Core Temperature Estimation for a Lithium ion 18650 Cell

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Abstract: This paper deals with the estimation of core temperature (T c) of a Lithium (Li) ion battery using measured ambient and surface temperatures. The temperatures were measured using thermocouples placed at appropriate locations. A second order thermal model was considered for the core temperature (T c) estimation. A set of coupled linear ordinary differential equations (ODEs) were obtained by applying Kirchhoff’s current and voltage laws to the thermal model. The coupled ODEs were redefined in the discrete state space representation. The thermal model did not account for small changes in surface temperature (T s) estimation. It was found that the temperatures closely followed the current patterns. For high currents, T c dominated the surface temperature by about 3 K. T c estimation plays a very important role in designing an effective thermal management and maintaining the state of health (SOH) during fast discharges under limits. Most of the battery management system (BMS) applications required T s as the input to the controller. Hence, an inverse calculation for estimating T c from known T s was carried out and found to be reasonably accurate. It was found that the thermal parameter C s played a major role in the accuracy of T s prediction and must have low values to minimize errors.

Keywords: battery core temperature; Kalman filter; Li ion battery; MATLAB/Simulink; thermal management system

1. Introduction

With fossil fuels depleting at a rapid rate, there is a need for automobiles to be driven from alternate sources of energy. A traditional automobile pollutes the environment by letting out harmful gases. A battery electric vehicle (BEV) does not require fossil fuels, is nonpolluting and has fewer moving parts requiring less maintenance than a conventional fossil-fuel powered vehicle. Hence, a BEV is considered superior compared to fossil-fuel powered cars. Hence, to maintain stable operation and obtain maximum power from a battery, temperature monitoring is called for. From practical considerations, it is not always possible to measure or monitor core temperature (T c) and take corrective action. But surface temperature (T s) and ambient temperature (T amb) can be measured. In the present work, T c of a battery was estimated using a Kalman filter. A thermal model of a battery was developed using convection resistances and convection capacitances. The governing equations for T s and T c were derived in terms of T amb from the developed thermal model. Since, T c cannot be measured directly, and estimation technique was used to predict it using a Kalman filter based on measured T s and T amb for different patterns of current. An inverse process of estimating T s from known T c was carried out and the role of the thermal parameter C s was studied. Since, the changes in T c were ignored, dT s/dt = 0. Hence, C s was not present in the state space equations. By integrating dT s/dt, T s was found in the inverse calculation.
**Major Contributions:** In this paper, $T_c$ for a Li (Lithium) ion battery was estimated using a thermal model using a Kalman Filter. The changes in $T_s$ for short intervals were ignored as they were very small. The thermal parameter $C_s$ did not contribute to $T_c$. For all BMS applications, the sensed temperature, $T_s$ is used as an input for the controller as homogeneity in $T_s$ exits. Hence, an attempt was made to estimate $T_s$ from known $T_c$ so as to build a wireless BMS (battery management system). It was observed that the parameter $C_s$ contributed to $T_s$ as $dT_s/dt$ was integrated to obtain $T_s$ from estimated $T_c$. Lower $C_s$ values provided better estimates for $T_s$.

2. Literature Review

Electric vehicle/hybrid electric vehicles (EV/HEV) generally use battery packs to drive vehicles. These battery packs are made of hundreds of cells connected in series and parallel combinations based on voltage and current requirement. Generally, Li ion cells are preferred due to several advantages like high energy density and high specific density [1]. However, they are highly sensitive to temperature (generally high temperature reduces battery life and capacity). Therefore, they must be operated under certain ranges of temperature for better performance and life [1].

