Thermal Analysis for Lithium-Ion Battery Pack based on Parameter Estimation based on Genetic Algorithm

Yong Wang¹, Yelin Deng²*, Weiwei Liu¹, Kunkun Hao¹ and Hongchao Zhang³

¹ School of Mechanical Engineering, Dalian University of Technology, Dalian, Liaoning, 116024, China
² School of Rail Transit, Soochow University, Suzhou, Jiangshu,215006, China
³ Industrial Engineering, Texas Tech University, Lubbock, TX 79409-3061, USA
*Corresponding author’s e-mail: yelin.deng@hotmail.com

Abstract. Thermal analysis of Lithium-ion battery pack is the important portion of battery management for electric vehicles. The heat produced in charging and discharging will bring about impairment of the safety and service life of batteries. It is thus important to monitor battery temperature for prevention of the battery failure. This paper first sets up a simulation model based on the second-order RC circuit model of the heat generation and dissipation of the battery pack using SIMULINK. The temperature of the battery pack is tested under the New European Driving Cycle conditions. And by comparing with the experimental data of the battery temperature, the heat dissipation coefficient in the simulation model will be optimized by the genetic algorithm using MATLAB. The optimization result shows that the difference between the simulated temperature and the actual temperature is within one degree, so the model based on the optimization result can accurately reflect the actual temperature change.

1. Introduction
As the situation of environmental pollution and energy consumption being serious, it is urgent to find sustainable energy alternative development methods [1]. Lithium-ion battery is growing in popularity for the electric vehicles (EVs) due to its advantages of high energy density, little or no memory effect, and low self-discharge [2]. The temperature state of the battery directly affects energy and efficiency issues during use. Thus, for further growth of Li-ion battery business, thermal management should attract enough attention.

There are many types of battery models to estimate the battery performance parameters and its state at different operating conditions. Common battery models include mathematical models, electrochemical models, equivalent circuit models, and coupling models. The equivalent circuit model does not need to study the electrochemical reaction inside the battery, and can be written to specific mathematical equations for analysis and application. Typical equivalent circuit models include General Nonlinear (GNL) model, Thevenin model, and Partnership for a New Generation of Vehicles (PNGV) model etc [3]. Second-order Thevenin circuit model can balance both steady-state and transient characteristics in the charge and discharge process. High order Thevenin circuit model is too complicated, which will cause too much calculation [4]. This paper chooses the second-order Thevenin circuit model.
The heat dissipation coefficient in the simulation model needs to be optimized to get accurate simulation results [5]. The general iterative method is liable to fall into the local minimum trap and the phenomenon of "endless loop" appears, which will make iteration impossible. Genetic algorithm is a global optimization algorithm which can overcome this shortcoming. There are no restrictions on the derivation and the continuity of the function [6]. So the genetic algorithm is suitable for optimization analysis of equivalent circuit model.

2. The design of simulation model

2.1. second-order Thevenin battery model
The Thevenin model is simpler than other models and can well reflect the dynamic characteristics of the battery. The second-order Thevenin model adds an additional RC loop to the first-order Thevenin model, which can accurately simulate the charge and discharge behavior of the battery.

![Second-order Thevenin Model](image)

Figure 1. Second-order Thevenin Model.

The mathematical expression of the model is as follows:

\[ U_{ocv} - U_1 - U_2 - IR_0 = U_0 \]  \hspace{1cm} (1)

\[ I = \frac{U_i}{R_i} + C_i \frac{dU_i}{dt} \]  \hspace{1cm} (2)

\[ \int I_i \, dt = U_i C_i = \frac{U_i \tau_i}{R_i} \]  \hspace{1cm} (3)

\[ I_R = \frac{U}{R_i} \]  \hspace{1cm} (4)

\[ I_{C_i} = I - I_R \]  \hspace{1cm} (5)

\[ \tau_i = R_i C_i \]  \hspace{1cm} (6)

In these formulas, \( U_{ocv} \) is the voltage across the battery, \( U_{ocv} \) is the battery internal voltage, \( R_0 \) is the ohmic resistance, \( R_i \) (\( i = 1, 2 \)) are the polarization resistances, \( I \) is the discharge current, \( C_i \) (\( i = 1, 2 \)) is the capacitance, \( \tau_i \) (\( i = 1, 2 \)) is the time constant of the RC loop.

2.2. Analysis of heat generation and heat dissipation
Calculation of heat generation for battery pack is according to the equivalent circuit model. In the second-order thevenin battery model, the heat generation from internal resistance is looked as the main heat generation. The heat generation rate \( Q \) is calculated by the product of each internal resistance and the square of each electric current:

\[ Q = I^2 R_0 + I_1 R_1 + I_2 R_2 \]  \hspace{1cm} (7)
The heat exchanged between the battery pack and the environment mainly proceed through heat conduction and heat convection. Heat conduction occurs mainly through solids, while heat convection and heat conduction occur simultaneously in the fluid. In this study, the battery pack is located in the car. The heat dissipation coefficient between the battery pack and the environment can be represented by a parameter.

