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Battery Pack Temperature Estimation Model for EVs and Its Semi-transient Case Study

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Lithium-ion (Li-ion) batteries may fail through thermal runaway caused by increased temperature. It is thus important to monitor battery temperature for prevention of the battery failure. Currently, thermal monitoring of the battery for electric vehicles (EVs) is being conducted by multiple thermostats. As the size of battery system increases and the cells are closely packed to exploit high power density, the number of thermostats is also increased to monitor the battery system. However, this increased number of sensors enhances the probability of the sensor malfunction, which prevents robust thermal monitoring, and causes increased maintenance cost and customer complaints. This paper thus proposes an online applicable temperature prediction model for EV battery pack while minimizing the number of sensors and keeping the monitoring capability. This was possible with three ideas: (a) devising battery thermal characterization test under various operating conditions, (b) development of the online-applicable temperature prediction model using artificial neural network (ANN), and (c) validation of the temperature prediction model. The proposed temperature prediction model was demonstrated with the EV battery pack that consists of twelve battery modules.

1. Introduction

Li-ion battery is growing in popularity for many engineering application due to its advantages of high energy density, little or no memory effect, and low self-discharge. In spite of many desirable features of Li-ion battery, it has one rare but severe failure mode of fire/explosion for the electric vehicles (EVs). Thus, for further growth of Li-ion battery business, the safety problem should be taken care.

Most failure modes of Li-ion battery are related to temperature increase. Increased temperature causes another side reaction in the battery which again causes further increase in temperature, resulting in thermal runaway. It is thus important to keep the temperature below a certain temperature limit for prevention of the battery failure due to thermal runaway. Even if not related to battery failure directly, temperature increase may degrade battery performance significantly. Such battery issues necessitate temperature monitoring as the size of battery system increases. In the auto industry, temperature monitoring is accomplished by the thermo sensors on each battery module. Although this monitoring method gives a quite good monitoring solution, it also gives rise to some problems: high chance of sensor malfunction due to a large number of thermo sensors, extra maintenance cost and customer complaints.

This paper thus suggests replacing some of thermo sensors with a temperature estimation model while maintaining good temperature monitoring performance. Temperature estimation could be conducted in various ways. Hossein Maleki et al. model the battery temperature distribution of the labtop computer reasonably well by the Ice-Pak simulation. Also Ralph E. White et al. and Chee Burm Shin et al. make the theoretical temperature model based on physics of a battery. Although those of a simulation and theoretical model gives a good temperature estimation, direct use of the simulation result is almost impossible for real-time temperature monitoring and it is difficult to develop theoretical models for different battery. Moreover, computer simulation delivers too much information than needed. Thermo sensors at some designated points on the battery pack give enough temperature information for the battery management system. This paper thus proposes an online applicable temperature prediction model for EV battery pack while minimizing the number of sensors and keeping the monitoring capability. This was

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possible with three ideas: (a) devising battery thermal characterization test under various operating conditions, (b) development of the online-applicable temperature prediction model using artificial neural network (ANN), and (c) validation of the temperature prediction model. The proposed temperature prediction model was demonstrated with the EV battery pack that consists of twelve battery modules

This paper is composed of three parts. In the first part, battery characteristics tests are executed to acquire battery thermal characteristics for the use in the battery simulation. Next, the simulation predicts temperature distribution of the battery pack and reads temperature data at designated locations under various battery conditions. Finally, ANN trains a temperature prediction model based on the predicted temperature database. The proposed idea was validated for the thermally steady-state and semi-transient cases of the EV battery pack.

2. Battery Thermal Characterization Test

Tests for battery thermal characterization is of great essence for development of the online temperature prediction model for EV battery pack. This study employed Li-ion battery cells with 50Ah capacity, 3.7V nominal voltage from SK Innovation. With the aim to model a battery heat generation rate, battery tests must be carefully designed under various conditions of charging/discharging rate and ambient temperature. MACCOR Series 4000 battery cycler and Espec heat chamber is used for the battery thermal characterization test. The three-step test was designed as: Step-1) battery heat capacity test, Step-2) a design of experiment (DoE) for acquisition of heat generation rate, and Step-3) equivalent heat generation rate modeling.

