Model identification and parameter estimation of lithium ion batteries for diagnostic purposes

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***Abstract*—A parameter estimation study is reported here to estimate the temperature-dependent internal resistance of a lithium ion battery that is connected to the state of its health. A simple equivalent electrical circuit model was used for this purpose that is nonlinear both in its variables and in its parameters. Parameter sensitivity analysis showed that under conditions of constant charging/discharging current there is a linear dependency between some model parameters.**

I. Introduction

In the past few years rising energy price of fossil based energy has led developments in the field of transportation, e.g. hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV) and electric vehicles (EV). The joint underlying energy source of them is the rechargeable battery module. Recently the NiMH and lithium ion batteries tend to eliminate the monopoly of lead acid batteries because of their higher energy density (especially in the fields of electrical vehicles and mobile IT devices). Due to safety and efficiency reasons their actual state of charge (SoC) and the actual state of health (SoH) must be monitored by a battery management system (BMS).

On the other hand, vehicles are used in a wide temperature region (-30 °C, 70 °C), so the temperature dependent behaviour of the substantial battery state indicators is a very important question. A precise battery management helps to avoid such unfortunate circumstances like over-discharging and thus premature ageing.

Because of the great practical importance of the battery management problem, various approaches have been proposed in the literature to solve it. In [1] multiple state space models has been obtained from the computational fluid dynamics of the battery and a linear parameter variant (LPV) model has been identified for them, with the mass flow rate being the parameter. Although the obtained model is precise, it is too complex for diagnostic purposes applied in a real-time battery management system.

The approach used in [2] is a grey box approach where a first order equivalent electrical circuit model (EECM) has been used for modeling SoC and output voltage dynamics of lithium ion batteries. The authors of [3] used a black box model of a $LiFePO_4$ battery widely used in EVs for describing the temperature dependency of the charging-discharging characteristics. A systematic review of the lithium-ion battery models used in practice is given in [4] where the emphasis was on the models for real time battery state estimation.

Battery state- and parameter estimation problems can be formulated in several different ways, e.g. [5] provides an estimation procedure for the battery internal temperature. On the other hand, several papers deal with the state of charge estimation of EV batteries [6].

Diagnostics and health monitoring is a key functionality of a BMS, since it is important to detect the unavoidable degradation due to aging, environmental effects and dynamic charging [7]. Internal resistance is shown to be a possible candidate for the indicator of battery degradation [8]. The aim of this work is to estimate the temperature-dependent internal resistance of a lithium ion battery model, which can be used for battery health diagnostics in the future.

II. Battery modeling

Batteries can be modeled by several modeling techniques, for example electrochemical, equivalent electrical circuit, empirical and black-box models [9]. Each model has its own advantages and disadvantages, therefore the used model should be selected according to the application purpose.

Electrochemical models use partial differential equations to describe the electric and chemical processes occurring in the battery. These models are very precise, but include lots of parameters which values are hard to determine. An other disadvantage of these kind of models that the solution of partial differential equations is also computationally expensive. The complexity and the solution of electrochemical models can be reduced by assuming additional conditions.

The equivalent electrical circuit model is a popular modeling technique due to its simplicity [4]. EECMs are composed of basic electrical components like voltage sources, resistances, capacitances and sometimes nonlinear elements. The advantages of EECMs are that the construction of the model is easy, it does not require much computational effort and only a few model parameters should be taken into consideration.

Besides the aforementioned methods, black-box models can also be used for battery modeling. They do not require any

TABLE I
NOTATIONS

I	current
z	state of charge
τ	sampling time
Q_n	battery capacity in Ah
V_b	battery cell voltage
R_1	parasitic resistance
C_1	auxiliary capacity
V_1	auxiliary voltage
V_{OC}	open circuit voltage
R_0	internal resistance
T	temperature in °C

knowledge about the physical or chemical properties of the battery. The accuracy of the black-box models (such as neural networks or fuzzy logic) usually depends on the training data.