The heat balance formula is:

\[ Q \Delta t - hS(T_{\text{battery}} - T_{\text{env}}) = cm(T_{\text{battery}} - T_0) \] (8)

In this formula, \( h \) is the heat dissipation coefficient between battery pack and environment, \( S \) is the heat dissipation area of the battery pack, \( c \) is specific heat capacity of the battery pack, and \( m \) is the quality of the battery pack. \( T_{\text{battery}} \) is the simulation temperature in model, \( T_{\text{env}} \) is the Ambient temperature, \( T_0 \) is the initial temperature of the battery pack.

And the values obtained in previous experiments are showed as follow: \( S \) is 1.5 \( m^2 \) for the pack, \( c \) is 1.026 J/g/K for one battery module, \( m \) is 2000g for one battery module. And there are 96 battery modules in the battery pack. The quality of the battery pack is 1.5 times as much as the 96 battery modules. And the ambient temperature during the experiment \( T_{\text{env}} \) is 25°C.

2.3. Simulation model and settings
The simulation model is built in SIMULINK by the analysis of heat generation and heat dissipation. The model inputs include current, SOC and battery pack temperature gotten from 1-D Look-up Tables, which is obtained through charge-discharge experiment by the The New European Driving Cycle (NEDC).

The experiment was performed by the NEDC cycle test. The initial SOC is 96% and the ending SOC is 7%. The initial battery pack temperature was 25 degrees Celsius, and the end temperature was 30 degrees Celsius.

The ohmic internal resistance( \( R_0 \) ), polarization internal resistance( \( R_i \) (\( i=1, 2 \))), and time constant( \( \tau_i \) (\( i=1, 2 \))) are affected by the SOC and temperature. And \( R_0, R_i \) (\( i=1, 2 \)) will also be affected by charge and discharge. So these parameters should be gotten from 2-D Look-up Tables.

The simulation model diagram is shown in Figure 2:
In the subsystem 2 showed on the figure 3, the heat dissipation coefficient $h$ is given a gain module $G$ to be a variable, which will be optimized through genetic algorithm.

![Subsystem 2 in the model.](image)

### 3. Parameter Optimization by Genetic Algorithm

In the simulation model, there is an uncertain parameter which is the heat dissipation coefficient $h$, which needs to get the optimized value by comparing with the experimental data. Parameter optimization is achieved by the Genetic Algorithm. In this paper, the heat dissipation coefficient $h$ is optimized by using the genetic algorithm toolbox that comes with MATLAB.

#### 3.1. Design of fitness function

The selection of fitness function directly affects the convergence speed of the genetic algorithm and determines whether it can find the optimal solution. Generally speaking, the fitness function is transformed from the objective function. In this paper, the fitness function is designed as the $1/2$ power of average value of the variance between the simulated value and the actual value. The formula is as follow:

$$F = \sqrt{\frac{1}{n} \sum_{k=1}^{n} [(T_m(k) - T_e(k))^2]}$$  \hspace{1cm} (9)

In this equation, $T_m(k)$ is the simulated temperature on every simulation moment, and $T_e(k)$ is the actual temperature.

#### 3.2. Optimization of Genetic Algorithm

The connection between the Genetic Algorithm Toolbox and SIMULINK is implemented by programming in MATLAB. The variable in the Genetic Algorithm Toolbox is the gain module $G$ in the simulation model, so the final result of the algorithm optimization is the heat dissipation coefficient $h$. The algorithm will be stopped when the average change in the fitness value is less than the Function Tolerance, which is set as $10^{-6}$.

![The result of the best fitness by the Genetic Algorithm Toolbox.](image)
And the result of the best fitness from the entire optimization process is shown as the figure 4. The fitness value shows that the basic genetic algorithm has evolved into the local optimal solution after about 10 generations. In the figure, the optimal solution is 0.385596 in the last generation, which is equal to the variable $F$ in the formula (9). And it can be looked as the fitting degree between the simulation temperature and the actual temperature.

During the optimization process, individuals of each generation will be displayed in $G$ of the Subsystem 2 on the figure 3. And final point of the best individual is 8.487, which is the final heat dissipation coefficient.

3.3. Result of the simulation
The heat dissipation coefficient $h$ is 8.487 getting from the optimization result in the simulation model. The comparison of simulation result and experimental data is shown on the figure 5. In the figure 5, the simulation curve can reasonably simulate the change of actual temperature.

![Figure 5. Comparison of simulation result and experimental data.](image)

4. Conclusions
Based on the genetic algorithm, the uncertain heat dissipation coefficient in the thermal model is optimized in this paper. The optimization result in the model shows that the difference between the simulated temperature and the actual temperature is within one degree in the whole process, which makes the simulation model more accurately simulate the temperature change of the actual operating conditions of the battery pack. And this study has certain reference value for the calibration of thermal parameters in battery management systems.

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