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Battery modeling using real driving cycle and Big-Bang Big-Crunch algorithm

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Abstract—The purpose of this study is to model battery packs integrated in a ten fuel cell hybrid electric vehicle fleet developed among the European project Mobypost dedicated to postal delivery applications. This project led to create and feed a big database as the vehicles were deeply monitored. Thanks to this database and Big-Bang Big-Crunch optimization algorithm this paper proposes a method to model battery using real driving cycle data in few minutes with a NRMSE less than 0.02.

I. INTRODUCTION

With the growing popularity of Electric Vehicles (EVs) and fuel cell hybrid electric vehicles (FCHEVs), batteries used in those applications are now a famous topic [1]. However it is frequently pointed out that the batteries are still too expensive and a very critical part among the entire electric power-train. Indeed their lifetime and their autonomy are still a limitation to a worldwide deployment as it cannot compete internal combustion engine (ICE) yet. Consequently in order to improve the energy management of the batteries and thus their autonomy and lifetime, a good understanding of the dynamic behavior is required. This is why mathematical models are needed in order to represent and predict this dynamic behavior. Generally battery models are determined from battery characterizations by using constant current or simplified current profile. Models can also be determined by using impedance spectroscopy. These processes require to set up experiments needing equipment, cost and time. The purpose of this paper is to present a fast way to model a battery cell through a Thevenin Electrical Equivalent Circuit (EEC) by using an optimization algorithm and field use experimental data. The particularity of this study is the use of a rich database created from an ten fuel cell hybrid electric vehicle fleet.

In a first part the Mobypost European project and the vehicles will be presented. In a second part the data used to model the batteries will be enumerated. In a third part Thevenin representation and mathematical equations will be presented. Then, in a fourth part, the optimization algorithm used to identified the model parameters will be explained. Finally in fifth part the results will be illustrated and discussed to go on conclusion and perspectives.

II. MOBYPOST PROJECT

A. Concept

The european project Mobypost aimed at developing and instrumenting a fleet of ten hybrid hydrogen vehicles powered by fuel cell for postal delivery applications (Fig. 1) [2], [3].



Fig. 1: 3 vehicles of the Mobypost fleet

The design of such vehicles, lightweight hybrid electric including fuel cell and batteries, includes a powertrain design and components sizing taking into account the type of application : postal delivering services. The powertrain was designed using serie architecture by operating the fuel cell as a range extender [4], [5].

The battery pack is composed of four modules (U24-12XP) connected in series and manufactured by Valence. Those modules, present a nominal voltage of 12.8V and a nominal capacity of 110Ah measured with a current C/5 at 23°C. Each module is also composed of four parallel 3.2V LiFeMgPO₄ cell groups in series.

B. fleet monitoring and used data

This project led to create a big database by monitoring ten postal delivery vehicles during almost three years. Physical

values from sensors are measured and saved on a server every second [3]. Now an access to data of more than 1500 real driving cycles can be used to model the battery cells and observe the aging. In this study the data used are the battery current (I_{batt}), the state of charge (SOC), the battery cell voltage (V_{cell}) and the battery temperature (T).

The following figures Fig. 2 Fig. 3 Fig. 4 Fig. 5 illustrate the data mentioned above recorded during one postal delivery. This driving cycle was realized using the vehicle only in pure electric mod (fuel cell shutdown).

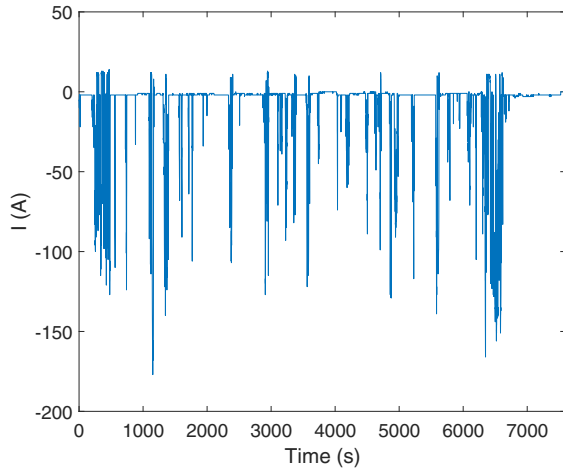


Fig. 2: Battery current during the driving cycle

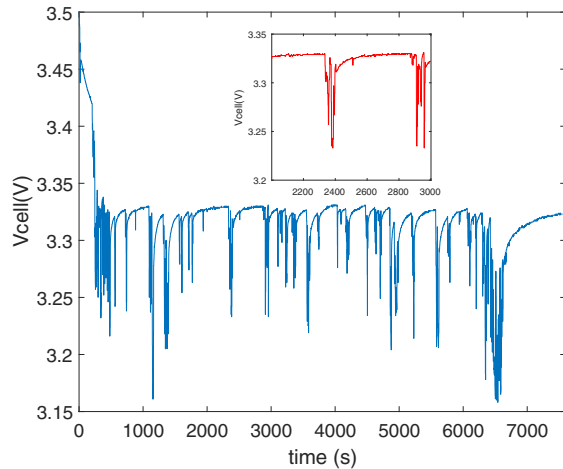


Fig. 3: Battery cell voltage in function of time

Fig. 4 illustrates the SOC evolution through this driving cycle. The SOC is determined by the battery management system developed by the battery manufacturer.