A. Equivalent electrical circuit model

The equivalent electrical circuit model type is selected from the potential modeling methodologies to describe the time and temperature-dependent behavior of our $LiFePO_4$ battery. According to [10] a first-order RC circuit model already gives relatively small modeling errors (see Fig. 1 below). The

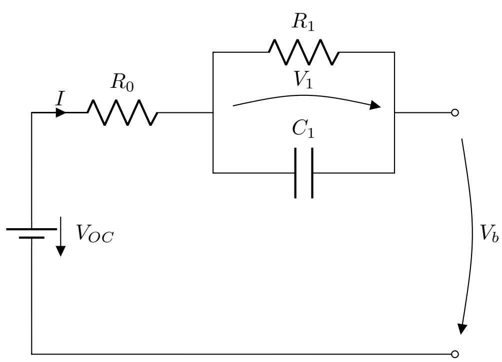

Fig. 1. First order RC equivalent circuit model of the battery

following discrete time state space model can be derived from the RC equivalent circuit:

$$\begin{bmatrix} z(k+1) \\ V_1(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\tau/(R_1C_1)} \end{bmatrix} \begin{bmatrix} z(k) \\ V_1(k) \end{bmatrix} + \\ + \begin{bmatrix} -\frac{\tau}{3600Q_n} \\ R_1(1-e^{-\tau/(R_1C_1)}) \end{bmatrix} I(k) \tag{1}$$

$$V_b(k) = V_{OC}(z(k)) - R_0(k)I(k) - V_1(k) \tag{2}$$

In realistic circumstances one can measure and set the current I and measure the battery voltage V_b. It is important to note, that the state of charge can be obtained by simply integrating the current values, as the first equation of (1) shows.

Since the open circuit voltage or EMF of the battery (denoted by V_{OC}) depends on the state of charge ($z(k)$), the output equation is nonlinear. According to [11] the open circuit voltage can be well approximated by a 6th order polynomial. Thus

$$V_{OC} = p_1z(k)^6 + p_2z(k)^5 + p_3z(k)^4 + p_4z(k)^3 + p_5z(k)^2 + \\ + p_6z(k) + p_7 \tag{3}$$

From the dynamic model equations (1)-(3) it can be seen that *the model is nonlinear both in its variables and its parameters*.

B. Nonlinear parameter-varying model

It is well known that battery performance and parameters vary with environmental and operating conditions. For example battery voltage depends on the load current and internal impedance.

One of the most important factors of the battery performance is the *environmental temperature*. The operating temperature has a great impact on the battery performance because reaction rate of chemical reactions taking place in the battery are influenced by the temperature. For example at low temperatures diffusion decreases which results in a reduced capacity, or liquid electrolyte may freeze. At high temperatures unwanted chemical reactions and physical transformations may occur (corrosion, bubble formation etc.) which also lead to deteriorating performance and shortened lifetime. Internal impedance, self discharge and cycle life of the battery cell are also affected by the temperature. Within limits of operating temperature the performance usually improves with the increasing temperature. In conclusion the temperature has impact on lots of parameters thus it can be a good candidate as a parameter of parameter-varying model.

Initially it is assumed that the parameters C_1, R_1, R_0 and $p1, ..., p7$ of the model (1)-(3) are temperature dependent. Then the parameter-varying modified model is given in the following form:

$$\begin{bmatrix} z(k+1) \\ V_1(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\tau/(R_1(T)C_1(T))} \end{bmatrix} \begin{bmatrix} z(k) \\ V_1(k) \end{bmatrix} + \\ + \begin{bmatrix} -\frac{\tau}{3600Q_n} \\ R_1(T)(1-e^{-\tau/(R_1(T)C_1(T))}) \end{bmatrix} I(k) \tag{4}$$

$$V_b(k) = V_{OC}(z(k), T) - R_0(T)(k)I(k) - V_1(k) \tag{5}$$

III. MODEL PARAMETER ESTIMATION

The experiments were carried out on a new $LiFePO_4$ battery with 60 Ah capacity. The operation voltage of the battery is 4.25 V (charge) and 2.5 V (discharge). We have measured the charging current and the battery voltage on different temperatures in order to investigate the temperature-dependent phenomena.