2.1 Step 1 – Battery Heat Capacity

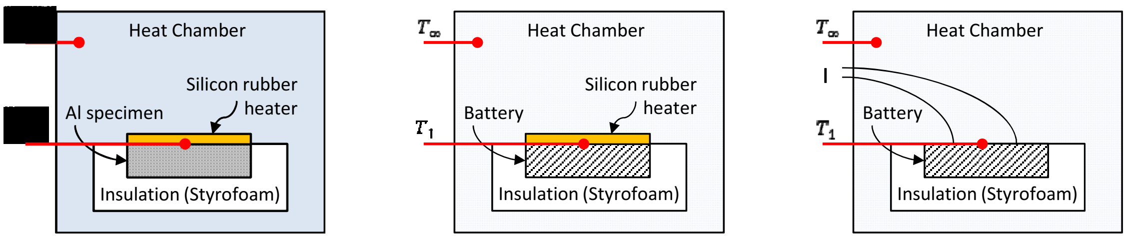
Heat generated from the battery (Qgen) is dissipated to the surroundings (Qconv) or stored in the specimen (Qstor). This can be expressed by the following governing equation:

$$\dot{Q}_{gen} = \dot{Q}_{stor} + \dot{Q}_{conv} = \rho \cdot V \cdot C \cdot \frac{dT}{dt} + h \cdot A \cdot (T - T_a) \quad (1)$$

where ρ is density, *V* is the volume, *C* is the heat capacity, *h* is the heat transfer coefficient, *A* is surface area, *T* and T_a is temperature of the specimen and ambient temperature, respectively. Before we use the equation (1), we must obtain the unknown parameters h and C of the battery first. Test conditions are as shown in Figure 1.

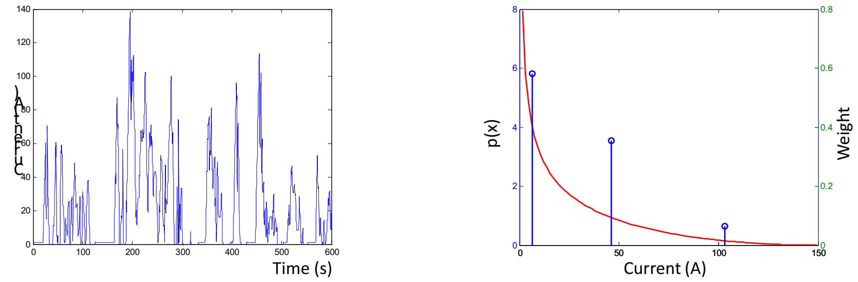
For the heat transfer coefficient, aluminum specimen is heated up by the silicon rubber heater until the temperature reaches and stabilizes to 40°C. Once the stabilized temperature is obtained, then the heat source is removed. In this case, total heat generation is zero owing to no heat source and the heat is only dissipated, not stored. Thus, only second term in the equation (1) remains with left-hand side zero. Therefore, the only unknown *h* can be estimated by measuring the temperature *T*. Through 20 experiments ensuring the value of *h*, mean *h* is 1.1153 (W/m^2K) with the standard deviation 0.0085 (W/m^2K). Similar with the first step for *h*, in next step, a battery instead of aluminum specimen is heated up to 40°C, stabilized and relaxed to the ambient temperature. For this case left-hand side is zero and the only unknown on the right-hand side is heat capacity of the battery, *C*. Through 20 experiments ensuring the value of *C*, mean *C* is 1.715 (J/gK) with standard deviation 0.0113 (J/gK).

