New Estimation Filtering for Battery Management Systems of Lead-Acid Cells in Hybrid Electric Vehicles

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Summary
This paper proposes a new estimation filtering for battery management systems of lead-acid cells in hybrid electric vehicles. The well known finite impulse response (FIR) filter is adopted for the estimation filtering. The proposed method provides the filtered estimates for the output voltage as well as voltages across the bulk and surface capacitors. These filtered estimates have good inherent properties. It is shown that the filtered estimate for the output voltage is not affected by voltages across capacitors when their initial values are constant on the window. It is also shown that the filtered estimate for voltages across capacitors is separated from the output voltage term. From discussions about the choice of window length and normalized noise covariance, it is shown that they can make the estimation performance of the proposed FIR filtering based method as good as possible. Numerical simulations show the performance of the proposed method is superior to the existing Kalman filtering based method.

Key words:
Battery management system, FIR filtering, Kalman filtering.

1. Introduction

With the increased need for mobility, people moved to portable power storage-first for wheeled applications, then for portable and finally nowadays wearable use. Several types of rechargeable battery systems, including those of lead-acid, nickel-cadmium, nickel-metal hydride, lithium-ion and lithium-ion polymer exist in the market.

It is of most importance that the battery management system (BMS) which controls charging and discharging of the battery, operates with an accurate estimate of the energy stored in the battery at any given time. The available fraction of the full capacity is called the State-of-Charge (SoC). An accurate SoC estimation which is one of the main tasks of the BMS, will improve the performance and reliability, and will ultimately lengthen the lifetime of the battery. Accurate SoC information allows the battery to be used within the design limits, so the pack does not need to be over-engineered. This allows a smaller, lighter battery, which costs less [1]-[10].

Several methods including those of direct measurements and book-keeping are known in the art for determining the SoC of a cell or battery of cells [1]-[3]. The main problem in designing an accurate SoC indication is the unpredictability of both battery and user behavior. However, existing methods in [1]-[3] did not consider this problem and thus can show poor accuracy and reliability in practice, when there are unpredictability and uncertainty for both battery and user behavior.

Therefore, in recent, to estimate battery SoC with the consideration of unpredictability and uncertainty for both battery and user behavior, the Kalman filtering based method has been made by posing the optimal filtering problem due to the compact representation and the efficient manner [4]-[10]. By employing a mathematical model of the battery system that includes the unknown quantities in the model state, the Kalman filtering is used to estimate them. An additional benefit of the Kalman filtering is that it automatically provides dynamic error bounds on these estimates.

However, the Kalman filter has an infinite impulse response (IIR) structure that utilizes all past information accomplished by equaling weighting and has a recursive formulation. Thus, the Kalman filter tends to accumulate the filtering error as time goes. In addition, the Kalman filter has known to be sensitive and show even divergence phenomenon for temporary modeling uncertainties and round-off errors [11]-[15].

Therefore, in the current paper, an alternative method is proposed for the real-time estimation filtering for BMS of lead-acid cells in hybrid electric vehicles. Although the proposed method will be implemented on a lead-acid battery (LiPB) pack, it can be expected for them to work well for other battery chemistries. For the filtering, the proposed method adopts the well known finite impulse response (FIR) filter that utilizes only finite information on the most recent window [13]-[15]. The proposed method provides the filtered estimates for the output voltage as well as voltages across the bulk and surface capacitors. These filtered estimates have good inherent properties such as unbiasedness, efficiency, time-invariance, deadbeat, and robustness due to the FIR structure. It is shown that the filtered estimate for the output voltage is not affected by voltages across capacitors when their initial values are constant on the observation window. It is also shown that the filtered estimate for voltages across capacitors is separated from the output voltage. Numerical simulations show the performance of the proposed method is superior to the existing Kalman filtering based method. These remarkable properties cannot be obtained from the Kalman filtering based method in [4]-[10].

Since the choice of an appropriate window length and normalized noise covariance is important issue to make the performance of the proposed FIR filtering based method as good as possible, some discussions about them will be done. From above discussions, it can be stated that they can be considered as useful design parameters to make the filtering performance as good as possible. Finally, the performance of the proposed method is shown to be superior to the existing Kalman filtering based method via numerical simulations.