In the past, several attempts have been made in estimating the $T_c$ of the battery. A lithium iron phosphate (LiFePO$_4$) battery of 40 Ah capacity was selected and its $T_c$ was estimated using a thermal model [2]. Three temperature sensors were placed at appropriate locations to estimate $T_c$. Surface temperature ($T_s$) sensors were placed at strategic locations and measured. The experiment was performed in a controlled temperature chamber and hence $T_{amb}$ was fixed to 25 °C. The battery thermal parameters where found using the least square algorithm. It was found that the values of thermal parameters $C_c$ and $C_s$ did not contribute to the steady state temperature. However, their effect was predominant in the transient period of $T_c$ estimation. Based on the thermal model, the governing equations were derived. A transfer function of $T_c/Q$ was extracted. The ABCD matrices (state space matrices) were obtained and fed to the Kalman filter. The states were $T_{is}$ and $T_{ss}$ where $T_{is}$ was $T_c$ and $T_{ss}$ was $T_s$.

MATLAB/Simulink was used for modelling and thermal parameters were obtained from experiments in [3,4]. A thermal model was developed based on the heat developed by (a) internal resistance $Q_{r0}$, (b) rate of mixing of materials $Q_{rev}$ and (c) environmental heat transfer $Q_{env}$. The equivalent battery parameters had two RC pairs and an internal resistance $R_0$ in series with open circuit voltage (OCV). It was observed that when the SOC ranged between 0.3 and 0.7, $Q_{rev}$ became negligible. This phenomenon was observed during battery discharge. The limitation in this paper was that the effect of $T_{amb}$ and the $T_s$ was not considered. LiFePO$_4$ battery of 40 Ah capacity was selected.

The quantity of heat generated was taken as a product of current squared and an estimated value of resistance in [5]. The ABCD matrices were obtained from the derived thermal model. The states were $T_c$ and $T_s$ and the inputs were $I^2$ and $T_{amb}$. A Luenberger observer was used to estimate $T_c$ based on output $T_s$. The thermal parameters were estimated using recursive least square (RLS) algorithm.

In order to estimate $T_c$, OCV, $V_T$, $T_s$ and $T_{amb}$ are required [6]. The OCV of a Li ion battery can be estimated using $V_T$. In this paper, the OCV was estimated using Thevenin’s model as shown in [7]. However, fast charging applications, higher order battery models need to be used to estimate OCV [8]. A five RC pair enhanced self-correcting (ESC) model was used to capture the high frequency components in current.

$T_c$ estimations were carried out mainly using a Kalman Filter (KF), finite element method (FEM) and extended Kalman filter (KF).

The general form of a KF and its governing equations are discussed in [9–11]. The output of the KF was $T_c$ and the inputs were OCV, $V_T$, $T_s$ and $T_{amb}$ [8]. The governing equations for a KF is shown in [12].

The finite element method (FEM) was the numerical approach used to model the thermal behavior of batteries. FEM finds an approximate answer to boundary value
problems for partial differential equations. The method takes the total problem area and divides it into a finite amount of elements and uses variation methods to solve the problem by minimizing the error [13–16]. The proposed model was based on Pade’s approximation method and simplified thermal model. Pade’s method computes total heat generation and feeds it into a finite amount of elements and uses variation methods to solve the problem.

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A sensor-less method for estimation of $T_c$ was proposed in [17]. An extended Kalman filter (EKF) was used to estimate $T_s$ and $T_c$. The validation was carried out by comparing measured $T_s$ with the estimated value. The thermal model considered was a PDE (partial differential equation) which was dependent on the geometry of the battery and thermal specifications. A 2.3 Ah LiFePO4 battery was considered.

3. Thermal Model

Figure 1 shows the thermal model considered for $T_c$ estimation. It consists of thermal resistances $R_c$ and $R_u$ (K/W) and heat capacity at the core and surface regions $C_c$ and $C_s$ (J/K).