A. Measurement data

The data acquisition setup consists of a 12 V, 20 A power supply and a programmable electronic load/current generator (30 V, 30 A). The measurement setup is depicted in Fig. 2. The measurement has been performed under different temperature and charging conditions. The applied environmental temperature values were $\{0\,°C, 25\,°C, 50\,°C, 70\,°C\}$. Due to technical reasons, measurements below $0\,°C$ could not be carried out. The measured signals were battery voltage, battery temperature, environmental temperature and charging current, with a constant 5 s sampling time. The resolution of the A/D converter being used is 12 bits for all signals that resulted in a $\pm 0.1\,°C$ precision for the temperature measurement.

The first approach was to examine only the charging process of the battery. The charging current was kept at constant 10 A in the charging period, while the actual SoC value was integrated from the current signal. Charging with constant voltage was not examined because only the charging current was controllable in the experiment configuration. Further experiments will be designed based on the results of the preliminary experiments.

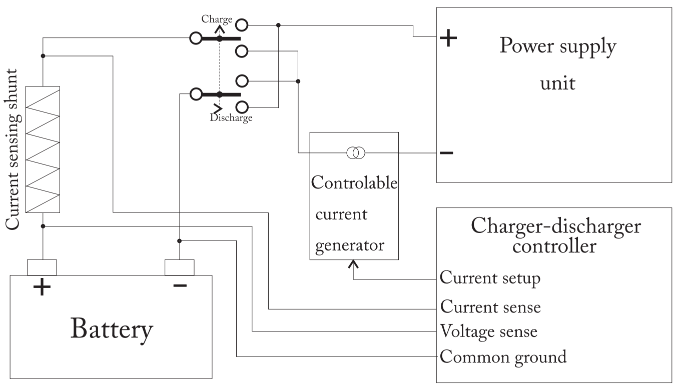

Fig. 2. Measurement configuration

B. Parameter estimation methods

At each of the four different temperatures the parameters ($\theta = [C_1, R_1, Q_n, R_0, p_1, ..., p_7]^T$) of the nonlinear discrete time state space model in the form of Eq. (1)-(3) were estimated using the System Identification Toolbox in Matlab. The least-square (LS) cost function of the least squares method is in the form

$$LS(\theta) = \frac{1}{N}\sum_{k=1}^{N}\frac{1}{2}(V_b(k) - \hat{V}_b(k,\theta))^2$$

were used, where $V_b(k)$ is the measured and $\hat{V}_b(k,\theta))$ is the model-predicted value of the battery cell voltage at the kth time interval in case the parameter vector is θ. An optimization procedure in the parameter space were used to determine the estimated parameters $\hat{\theta}$ that correspond to the minimal value of LS. The lower bounds of the physical parameters (C_1, R_1, Q_n, R_0) were set to zero in order to get realistic values.

1) Raw estimated parameters: The estimated physical parameters as functions of the temperature can be seen in Fig. 3. For better visibility, Q_n is scaled down to $Q_n/10$. On the horizontal axis the temperature is mean temperature of the measured environmental temperature. It can be seen, the values of parameters do not show any tendency. The results indicate that further analysis of the parameters and the relationship between them is required.