The paper is organized as follows. In Section 2, an alternative method is proposed for the real-time estimation filtering for BMS of lead-acid cells in hybrid electric vehicles. In Section 3, inherent properties of the proposed method are shown. In Section 4, the choice of the window length and the normalized noise covariance is discussed. Finally, concluding remarks are made in Section 5.

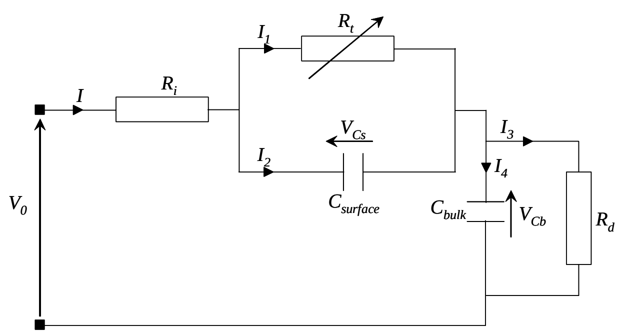

Fig. 1. Randles' type equivalent circuit of a lead-acid cell

2. Proposed Method Using FIR Filtering

The simplified equivalent circuit [16] of a lead-acid cell is shown in Fig. 1. As shown in [4]-[10], a dynamic model of this equivalent circuit is constructed as the following discrete-time state space model:

$$\begin{aligned} x(i+1) &= Ax(i) + Bu(i) + Gw(i), \\ z(i) &= Cx(i) + v(i), \end{aligned} \tag{1}$$

where

$$x(i) = \begin{bmatrix} x_c(i) \\ x_o(i) \end{bmatrix}, \; w(i) = \begin{bmatrix} w_c(i) \\ w_o(i) \end{bmatrix},$$

$$A = \begin{bmatrix} A_c & 0 \\ E & A_o \end{bmatrix}, B = \begin{bmatrix} B_c \\ B_o \end{bmatrix}, G = I, \quad C = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}$$

where

$$A_c = \begin{bmatrix} 1 - \dfrac{T_C}{C_{bulk} R_d} & 0 \\ 0 & 1 - \dfrac{T_C}{C_{surface} R_t} \end{bmatrix},$$

$$E = \begin{bmatrix} 1 - \dfrac{T_C}{C_{surface} R_t} & -\dfrac{T_C}{C_{surface} R_t} \end{bmatrix},$$

$$A_o = 1,$$

$$B_c = \begin{bmatrix} \dfrac{T_C}{C_{bulk}} \\ \dfrac{T_C}{C_{surface}} \end{bmatrix}, B_o = \frac{T_C}{C_{bulk}} + \frac{T_C}{C_{surface}}.$$

The state $x_c(i) = \begin{bmatrix} V_{Cb} & V_{Cs} \end{bmatrix}^T$ represents voltages across the bulk and surface capacitors and the state $x_o(i) = V_o$ represents the output voltage. The input is defined as $u(i) = I$. The process noise $w(i)$ is used to represent system disturbances and model inaccuracies. The observation noise $v(i)$ is representing the effects of measurement noise. They are zero-mean white noises with covariance Q and r , respectively. Note that noise covariances Q and r can be determined via experiments or left as a design parameter. Parameters for the dynamic model (1) are defined as follows:

- $C_{surface}$: surface capacitor
- C_{bulk} : bulk capacitor
- R_t : resistance for transfer polarization
- R_d : resistance for self-discharge of the cell.

The main task of the proposed method is the filtering of output voltage as well as voltages across the bulk and surface capacitors in real-time. For the filtering, the well known FIR filter in [13]-[15] is adopted. For the state-space model (1), the FIR filter $\hat{x}(i)$ processes linearly the only finite observations and inputs on the most recent window $[i-M,i]$ as the following simple form:

$$\begin{aligned}\hat{x}(i) &= \begin{bmatrix}\hat{x}_c(i)\\ \hat{x}_o(i)\end{bmatrix}\\ &= H\big[Z_M(i)-\Lambda_M U_M(i)\big]\\ &= \begin{bmatrix}H_c\\ H_o\end{bmatrix}\big[Z_M(i)-\Lambda_M U_M(i)\big],\end{aligned} \tag{2}$$