From the two steps of experiments, every unknown parameter is verified. Now we can evaluate the heat generation rate of the battery during the charging/discharging by tracking the temperature change. This test conditions are shown in Figure 1 (c).



(a) (b) (c)

Figure 1: Test conditions of (a) heat transfer coefficient, h (b) heat capacity, C and heat generation rate (c)



(a) (b)

Figure 2: Driving profile (a) Beta distribution and weights for the Gaussian-quadrature formula (b)

2.2 Step 2 – DoE for Acquisition of Heat Generation Rate

It is known that the battery heat generation rate is dependent on many factors which are complicatedly related. Here we consider three factors charging/discharging rate which obviously the most significant factors of the heat generation rate, SOC and ambient temperature.

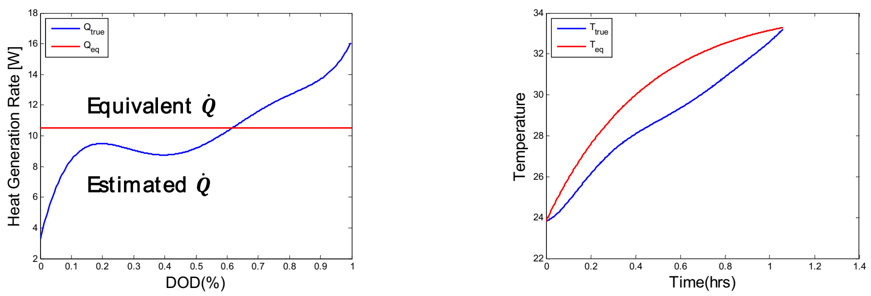
Charging/discharging rate fluctuates during the operation of the EVs. To reflect this fluctuation and choose reasonable test point, we consider the frequency of the charging/discharging rate from the dynamic current profile during EV driving test shown in Figure 2. The histogram from this profile is built and fitted to the beta distribution. By employing Gauss-type quadrature formula the test conditions are determined as 6, 46, 103A. For temperature conditions, the auto company informs us that the air coolant temperature on average is maintained as room temperature, because the air inside the car is used as coolant air, so we assume that the temperature follows Gaussian distribution with mean 22.5°C. Same as before, using Gaussian-type quadrature formula, test conditions are chosen as 14, 22.5 and 31°C. Fully charged battery is fully discharged under selected discharging rate, it naturally includes SOC variation.

2.3 Step 3 – Equivalent Heat Generation Rate Modeling

Unfortunately, time varying (or SOC varying) heat generation rate cannot be applied to the computer simulation, ANSYS FLUENT 13 which only supports constant heat generation rate. For this reason we have to find the constant value equivalent to the time varying heat generation rate. We choose the equivalent heat generation rate to reach the same temperature at the end of the fully discharged state. Figure 3 explains this condition.

In Figure 3, the temperature with equivalent heat generation rate overestimates the true temperature, but from an aspect of safety, this over estimation can be admitted. Table 1 shows the equivalent heat generation rate under test conditions.

Base on the data in the Table 1, response surface model is built. Cubic spline interpolation method is used. This heat generation response surface model will be used for the battery temperature simulation under different conditions with the test in Table 1. Figure 4 shows the result of the response surface model. As expected, the current level is the most severe factor to the heat generation rate, while temperature has little influence.



(a) (b)

Figure 3: Equivalent heat generation rate (a), temperature change with equivalent and estimated heat generation rate (b)

Table 1: Experiment settings

	Current		
Temp. [°C]	6 [A]	46 [A]	103 [A]
14	0.7025 [W]	4.1370 [W]	14.5123 [W]
22.5	0.6258 [W]	4.0218 [W]	12.9128 [W]
31	0.7324 [W]	3.0434 [W]	12.3969 [W]

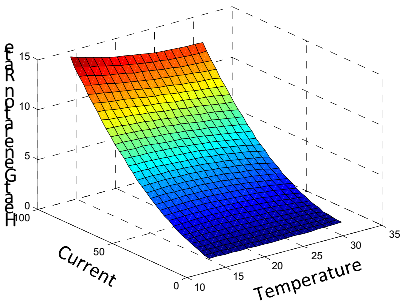


Figure 4: Response surface model of a heat generation rate

3. Temperature Prediction Model

In this Section, we develop temperature prediction model with the two methods, one by the computer simulation and the other by the ANN. The computer simulation model gives training data to the ANN model. By ANN model we have lighter model with designated information for temperature estimation.