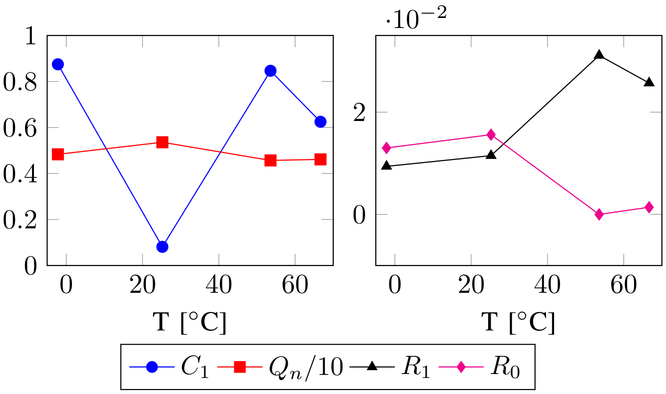

Fig. 3. Raw estimated parameters and their temperature dependence

2) Refinement of the estimation: As a first step to regularize the estimates, we noticed that the estimated battery capacity Q_n was not influenced by the temperature, so we fixed it at its nominal capacity, i.e. Q_n = 60 Ah, and we repeated the estimation. The results of the parameter estimation procedure when Q_n is fixed to 60 Ah can be seen in Fig. 4 and Fig. 5.

C. Parameter sensitivity analysis

In order to get reliable estimates of the important parameters with physical meaning, a simple sensitivity analysis was carried out only for the remaining three parameters (C_1, R_1, R_0). We changed their estimated "nominal" values by $\pm 10\%$ one-by-one keeping all the other parameters constant. Fig. 6 shows how the root of the mean square error ($RMSE$)

$$RMSE(\theta) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\frac{1}{2}(V_b(k) - \hat{V}_b(k,\theta))^2}$$

changes with the changing parameter values. It can be concluded that the auxiliary capacity C_1 does not have any influence on the $RMSE$. The same conclusion can be drawn if we compute the simulated output values $\hat{V}_b$ as a function of time with changing parameter values as above, see in Figures 7, 8 and 9.

A more detailed analysis of the $RMSE$ as a function of the three parameters (C_1, R_1, R_0) with physical meaning can be obtained if one plots $RMSE$ as a function of the parameters, as it is seen in Figures 11 and 10.

D. Discussion on the parameter estimation results

As a conclusion of sensitivity analysis, we decided to fix also the parameter C_1 to a constant value ($C_1 = 0.5$), in order to obtain a reliable estimate of the resistances R_0 and R_1. The reliable estimate of R_0 is critically important from diagnostic point of view, as it carries information about the state of health of the battery.

Repeating the parameter estimation procedure with fixed C_1 for each of the four operating temperatures, the results depicted in Fig. 12 could be obtained. Here we can see a nice monotonous approximately second order temperature-dependence for both resistances.

