HYBRID ELECTRICAL MODEL STATES AND PARAMETERS

In the previous section all battery parameters are calculated for each resting period according to the equivalent model. Their mean values are used in the hybrid battery model implemented in Matlab/Simulink environment. In order to validate the equivalent battery model, model simulations are compared to actual charge/discharge test measurements.

If verification of the proposed model showed that hybrid electrical model gives a good approximation of actual test measurements, this model will be used for validation of joint estimation algorithm of states and parameters.

A. Model validation

The hybrid electrical model (Fig.1) is implemented in Matlab/Simulink environment. The calculated values of battery parameters from charge/discharge voltage-time curves are used in model elements, as well as manufacturer data for upper voltage limit of charge (54.48 V) and lower voltage limit of discharge (43.2 V). In order to validate equivalent model, a comparison between model charge/discharge simulations and actual test measurements is analyzed (Figures 13 and 14)[5].

As shown, it can be concluded that this battery model represents well these charge/discharge tests. Small deviations of simulation values occur towards the end of both tests, which is partly result of one 12 V battery lower capacity in the tested battery stack.

Fig. 12. Comparison between model output and test data - discharge

Fig. 13. Comparison between model output and test data - charge
B. Estimation of model states and parameters

In order to initiate a joint estimation of hybrid electrical model states and parameters using SPKF algorithm, augmented state and parameter vector is firstly defined [7], [8]:

\[
x_k = \begin{bmatrix} V_{SOC} & V_{fast} & V_{slow} & R_{fast} & R_{slow} & R_{serial} \end{bmatrix}^T
\]

(7)

where \( V_{SOC} \) is open-circuit voltage, \( V_{fast} \) is voltage at fast transient RC network and \( V_{slow} \) is voltage at slow transient RC network [9], [10].

System output – terminal voltage of battery stack is defined as follows:

\[
y_k = (a \cdot V_{SOC} + b) - (i_{bat} \cdot R_{serial} + V_{fast} + V_{slow})
\]

(8)

where \( a \) and \( b \) are coefficients which define open-circuit voltage and are usually provided by manufacturers.

The initial covariance matrix is as follows:

\[
P_{x_k} = \text{diag} \begin{bmatrix} 5 & 50 & 50 & 1 & 1 & 1 \end{bmatrix} \cdot 10^{-3}
\]

(9)

The process noise covariance matrix is defined:

\[
P_w = \text{diag} \begin{bmatrix} 5 & 5000 & 5000 & 5 & 5 \end{bmatrix} \cdot 10^{-5}
\]

(10)

The measurement noise variance is determined: \( P_v = 0.09 \).

After the initial conditions were defined, joint estimation of model states and parameters is initiated. Model simulations for charging and discharging are used as inputs in algorithm.

Joint estimation was successfully implemented using UKF method and obtained estimations for battery voltage \( U_{bat} \), voltage at fast transient RC network \( V_{fast} \), voltage at slow transient RC network \( V_{slow} \), battery resistances and SOC are in figures 14-17 for discharging and in figures 18-21 for charging.

The model simulations are shown also on these figures and give good verification results with values obtained by joint estimation. As shown, it can be concluded that applied joint estimation using SPKF algorithm is valid and can be implemented to actual test charge/discharge measurements of battery stack.

IV. ESTIMATION OF BATTERY STATES AND PARAMETERS

Validation of joint estimation using SPKF algorithm and its implementation in Matlab environment was confirmed on model simulations in previous section.
In the next steps joint estimation of battery states and parameters will be performed on charge/discharge test of VRLA 48 V 150 Ahr battery stack using UKF method of SPKF algorithm. The initial state and parameter vector, initial covariance matrix, process noise covariance matrix and measurement noise variance are defined same as in the previous section. Joint estimation was successfully implemented using UKF method and obtained estimations for battery voltage $U_{\text{batt}}$, voltage at fast transient RC network $V_{\text{fast}}$, voltage at slow transient RC network $V_{\text{slow}}$, battery resistances and SOC are in figures 22-25 for discharging and in figures 26-29 for charging.
battery temperature. This temperature dependence will be subject of further research.

Battery capacity varies as the battery gets older and battery suppliers usually provide its dependence with respect to number of charge/discharge cycles, temperature and charge/discharge current [11]. This dependence can be also included in the model used for SPKF based estimation of battery resistances and SOC.

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**Fig. 25.** Estimation of battery filter voltages - discharge

**Fig. 26.** Estimation of battery voltage - charge

**Fig. 27.** Estimation of battery SOC - charge

**Fig. 28.** Estimation of battery resistances – charge

**Fig. 29.** Estimation of filter voltages - charge

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**V. CONCLUSION**

VRLA batteries are still optimal choice for telecommunication base stations considering price and service life.

This paper presents hybrid electrical model that accurately describes the behaviour of this battery type. Its validity was confirmed by comparing charge/discharge model simulations with actual test data in Matlab/Simulink environment. Joint estimation of model states and parameters was carried out using UKF method of SPKF algorithm. Verification results of performed joint estimation corresponded to model simulations and it was shown that the SPKF algorithm was good for estimation of model states and parameters. After validation of the hybrid electrical model and validation of SPKF algorithm, joint estimation of battery states and parameters was performed to actual charge/discharge test data of VRLA battery stack.

In the further research temperature model will be included and connected with hybrid electrical model, in order to get battery state and parameter dependence of temperature. In such a way, even more precise behaviour of VRLA battery would be resembled, as well as estimations of battery states and parameters. Combined temperature and hybrid electrical model will be used in further steps for battery management system design used as subsystem for optimal exploitation of batteries in the microgrid environment.
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REFERENCES


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