![Figure 1. Second order thermal model of a battery [18].](image)

Equations (1) and (2) are used to estimate the value of $T_c$ for various current patterns.

$$C_c \frac{dT_c}{dt} = Q + \frac{(T_s - T_c)}{R_c}$$

$$C_s \frac{dT_s}{dt} = \frac{(T_{amb} - T_s)}{R_u} - \frac{(T_s - T_c)}{R_c}$$

$$T_s = \int \left[ \frac{T_{amb} - T_s}{C_s R_u} - \frac{T_s - T_c}{R_c C_s} \right]$$

$$T_c = \int \left[ \frac{1}{C_c} \cdot Q + \frac{T_s - T_c}{C_c R_c} \right]$$

$$Q = I \ast (V_T - V_{OCV})$$

The state model of a KF are shown in (8) and (9).

$$X_k = A_{k-1} \ast X_{k-1} + B_{k-1} u_{k-1} + W_{k-1}$$

$$Y_k = C_k \ast X_k + D_k \ast U_k + V_k$$

where $X_t$ is state of the system ($T_{c,t}$), $Y_t$ = output of the system ($T_{s,t}$), $u_t$ is the input to the system ($[T_{amb,t} Q]^T$), $t = $ present state of the system and $t-1 = $ previous state of the system.

Rewriting Equations (1) and (2) in discrete time:

$$[T_{c,t}] = \left[ 1 - \frac{1}{C_c (R_c + R_u)} \right] [T_{c,t-1}] + \left[ \frac{1}{C_c (R_c + R_u)} \right] \frac{1}{C_c} \begin{bmatrix} Q \\ T_f \end{bmatrix}$$

$$[T_{s,t}] = \left[ \frac{R_u}{R_c + R_u} \right] [T_{c,t-1}] + \left[ \frac{R_c}{R_c + R_u} \right] 0 \begin{bmatrix} Q \\ T_f \end{bmatrix}$$
LMX35 series from Texas Instruments was used to measure $T_s$ and $T_{amb}$ and the accuracy in the measurement was 1 K.

The governing equations of the Kalman filter were simulated using MATLAB/Simulink with the help of ‘Commonly Used Blocks’.

4. Experimental Setup

A MATLAB script based automated battery test system (BAS) which runs on Windows 10 was used for the experimentation. This had the capability of providing 100 ms latency between real time experiment and the operational system. Since, the control is based on temperature response, which has latency in the range of minutes; it is possible to implement the controller in such manner. Figure 2 shows the components of BAS and their integration. The power paths are represented by solid lines, communication and signal paths are represented by dashed lines. Standard commands for programmable instruments (SCPI) protocol are used for controlling action. Table 1 shows the battery specifications.

![Block Diagram of a battery test system (BAS)](image)

**Table 1. Specifications of NMC (Lithium Nickel Manganese Cobalt Oxide) Lithium-ion battery.**

| Specifications                  | Values                                      |
|--------------------------------|---------------------------------------------|
| Manufacturer                   | LG Chem                                     |
| Model                          | INR18650HG2                                 |
| Chemical System                | LiNiMnCo02HNMC                              |
| Nominal Voltage                | 3.6 V                                       |
| Nominal Capacity               | 3000 mAh                                    |
| Standard Charging (CC-CV)      | 1.5 A, 4.2 V max, Cut Off: 50 mA            |
| Fast Charging (CC-CV)          | 4 A, 4.2 V max, Cut Off: 100 mA             |
| Discharging Condition          | 20 A                                        |
| Discharge Cut Off Voltage      | 2 V                                         |
| Operating Temperature          | Charge: 0 to 50 °C, Discharge: −30 to 60 °C |
| Weight                         | 48 g                                        |

For charging the battery, a programmable power supply E36313A from Keysight was used. 6 A and 10 A were delivered at the first channel, with a least count of 350 µV. This provided four wire configurations helpful to remove the losses. Second and third channels
were utilized to control the relays, SW_CHAR and SW_DISC as shown in Figure 2. In order to provide protection during charge and discharge cycles, relays were used. A detailed explanation regarding the setup is provided in [19]. Figure 3 shows the experimental setup for measurement of $T_{\text{amb}}$, $T_s$, Current and $V_T$.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure3.png}
\caption{Schematic of experimental setup. 1. Battery under test. 2. Temperature Sensor. 3. Thermal chamber.}
\end{figure}

$T_{\text{amb}}$ could be maintained at $-273$ K, $293$ K and $323$ K with an auxiliary temperature chamber from associated environmental system. It had the capability to operate in the range of $233$ K to $358$ K. The geometry of the battery had a diameter of 18.5 mm and height of 65.2 mm.