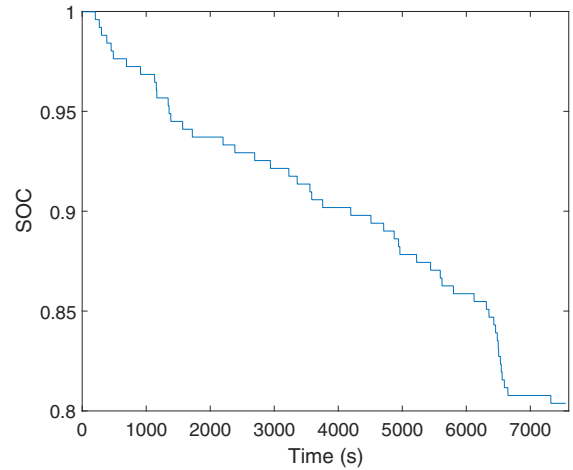


Fig. 4: State of charge evolution along the driving cycle

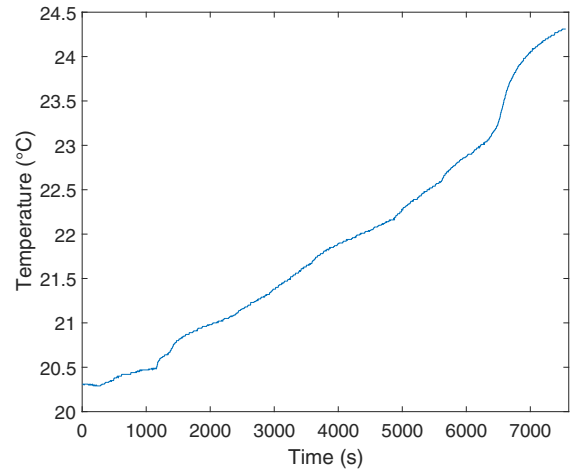


Fig. 5: Temperature evolution along the driving cycle

III. BATTERY MODELING

A. Thevenin model

Thevenin electrical equivalent circuit can be used to represent the temporal voltage response of a battery. Among all the equivalent circuits which can be found in the literature, a most common structure is illustrated in the Fig. 6. The battery cell voltage response being composed of transient periods of many different duration, this is necessary to add several R//C circuits. The R//C circuits will get different time constants (τ) in order to make the model capable to reproduce larger interval of transient periods duration. In this structure, R//C series circuits are used to represent impedances linked to the charge transfers effects, double layer and diffusion effects. In the literature, models can be found integrating only one R//C circuit as in [6]–[8], with two R//C circuits [9]–[14], or again with three R//C circuits [15] [16].

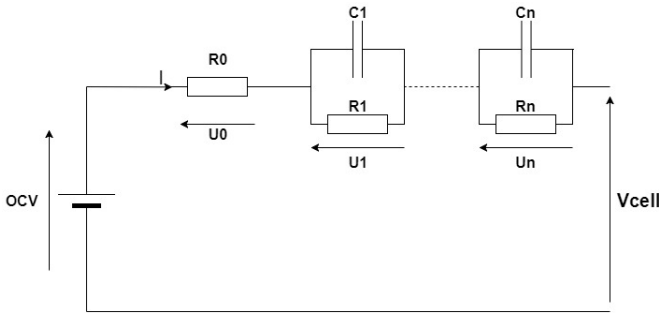


Fig. 6: Battery RC model

In this study the Thevenin structure is used with three R//C circuits in order to get more accuracy. Indeed these three R//C circuits are used to represent the charge/discharge phases, the diffusion phases and the relaxation phases.