where the finite observations $Z_M(i)$ and inputs $U_M(i)$ are represented by

$$\begin{aligned}Z_M(i) &\equiv \big[z^T(i-M)\quad z^T(i-M+1)\quad\cdots\quad z^T(i)\big]^T\\ U_M(i) &\equiv \big[u^T(i-M)\quad u^T(i-M+1)\quad\cdots\quad u^T(i)\big]^T\end{aligned} \tag{3}$$

and the gain matrix H can be obtained from [13]-[15] as follows:

$$H \equiv A^M(\Gamma_M^T\Pi_M^{-1}\Gamma_M)^{-1}\Gamma_M^T\Pi_M^{-1},$$

where

$$\Pi_M \equiv \Theta_M\big[diag(Q\,Q\cdots Q)\big]\Theta_M^T + \big[diag(r\,r\cdots r)\big],$$

$$\Gamma_M \equiv \begin{bmatrix}C\\ CA\\ CA^2\\ \vdots\\ CA^M\end{bmatrix},$$

$$\Theta_M \equiv \begin{bmatrix}CA^{-1}G & CA^{-2}G & \cdots & CA^M G & 0\\ 0 & 0 & \cdots & CA^{M-1}G & 0\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ 0 & 0 & \cdots & CA^{-1}G & 0\\ 0 & 0 & \cdots & 0 & 0\end{bmatrix},$$

$$\Lambda_M \equiv \begin{bmatrix}CA^{-1}B & CA^{-2}B & \cdots & CA^M B & 0\\ 0 & 0 & \cdots & CA^{M-1}B & 0\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ 0 & 0 & \cdots & CA^{-1}B & 0\\ 0 & 0 & \cdots & 0 & 0\end{bmatrix}.$$

Note that H_c and H_o are the first 2 rows and the last row of H, respectively. Note that $Z_M(i)$ in (3) can be represented in the following regression form:

$$\begin{aligned}Z_M(i) &= L_M x_o(i-M) + B_M U(i)\\ &\quad + N_M X_c(i) + G_M W_o(i) + V(i),\end{aligned} \tag{4}$$

where matrices L_M, B_M, N_M, G_M are defined as follows:

$$L_M \equiv \begin{bmatrix}I\\ I\\ \vdots\\ I\end{bmatrix},\quad N_M \equiv \begin{bmatrix}0 & 0 & \cdots & 0 & 0\\ E & 0 & \cdots & 0 & 0\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ E & E & \cdots & E & 0\end{bmatrix},$$

$$B_M \equiv \begin{bmatrix}0 & 0 & \cdots & 0 & 0\\ B_o & 0 & \cdots & 0 & 0\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ B_o & B_o & \cdots & B_o & 0\end{bmatrix},$$

$$G_M \equiv \begin{bmatrix}0 & 0 & \cdots & 0 & 0\\ I & 0 & \cdots & 0 & 0\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ I & I & \cdots & I & 0\end{bmatrix}.$$

and $X_c(i)$, $U(i)$, $W_o(i)$, $V(i)$ have the same form as (3) for $x_c(i)$, $u(i)$, $w_o(i)$, $v(i)$, respectively.

3. Remarkable Properties

Ultimately, filtered estimates $\hat{x}_o(i)$ for output voltage and $\hat{x}_c(i)$ for voltages across the bulk and surface capacitors are obtained from (2) as follows:

$$\begin{aligned}\hat{x}_o(i) &= H_o\big[Z_M(i)-\Lambda_M U_M(i)\big],\\ \hat{x}_c(i) &= H_c\big[Z_M(i)-\Lambda_M U_M(i)\big].\end{aligned} \tag{5}$$

Filtered estimates $\hat{x}_o(i)$ and $\hat{x}_c(i)$ have good inherent properties of unbiasedness, efficiency, time-invariance and deadbeat since the FIR filter used provides these properties. The Kalman filter used in [4]-[10] does not have these properties unless the mean and covariance of the initial state is completely known. Among them, the remarkable one is the deadbeat property which filtered estimates $\hat{x}_o(i)$ and $\hat{x}_c(i)$ track actual values $x_o(i)$ and $x_c(i)$ exactly in the absence of noises. The deadbeat property gives the following matrix equality as shown in [13]-[15] :

$$H\Gamma_M = A^M,$$

and then

$$\begin{bmatrix} H_c \\ H_o \end{bmatrix} \begin{bmatrix} \overline{N}_M & L_M \end{bmatrix} = \begin{bmatrix} A_c^M & 0 \\ \sum_{l=0}^{M-1} EA_c^{\,l} & I \end{bmatrix},$$

where

$$\overline{N}_M \equiv \begin{bmatrix} 0 \\ E \\ EA_c + E \\ \vdots \\ \sum_{l=0}^{M-1} EA_c^l \end{bmatrix}.$$