5. Results and Analysis

$T_c$ was estimated using a KF for various patterns for currents depending on the datasheet for the Li ion cell so that no capacity fade occurred. Four test cases numbered 1 to 4, were considered. The results obtained are discussed below:

5.1. Case 1

The pattern of current is shown in Figure 4. $T_c$ was initialized to $T_s$ and $T_{\text{amb}} = 273.4$ K taken as the initial condition is shown in Figure 5. It may be noted that $T_c$ and $T_s$ closely followed the current pattern. As observed from Figure 6, $T_c$ and $T_s$ closely followed each other and the current profile. Figure 7 shows $(T_c - T_s)$ with respect to time. As the rate of current drawn from the battery increased, $T_c >> T_s$ and the maximum deviation was of the order of 5 K.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure4.png}
\caption{Current vs. Time.}
\end{figure}
Figure 5. $T_{amb}$ vs. Time.

Figure 6. Variation of estimated $T_c$ and measured $T_s$.

Figure 7. Variation of $(T_c - T_s)$.

5.2. Case 2

In this case, the current profile was altered as shown in Figure 8. $T_c$ was initialized to $T_s$ and $T_{amb} = 323$ K as per Figure 9. Figure 10 shows the variation of $T_c$ with respect to $T_s$ and Figure 11 shows the difference between $T_c$ and $T_s$ as a function of time. It may be noted that $T_c$ and $T_s$ followed the current pattern, as in Case 1 and the maximum difference between $T_c$ and $T_s$ was about 1.5 K, which occurred when the current was maximum.
5.2. Case 2
In this case, the current profile was altered as shown in Figure 8. Tc was initialized to Ts and Tamb = 323 K as per Figure 9. Figure 10 shows the variation of Tc with respect to Ts and Figure 11 shows the difference between Tc and Ts as a function of time. It may be noted that Tc and Ts followed the current pattern, as in Case 1 and the maximum difference between Tc and Ts was about 1.5 K, which occurred when the current was maximum.

Figure 8. Current vs. Time.

Figure 9. Tamb vs. Time.

It may be noted from Case 1 and 2 studies, that the deviations in the estimates were relatively high (~5 K) whenever the current changed as a large step-function. It seems that the equations used cannot satisfactorily resolve such profiles.

5.3. Case 3
The profile of current discharge is shown in Figure 12. Tamb = 274 K was chosen, as per Figure 13. Figure 14 shows the estimated Tc and measured Ts variations. As the current rose to 0.6 A, Tc also increased to about 276 K causing a difference of about 1.2 K with respect to Ts. At lower current values, Ts dominated Tc and the difference was about 0.5 K. Figure 15 shows the difference between Tc and Ts.

Figure 10. Tc and Ts vs. Time.

Figure 11. (Tc − Ts) vs. Time.

Figure 12. Current vs. Time.

Figure 13. Tamb vs. Time.

Figure 14. Estimated Core Temperature vs. Measured Surface Temperature.

Figure 15. Temperature vs. Time.
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5.3. Case 3

The profile of current discharge is shown in Figure 12. $T_{amb} = 274$ K was chosen, as per Figure 13. Figure 14 shows the estimated $T_c$ and measured $T_s$ variations. As the current rose to 0.6 A, $T_c$ also increased to about 276 K causing a difference of about 1.2 K with respect to $T_s$. At lower current values, $T_s$ dominated $T_c$ and the difference was about 0.5 K. Figure 15 shows the difference between $T_c$ and $T_s$.

5.4. Case 4

The current profile is shown in Figure 16. Figure 17 shows the $T_{amb}$ variation. Figure 18 shows the variation of estimated $T_c$ and measured $T_s$ and Figure 19 shows the variations of $(T_c - T_s)$. Since the rate of current discharge was very small, $T_s > T_c$ and difference was very small. Hence, it can be noted that at lower current discharges, $T_s > T_c$ which is shown in Figure 19.
Figure 12. Current vs. Time.

Figure 13. Variation of Tamb.