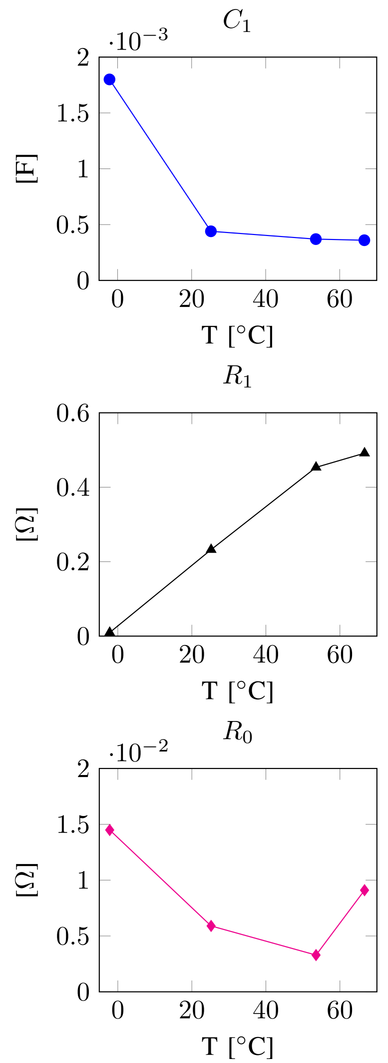

Fig. 4. Estimated parameters if Q_n = 60 Ah

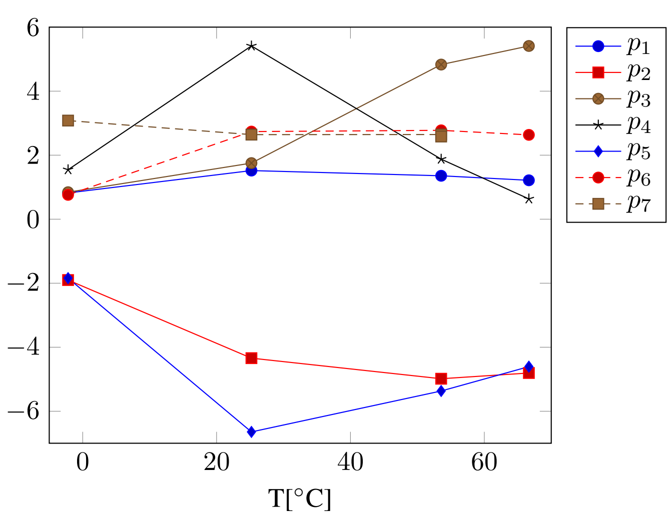

Fig. 5. Estimated parameters if Q_n = 60 Ah (cont.)

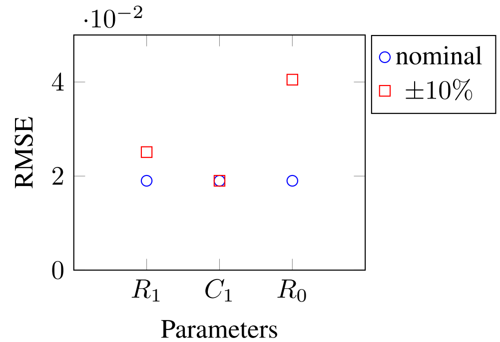

Fig. 6. Parameter sensitivity of the RMSE

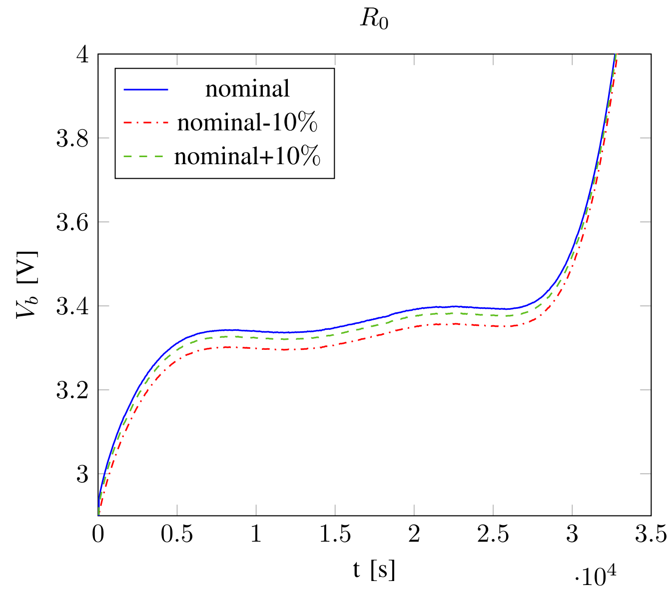

Fig. 7. Simulated output voltage of the battery at 25°C. The value of R_0 changes between ±10% of its nominal value. The other parameters are fixed.

As a final step in parameter estimation, we wanted to determine an approximate confidence region for the parameters R_1 and R_0 using the level sets of the $RMSE$ loss function. Therefore the $RMSE$ was depicted as a function of R_1 and R_0 (with C_1 fixed) as it is seen in Fig. 13.

Unfortunately, Fig. 13 shows that the estimates of R_1 and R_0 are not independent of each other, but a static (probably linear) dependence between them is present. This could be caused by the not sufficient excitation [12] (i.e. the constantly held charging current value) that may cause such an anomaly.

Therefore, it is recommended to use *a varying charging current value if the estimation of R_0 is used in a battery management system for health diagnostic purposes.*

IV. Conclusion and Future Work

The estimation of the temperature-dependent internal resistance of a lithium ion battery has been performed in this work. A simple equivalent electrical circuit model was used for this purpose that is nonlinear both in its variables and in its parameters.