3.1 Artificial Neural Network

Artificial neural network is a function established to explain the given desired output to the corresponding input pattern of training data without knowing complex physics behind it. The relationship between inputs and outputs are found by adjusting weight parameters of ANN. One example of structures is as follows.

Figure 5 is the two layer network structure. p is input and a^2 is output. In the first layer, layer input p is multiplied by the layer weight $\mathbf{W}^1$ and then the result n^1 goes to the activation function f^1 to give hidden layer output a^1. Same procedure repeated in the next layer to give target output a^2. To sum up, target output is written by

$$a^2 = f^2(W^2 f^1(W^1 p)) \tag{2}$$

During training, weight matrix **W** to give training output is determined. In this research, we choose two layer structure with 10 neurons in the hidden layer, and logistic sigmoidal and linear activation functions for

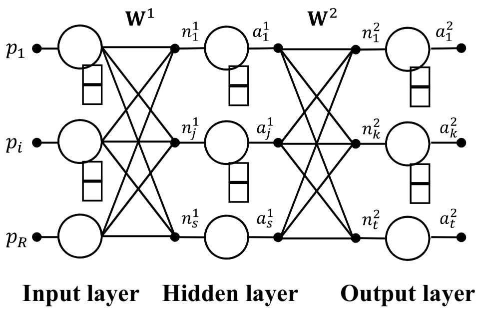


Figure 5: Two layer network structure

the first and second layer, respectively.

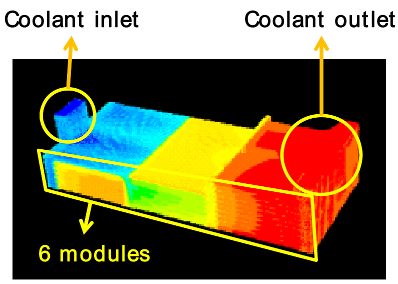


Figure 6: Temperature distribution model for the EV battery pack by ANSYS FLUENT

3.2 Simulation Model and ANN Model

A battery pack we try to model is for the EV applications. It contains total 12 modules but only 6 modules are modeled by the ANSYS FLUENT because the other 6 modules are placed in symmetric. Coolant air comes in from the front top and goes out to back top (Figure 6). This model is provided from the auto company and the validity is ensured by them. A heat generation rate as one of the inputs is determined from the response surface model in the Figure 4. An example of computational fluid dynamics (CFD) simulation is shown in the Figure 6.

As mentioned earlier, this computer model gives accurate temperature result but it is too costly. To have a result under very simple condition, it requires more than 2 hours. Also, it contains too much information than we need. For temperature control of this battery pack model, we need only 12 temperature values for each module, but simulation result gives whole temperature distribution. From this aspect, we remodel the simulation by ANN to have computationally efficient model with essential information.