Figure 14. Variations of estimated $T_c$ and measured $T_s$.

Figure 15. $(T_c - T_s)$ vs. Time.

5.4. Case 4

The current profile is shown in Figure 16. Figure 17 shows the Tamb variation. Figure 18 shows the variation of estimated $T_c$ and measured $T_s$ and Figure 19 shows the variations of $(T_c - T_s)$. Since the rate of current discharge was very small, $T_s > T_c$ and difference was very small. Hence, it can be noted that at lower current discharges, $T_s > T_c$ which is shown in Figure 19.
5.4. Case 4

The current profile is shown in Figure 16. Figure 17 shows the Tamb variation. Figure 18 shows the variation of estimated Tc and measured Ts and Figure 19 shows the variations of \( (T_c - T_s) \). Since the rate of current discharge was very small, \( T_s > T_c \) and difference was very small. Hence, it can be noted that at lower current discharges, \( T_s > T_c \) which is shown in Figure 19.

Figure 16. Current vs. Time.

Figure 17. Tamb vs. Time.

Figure 18. Estimated \( T_c \) and \( T_s \) vs. Time.

As seen in Figures 14–19, a noisy response was observed. This noise in the signal was due to the temperature chamber cooling system and this had no effect on the temperature measurement.

6. Inverse Calculation for the Verification of the Algorithm

For verifying the algorithm, estimated \( T_c \) was used to predict and compare with measured \( T_s \). The initial condition for recalculating \( T_s \) was based on that of \( T_c \) using Equation (5). The differences between \( T_c \) estimated and \( T_c \) measured were compared and the error vs. time was plotted. In these estimates, \( C_s \) was found to be an important parameter which decided the accuracy of prediction. However, its contribution in \( T_c \) estimation was insignificant.

Sensitivity analysis for \( C_s \) was carried out. It was observed that low values of \( C_s \) showed minimal error in \( T_s \) estimation. Simulations were carried out for Case 1 for various values \( C_s \) as shown in Table 2.

Table 2. Sensitivity analysis of \( C_s \) for Case 1.

| SL. NO | \( C_s \) (J/K) | Max Error (\( T_s \) estimation~\( T_s \) measured) |
|--------|----------------|--------------------------------------------------|
| 1      | 0.05           | 0.02                                             |
| 2      | 0.50           | 0.11                                             |
| 3      | 1.00           | 0.18                                             |
| 4      | 5.00           | 0.32                                             |
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Table 2. Sensitivity analysis of \( C_s \) for Case 1.

| SL. NO | \( C_s \) (J/K) | Max Error \( (T_s \text{ estimation} - T_s \text{ measured}) \) |
|--------|-----------------|----------------------------------------------------------|
| 1      | 0.05            | 0.02                                                     |
| 2      | 0.50            | 0.11                                                     |
| 3      | 1.00            | 0.18                                                     |
| 4      | 5.00            | 0.32                                                     |

Figure 20a,b show the plots for inverse calculation for \( T_s \) estimation from known \( T_c \) for \( C_s = 0.05 \) and 12 J/K, respectively, for Case 1, and Figure 21a,b shows the error between the estimated and measured \( T_s \), respectively.
Figure 20a,b show the plots for inverse calculation for $T_s$ estimation from known $T_c$ for $C_s = 0.05$ and $12$ J/K, respectively, for Case 1, and Figure 21a,b shows the error between the estimated and measured $T_s$, respectively.

(a) $C_s = 0.05$ J/K

(b) $C_s = 12$ J/K

Figure 20. Variation of (estimated $T_s$ − measured $T_s$) for various $C_s$. 
Figure 21. Error in estimation for various $C_s$.

Figure 22a,b shows the plots for inverse calculation for $T_s$ estimation from known $T_c$ for $C_s = 0.05$ and 12 J/K, respectively (Case 2), and Figure 23a,b shows their error in estimation, respectively.
Figure 22. Variation of (estimated $T_s - measured T_s$) for various $C_s$.

(a) $C_s = 0.05$ J/K

(b) $C_s = 12$ J/K
Figure 23. Error in estimation for various $C_s$.