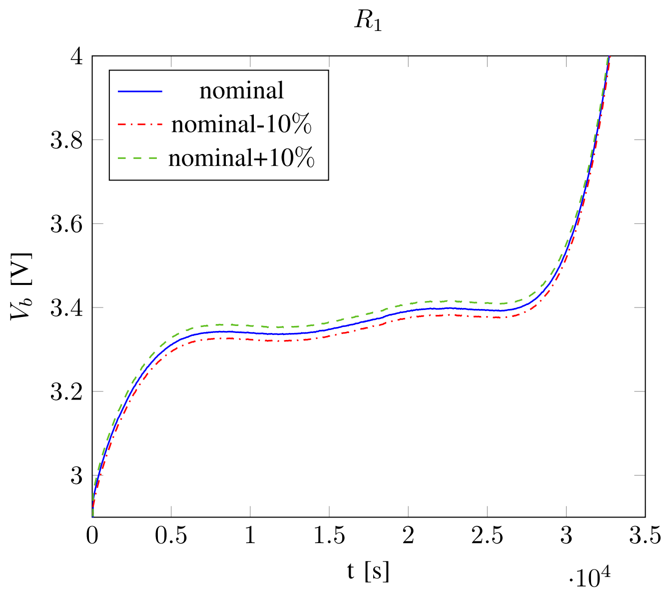

Fig. 8. Simulated output voltage of the battery at 25°C. The value of R_1 changes between ±10% of its nominal value. The other parameters are fixed.

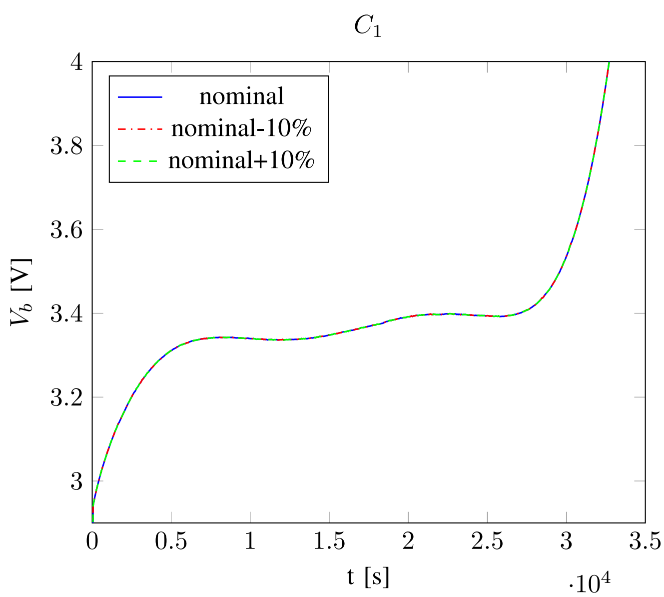

Fig. 9. Simulated output voltage of the battery at 25°C. The value of C_1 is set to 1,0.9 and 1.1, the other parameters are fixed.

