Electrochemical impedance spectroscopy based Internal temperature estimation for 10 high capacity lithium-ion battery cells with initial manufacturing deviation using Pattern recognition methods

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ABSTRACT

Electrical vehicles Lithium-ion battery-based energy storage have been having recent fires occurring, although the development to prevent fires is being actively carried out. Battery thermal management system (BTMS) is definitely the key system to focus on, this system requires precise and accurate temperature inputs, but it is limited with the number of measurement sensors and measurement specific locations. In situ based electrochemical have a close correlation with the internal temperature of the battery for temperature estimation. For this paper, a sensorless EIS based Gaussian process regression model is proposed to predict the internal temperature of each cell while surpassing the manufacturing ununiformed impact on the EIS impedance values.

1. Introduction

EIS is a method that measures impedance from current or voltage response characteristics of battery manifested by applying an AC sinusoidal voltage or current to the battery.

This paper performs the galvanostatic EIS (GEIS) on 10 fully charged 70Ah (Nickel manganese cobalt) NMC pouch batteries from the same Manufacturer one at a time, in order to design an internal temperature estimation model capable of modelling the 10 cells and surpassing the impedance measurements differences resulting from manufacturing deviations.

The GEIS measures impedance by applying a 7A_{rms} sine wave current from 10 kHz to 1 mHz after reaching the thermal equilibrium state inside the battery through sufficient rest time. The measures are taken at 5℃ intervals from 0℃ to 60℃.

Many papers have already proven the existing correlation between EIS extracted impedance parameters and the characteristics of the battery (state-of-health (SOH), temperature...[1-3], many articles have also shown that the temperature can be estimated from the use of a single frequency phase shift measurements[2-3], more precisely using the phase shift at 40Hz as the impedance in this frequency is more anode related and thus have very low SOH and state-of-charge (SOC) dependence. A polynomial fitting of the data is enough to have a sensorless offline temperature estimation model as shown in [3-4].

Although All the stated above is applicable for estimating the temperature of a single cell, it is heavily dependent on the nature of the cell, meaning that the EIS parameter values vary from one cell to another if the manufacturing quality process isn’t meticulously controlled at each step of the production, and even in the opposite case batteries still tend to have different EIS values.

Fig.1 shows the phase shift in function of the temperature using linear interpolation between the experimentally measured data. It can clearly be seen that for a single temperature we have many phase values with different distances in between as the temperatures change.
It can be seen that the models have different accelerations and various Y=Axis intercepts, thus using 1 polynomial function to model all the cells is resulting in unacceptable RMSE (RMSE=47.6) and residuals errors as big as 15 degree Celsius as shown in fig.2.

This is overcome in most cases by measuring the EIS of the full cell pack, but that doesn’t give us the possibility to have the sensorless information of the temperature of each cell in the pack separately.

In this poster we will be using a gaussian process regression model to overcome the cells’ manufacturing deviation and have a model that can accurately predict the internal temperature of new cells, the validation of the model is done with a 10-fold cross validation method and the performance of the model is verified with Root Mean Square Error as an evaluation indicator.

2. Gaussian Process Regression

In probability theory and statistics, a Gaussian process is a stochastic process (a collection of random variables indexed by time or space), such that every finite collection of those random variables has a multivariate normal distribution, i.e. every finite linear combination of them is normally distributed. The distribution of a Gaussian process is the joint distribution of all those (infinitely many) random variables, and as such, it is a distribution over functions with a continuous domain, e.g. time or space[5-6]. Practically, Gaussian process regression (GPR) models are nonparametric kernel-based probabilistic models.

Considering the training set \(\{(x_i, y_i); \ i = 1, 2, ..., n\}\), where \(x_i \in \mathbb{R}\) and \(y_i \in \mathbb{R}\) drawn from an unknown distribution. A GPR model addresses the question of predicting the value of a response variable \(y\) new, given the new input vector \(x\) new, and the training data. A linear regression model is of the form:

\[
y = x^T \beta + \varepsilon, \tag{1}
\]

where \(\varepsilon \sim N(0, \sigma^2)\). The error variance \(\sigma^2\) and the coefficients \(\beta\) are estimated from the data. A GPR model explains the response by introducing latent variables, \(f(x)\), \(i = 1, 2, ..., n\), from a Gaussian process (GP), and explicit basis functions, \(h\). The covariance function of the latent variables captures the smoothness of the response and basic functions project the inputs \(x\) into a \(p\)-dimensional feature space.

We will be using the GRP found in regression learner app in MATLAB which estimates the basis function coefficients, \(\beta\), the noise variance, \(\sigma^2\), and the hyperparameters \(\theta\) of the kernel function from the data while training the GPR model. Because a GPR model is probabilistic, the more temperature related input predictors we provide for the training data the more we can reduce the standard deviation. In the next section session, we will be comparing between different numbers of input predictors starting from using the measured phase \(Z_{\text{phase}}\) alone, till \((Z_{\text{phase}}, Z_{\text{re}}, Z_{\text{mag}}, Z_{\text{im}})\) which are also extracted from the EIS data at 40hz frequency and are impedance’s phase, real, magnitude, imaginary, respectively. We will also compute the regression error to compare between the models.

3. Simulation Results and analysis

The first prediction model is trained only using \(Z_{\text{phase}}\) as for a single cell phase values are enough to estimate the temperature. Fig.3 shows the predicted values in the function of the true values, and Fig.4 shows the residuals for each prediction, the RMSE= 4.43 has improved drastically but still far from being accurate enough for a predictive model.

In the following we trained the model by adding one more predictor at a time in order to find the optimal predicting GPR model. Fig.5 shows the predicted values corresponding to the true values when using \(Z_{\text{phase}}, Z_{\text{re}}\) as input predictors for our model. Fig.6 shows the residuals of the prediction at each point.

Table 1 groups the performances for each model i.e. the corresponding training times and RMSE.
As seen from the table above, the predicted response is a function of the true response figures and the residual figures, using a second predictor improved drastically the predictions and although the RMSE is slightly above 1, it is very acceptable for a temperature prediction model. We can also see that adding a 3rd predictor didn’t improve much the RMSE but had a slight faster time showing an existing correlation in the data. But on the other hand, adding a 4th predictor had the opposite effect on the RMSE and a big increase on the training time which is a sign of overfitting the data. A 2 predictors GPR model is good enough to predict the internal temperature of a new manufactured cell. From the benefits of using the GPR model is that we don’t have to go through the training again and only using the pair ($Z_{\text{phase}}$, $Z_r$) we would be able to estimate the temperature.

4. Conclusion

This work presented a very accurate sensorless internal temperature prediction GPR model using EIS impedance data at a single frequency, the model allows to overcome initial cells manufacturing deviation impact on the internal impedance and eases up the quality requirements, which is achieved through training based on previously collected EIS cells’ experimental data.

References