Therefore, the following matrix equalities are obtained:

$$\begin{aligned} &H_c\overline{N}_M = A_c^M, \quad H_c L_M = 0, \\ &H_o\overline{N}_M = \sum_{l=0}^{M-1} EA_c^l, \quad H_o L_M = I, \end{aligned} \tag{6}$$

which gives following remarkable properties.

It will be shown in the following theorem that the filtered estimate $\hat{x}_o(i)$ for output voltage in (5) is not affected by voltages across the bulk and surface capacitors when their initial values are constant on the observation window $[i-M, i]$.

Theorem 1: *When initial values of voltages across the bulk and surface capacitors are constant on the observation window* $[i-M, i]$, *the filtered estimate* $\hat{x}_o(i)$ *for output voltage in (5) is not affected by the velocity.*

Proof: When initial values of voltages across the bulk and surface capacitors are constant as $\overline{x}_c$ on the observation window $[i-M, i]$, the finite observations $Z_M(i)$ in (4) can be represented in

$$\begin{aligned} &Z_M(i) \mid \{x_c(i) = \overline{x}_c \;\; for\; [i-M, i]\} \\ &\quad = L_M x_c(i-M) + \overline{N}_M \overline{x}_c + B_M U(i) \\ &\qquad + G_M W_o(i) + V(i). \end{aligned} \tag{7}$$

Then, the filtered estimate $\hat{x}_o(i)$ for output voltage is derived from (5)-(7) as

$$\begin{aligned} \hat{x}_o(i) &= H_o Z_M(i) \\ &= H_o[L_M x_o(i-M) + \overline{N}_M \overline{x}_c + B_M U(i) \\ &\quad + G_M W_o(i) + V(i)] \\ &= H_o L_M x_o(i-M) + H_o \overline{N}_M \overline{x}_c \\ &\quad + H_o[B_M U(i) + G_M W_o(i) + V(i)] \\ &= x_o(i-M) + \sum_{l=0}^{M-1} EA_c^l \overline{x}_c + H_o[B_M U(i) \\ &\quad + G_M W_o(i) + V(i)]. \end{aligned} \tag{8}$$

From (1), the actual output voltage $x_o(i)$ can be represented on $[i-M, i]$ as follow:

$$\begin{aligned} &x_o(i) \mid \{x_o(i) = \overline{x}_o \;\; for\; [i-M, i]\} \\ &\quad = x_o(i-M) + \sum_{l=0}^{M-1} EA_c^l \overline{x}_c + \overline{B}_M U(i) + \overline{G}_M W_o(i), \end{aligned} \tag{9}$$

where $\overline{G}_M = \begin{bmatrix} I & I & \cdots & I & 0 \end{bmatrix}$ and $\overline{B}_M = \begin{bmatrix} B_o & B_o & \cdots & B_o & 0 \end{bmatrix}$.

Thus, using (8) and (9), the error of the filtered estimate $\hat{x}_o(i)$ for output voltage is

$$\begin{aligned} \hat{x}_o(i) - x_o(i) &= H_o[B_M U(i) + G_M W_o(i) + V(i)] \\ &\quad - \left[\overline{B}_M U(i) + \overline{G}_M W_o(i)\right], \end{aligned}$$

which does not include the term of voltages across the bulk and surface capacitors. This completes the proof. □

The filtered estimate for voltages across the bulk and surface capacitors is shown to be separated from the output voltage term.