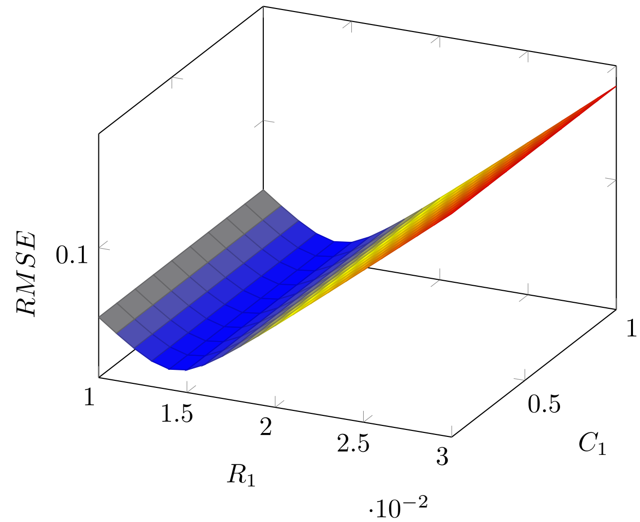

Fig. 10. RMS error if R_0 is fixed and R_1,C_1 change

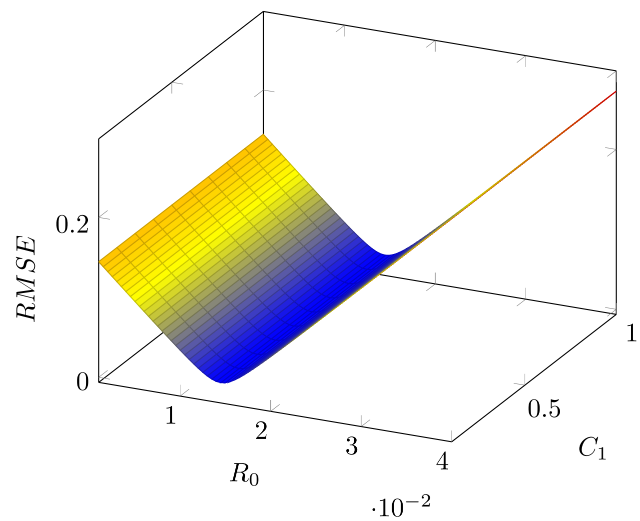

Fig. 11. RMS error if R_1 is fixed and R_0,C_1 can change

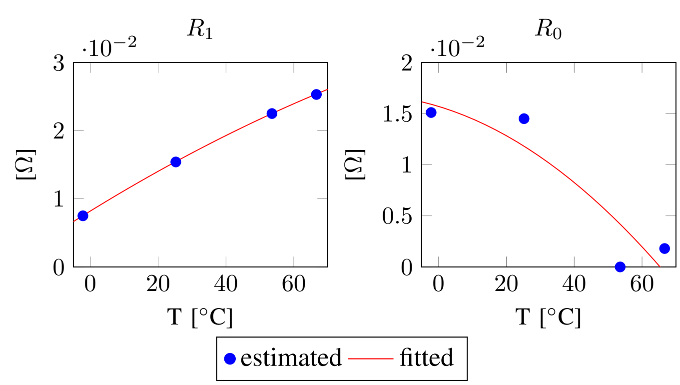

Fig. 12. Estimated and fitted values of R_1 and R_0

It has been shown that charging the battery with constant current yields an insufficient excitation current input that results in linearly dependent parameters.

The further step of this research is to develop a parameter estimation based diagnostic tool that estimates the battery state of health independently of the distortion effect of the actual environmental temperature. Further experiments should be carried out with different charging profiles and the discharge of the battery should be also examined. The further work also includes additional climate chamber experiments (even below 0°C) resulting in good quality measurements that will serve as a basis for the further research. A preliminary step before performing the measurements is an experiment design taking real life operation profiles into consideration.

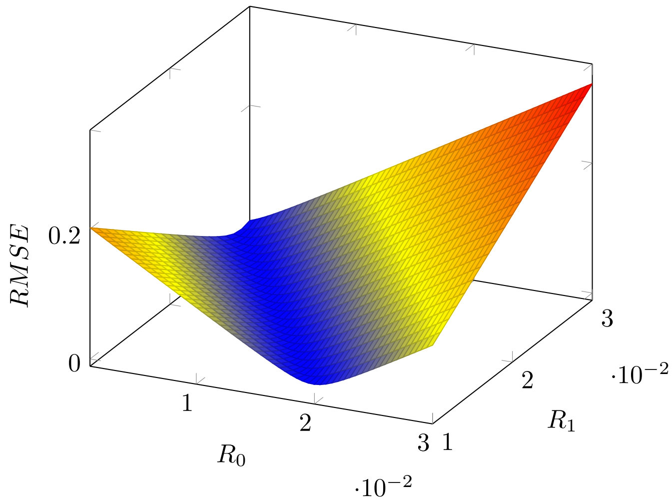

Fig. 13. RMS error if C_1 is fixed and R_0, R_1 can change

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