Figure 24a,b shows the plots for inverse calculation for $T_s$ estimation from known $T_c$ for $C_s = 0.05$ and $12$ J/K, respectively (Case 3) and Figure 25a,b shows their error in estimation, respectively.
Figure 24. Variation of (estimated $T_s$ − measured $T_s$) for various $C_s$. 

(a) $C_s = 0.05$ J/K

(b) $C_s = 12$ J/K
Figure 25. Error in estimation for various $C_s$.

Figure 26a,b shows the plots for inverse calculation for $T_s$ estimation from known $T_c$ for $C_s = 0.05$ and 12 J/K respectively (Case 4) and Figure 27a,b shows their error in estimation.
Figure 26. Variation of (estimated $T_s -$ measured $T_s$) for various $C_s$.

(a) $C_s = 0.05$ J/K

(b) $C_s = 12$ J/K
Figure 27. Error in estimation for various $C_s$.

It can be concluded from the above plots that smaller values of $C_s$ provide better $T_s$ estimates leading to minimum deviations. Table 3 shows a comparative percentage change in $T_c$ for various types of batteries based on different current discharge profiles.
Table 3. Percentage change in $T_c$ for various current discharge profiles.

| SL.NO | Capacity (Ah) | Type of Chemistry | % Change in $T_c$ |
|-------|---------------|-------------------|------------------|
| 1     | 40            | LiFePO$_4$        | About 37         |
| 2     | 60            | Lead acid         | About 40         |
| 3     | 68            | Lead acid         | About 25         |
| 4     | 3             | LiNiMnCo02HNMU    | About 1          |

7. Conclusions

The governing equations for a thermal model were derived for a Li ion battery. Since, the sampling time was 1 s, the step size for solving the equation was chosen as 100 ms to capture transients. It was noted that $T_c > T_s$ whenever the magnitude of current discharge was large. The thermal capacitance $C_s$ had no effect on the estimation of $T_c$. The thermal parameters chosen were $R_c = 11.8 \text{ K/W}$, $R_u = 10 \text{ K/W}$, $C_c = 110 \text{ J/K}$. These values would depend on the order of the thermal model. The error percentage in estimating the thermal parameters for higher order thermal models with respect to the thermal model used would be $<0.1\%$, which is acceptable. $T_c$ estimation for higher order thermal models will be presented in the future papers. For every 273.25 K increase in temperature, battery capacity is affected by 5%. In order to avoid capacity fade, temperature has to be kept under control. Hence, $T_c$ estimation is carried out. Inverse calculation was performed to obtain $T_s$ from estimated $T_c$. For all BMS applications, the sensed temperature, $T_s$ was used as an input for controller as homogeneity in $T_s$ exists. Hence, inverse calculation was performed. Sensitivity was carried out and it was found that $C_s$ and $R_c$ majorly contributed to $T_c$. It was found that low values of $C_s$ ($0.05 \text{ J/K}$) provided minimal errors in estimation. As the value of $C_s$ increased ($C_s = 12 \text{ J/K}$), the error in estimations increased. Hence, optimization of $C_s$ is an important contributor in inverse estimates.

Author Contributions: S.S.—Development of mathematical models for core temperature estimation and Kalman Filter using MATLAB/Simulink; V.M.—Carried out experimental work by measuring the battery current, ambient and surface temperatures using appropriate sensors; S.W.—Provided technical advice. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

| SL.No | Abbreviation | Meaning |
|-------|--------------|---------|
| 1     | $T_{\text{amb}}$ | Ambient temperature |
| 2     | $T_s$         | Surface temperature |
| 3     | $T_c$         | Core temperature |
| 4     | $R_c$         | Convective resistance between core and surface temperatures |
| 5     | $R_u$         | Convective resistance between surface and ambient temperatures |
| 6     | $C_c$         | Heat capacity of the core of the battery |
| 7     | $C_s$         | Heat capacity of the surface of the battery |
| 8     | $Q$           | Quantity of heat |
| 9     | $I$           | Current |

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