Theorem 2: *The filtered estimate* $\hat{x}_c(i)$ *for across the bulk and surface capacitors in (2) is separated from the output voltage term.*

Proof: The filtered estimate $\hat{x}_c(i)$ is derived from (2) and (6) as

$$
\begin{aligned}
\hat{x}_c(i) &= H_c Z_M(i) \\
&= H_c[L_M x_o(i-M) + N_M X_c(i) + B_M U(i) \\
&\quad + G_M W_o(i) + V(i)] \\
&= H_c[N_M X_c(i) + B_M U(i) + G_M W_o(i) + V(i)],
\end{aligned}
$$

which does not include the output voltage term. This completes the proof. □

Above remarkable properties of the proposed FIR filtering based method cannot be obtained from the existing Kalman filtering based method in [4]-[10]. In addition, as mentioned previously, the proposed method has the deadbeat property, which means the fast tracking ability of the proposed method. Furthermore, due to the FIR structure and the batch formulation, the proposed method might be robust to temporary modeling uncertainties and to round-off errors, while the Kalman filtering based method might be sensitive for these situations.

4. Choice of Window Length and Normalized Noise Covariance

The important issue here is how to choose an appropriate window length M and normalized noise covariance Q/r to make the filtering performance as good as possible. They affect differently the performance of the proposed FIR filtering based method.

The noise suppression of the proposed method might be closely related to the window length M . However, although the proposed method can have greater noise suppression as the window length M increases, too large M may yield the long convergence time of the filtered estimates for the output voltage as well as voltages across the bulk and surface capacitors, which degrades the filtering performance of the proposed method. This illustrates the proposed method's compromise between the noise suppression and the tracking speed of the filtered estimates. Since M is an integer, fine adjustment of the properties with M is difficult. Moreover, it is difficult to determine the window length is systematic ways. In applications, one way to determine the window length is to take the appropriate value that can provide enough noise suppression.

The tracking ability is closely related with the normalized noise covariance Q/r when the window length is determined. When the window length is fixed, the tracking ability of a filter increases and the noise-suppressing ability decreases as Q/r increases, and vice versa. Thus, the normalized noise covariance Q/r is a useful parameter in the adjustment of the tracking and noise-suppressing properties of the proposed method.

Therefore, it can be stated from above discussions that both the window length M and the normalized noise covariance Q/r can be considered as useful parameters to make the performance of the proposed FIR filtering based method as good as possible.

Parameters	Values
$C_{surface}$	88372 F
C_{bulk}	23 F
R_t	0.0005 Ω
R_d	10000 Ω

Table 1. Parameters for battery's dynamic model (1)

5. Computer Simulation

The performance of the proposed FIR filtering based method is evaluated via a numerical simulation. In this paper, the proposed FIR filtering method will be compared with the Kalman filtering based method [4]-[10]. As derived in [9], parameters for the dynamic model (1) are shown in Table 1. Noise covariances are also taken by

$$
Q = \begin{bmatrix} 1.549\times10^{-5} & 0 & 0 \\ 0 & 0.4191 & 0 \\ 0 & 0 & 0.8143 \end{bmatrix}, \; r = 10 .
$$

The window length and the initial state are taken by M = 20 and $\hat{x}_o(0)$ = 2.2, respectively. As shown in Fig. 2, a discharge pulse of 1.53A is applied to both methods with feedback of terminal current as its input, which was described previously in [4]. To make a clearer comparison, thirty Monte Carlo runs are performed and each single run lasts for 600 samples. Fig. 3 shows root-mean-square (RMS) errors of the filtered estimate $\hat{x}_o(i)$ for output voltage. Simulation results show that the performance of the proposed FIR filtering based method is superior to the existing Kalman filtering based method.

6. Conclusion

In this paper, the new estimation filtering method has been proposed for battery management systems of lead-acid cells in hybrid electric vehicles. The well known FIR filter is adopted for the estimation filtering. The proposed method provides the filtered estimates for the output voltage as well as voltages across the bulk and surface capacitors. These filtered estimates have good inherent properties. It is shown that the filtered estimate for the output voltage is not affected by voltages across capacitors when their initial values are constant on the window. It is also shown that the filtered estimate for voltages across capacitors is separated from the output voltage term. From discussions about the choice of window length and normalized noise covariance, it is shown that they can make the estimation performance of the proposed FIR filtering based method as good as possible. Finally, the performance of the proposed method is shown to be superior to the existing Kalman filtering based method via numerical simulations.

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