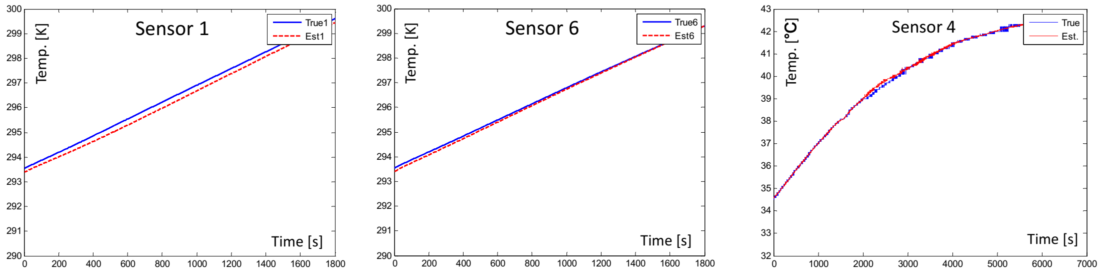
ANN input is composed of 3 dimensions containing coolant fan velocity, heat generation rate and one sensed temperature located at one of the 6 modules. ANN target is then rest of the 5 temperature of modules. Ideally temperature estimation without sensor data is desired but for now it is difficult task and involves risk of erroneous estimation as time goes on. However, by using one sensed temperature as an input of the ANN model, we can enhance the accuracy of temperature estimation, because sensor data are highly correlated. That is, we expect that if the temperature of one module is high, rest of them are accordingly high. Also, using 1 sensor data does not affect the intended goal of reducing total number of sensors.

Training data for the weight parameters optimization is obtained from the simulation results. The simulation is conducted under constant discharging conditions represented by the constant heat generation rate. The obtained output is the steady state temperature. Training conditions and corresponding heat generation rates are calculated by interpolation method. Once the model is trained, it must be validated. Validation is conducted under different conditions with the training conditions. Some of the validation conditions and results are shown in Table 2. We see that the estimated temperatures are close to the simulated temperature. Based on this steady-state result, we proceed to the temperature estimation for the semi-transient case. Semi-transient case means temperature estimation along time under the constant charging/discharging conditions. This condition is found in the constant speed driving test of EVs or a battery charging during the night. After training, it is validated under the same conditions as in as in Table 2.

The training input contains the coolant fan velocity, heat generation rate, time and one sensed temperature and the output has the rest of the 5 temperature estimation. In Figure 7, the estimated result of the sensor 1 and 6 by ANN model under the 31°C and 99A discharging are plotted. The maximum error is 0.2722°C and the average error is 0.1951°C. This estimation is conducted for 1800 seconds in simulation time. For this time, the temperature increases linearly but later the rate of temperature increase slows down and reaches in steady-state. Although the estimation after 1800 seconds is not estimated in this simulation due to the computational time, it is verified using the battery pack test data. The result is shown in Figure 7 (c).

Table 2: Validation conditions and result

	Case	Current [A]	Air Temp. [°C]	Heat Gen. Rate [W/m^3]	Sensor1 [K]	Sensor3 [K]	Sensor4 [K]	Sensor5 [K]
True	1	36	20	4826	306.55	309.64	309.64	303.01
	2	36	24	4545	301.05	303.17	303.17	299.31
	3	59	20	9199	309.62	312.26	312.25	306.24
	4	59	24	8715	304.37	306.09	306.09	302.72
Est.	1	36	20	4826	306.51	309.59	309.58	302.96
	2	36	24	4545	301.08	303.20	303.20	299.34
	3	59	20	9199	309.60	312.23	312.23	306.22
	4	59	24	8715	304.41	306.12	306.12	302.75



(a) (b) (c)

Figure 7: Estimated temperature of sensor 1 (a), sensor 6 (b) in simulation and sensor 4 in test (c)

4. Conclusion

In this study, we introduce the temperature estimation model for the semi-transient case. First, experiments to know battery properties especially the heat generation rate are conducted. Based on this experimental information, we obtain the battery temperature under various conditions which is used as a training data of ANN. By changing the simulation model to the ANN model we take the advantage of having lighter model with reasonable accuracy.

Although this study shows temperature estimation under semi-transient conditions, it is limited to the constant charging and discharging conditions. For better profit of temperature estimation, temperature estimation under dynamic current should be accomplished. In the next research, we will conduct the temperature estimation of this dynamic condition.

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