B. Model equations

Using Kirchoff's circuit laws from the Fig. 6, the equation (1) can be used to determine V_{cell} , the estimated voltage response of the battery.

$$estimated_{V_{cell}} = OCV - U0 - U1 - \dots - Un \quad (1)$$

The next step is to resolve the differential equation (2) due to the capacitor. After having resolved (2), the equation (3) was deduced as solution in order to express Un . It has to be notified, since the acquisition frequency is $1Hz$, t is then discretized with a range of 1 second to solve the equation.

$$\dot{U}_n = \frac{1}{C_n} \cdot I - \frac{1}{R_n \cdot C_n} \cdot U_n \quad (2)$$

$$U_n(t) = U_n(t-1) \cdot e^{-1/(R_n \cdot C_n)} + R_n \cdot (1 - e^{-1/(R_n \cdot C_n)}) \cdot I(t) \quad (3)$$

In order to improve both accuracy and reality meaning, some dependencies have to be taken into account. Open Circuit Voltage (OCV) will be dependent on the SOC and on the Temperature as in the function (4). This OCV expression has been deduced during this study after a long work to find out how to reproduce OCV evolution versus the SOC and the temperature. Internal resistances will be dependent only on the temperature as in the function (5).

$$OCV(t) = a + \frac{b \cdot (25 - T(t))}{SOC(t)} + \frac{c}{SOC(t)} + d \cdot SOC(t) + e \cdot \ln(SOC(t)) + f \cdot \ln(1.001 - SOC(t)) + g \cdot \ln(1.01 - SOC(t)) + h \cdot \exp(i \cdot T(t)) \quad (4)$$

a, b, c, d, e, f, g, h and i being constants to be identified

$$R_n(t) = a_n \cdot \exp(b_n \cdot T) \quad (5)$$

a_n and b_n being constants to be identified

From these equations, an objective function can be deduced. Then an optimization algorithm is run using the objective function : Normalized Root Mean Square Error (NRMSE) (8) in order to determine the parameter values of the model. This NRMSE is obtained from the following equations : Error (6) and Root Mean Square Error (RMSE) (7).

$$Error = real_{V_{cell}} - estimated_{V_{cell}} \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^n Error^2} \quad (7)$$

$$NRMSE = \frac{RMSE}{max(real_{V_{cell}}) - min(real_{V_{cell}})} \quad (8)$$

IV. OPTIMIZATION ALGORITHM

A. Optimization concept

Optimization problem can be summarized as finding the set of input parameters (x_n) minimizing a mathematical function $f(x_n)$. Nature is a main source for proposing optimization methods such as ant colony system (ACO), genetic algorithms (GA) or again big-bang big-crunch (BB-BC). In this paper, the objective is to identify the set of inputs parameters (parameters of the Thevenin structure), minimizing the NRMSE which means the $estimated_{V_{cell}}$ is as close as possible than the $real_{V_{cell}}$.

B. Big-Bang Big-Crunch algorithm

In this study the BB-BC algorithm has been used. This optimization algorithm relies on one of the theories of the universe evolution [17] [18]. This theory, based on the general relativity of Einstein, explains that the expansion phase of the universe due to the big bang will end to be replaced by the big crunch phase which consists of the universe contraction.

This algorithm is used in this study as it shows good results and efficiency in [17]. It refers to the creation of the initial population randomly. This phase consists in spreading the candidates solutions all over the search space in an uniform manner.

The BB-BC optimization algorithm is based on the sequence of the following steps :

Step 1: Create an initial population of N_{pop} candidates randomly, respecting the limits of the search space.

Step 2: Evaluate the objective function value of all candidate solutions from the initial population.

Step 3: Find the center of mass referring to the best candidate solution. (candidate giving the lower error).

Step 4: Calculate new candidates around the center of mass by adding or subtracting a normal random number which its value decreases as the iterations elapse (reduction of the search space). Also an exploration probability is integrated in order to get out of an eventual local minimum.

Step 5: Return to step 2 until stopping criteria is met.

The reduction of the search space is represented by a function inversely proportional to the number of generation. The equation (9) illustrates the research space division according to the number of generations.

$$RS_{div}(gen) = \frac{1}{gen} \quad (9)$$

This function drastically reduces the search space for the first generations and this can lead to progress to a local minimum instead of the desired global minimum. In order to avoid this, another way to reduce the search space, proposed in [17], has been used in this study. Indeed this way divides more slowly the search space during first generations and then accelerate to find the results more efficiently. The proposed algorithm replaces the linear function by a translated exponential function.

It has to be specified that this algorithm is stochastic and to be sure to achieve the global minimum, an infinite number of iterations is required. In this study what is desired is a set of inputs parameters which will be able to reproduce the voltage for the entire temperature range with a good accuracy. Also as a short computing duration, is desired, a big population is avoided, and not a lot of generations are proceeded so here finding the global minimum is not the target.

V. RESULTS

Figures 7 and 10 compare the estimated battery voltage from the model regarding the real measured cell voltage from the database. The error that presents the model is $NRMSE = 0.0185$ proving the effectiveness of the proposed method.

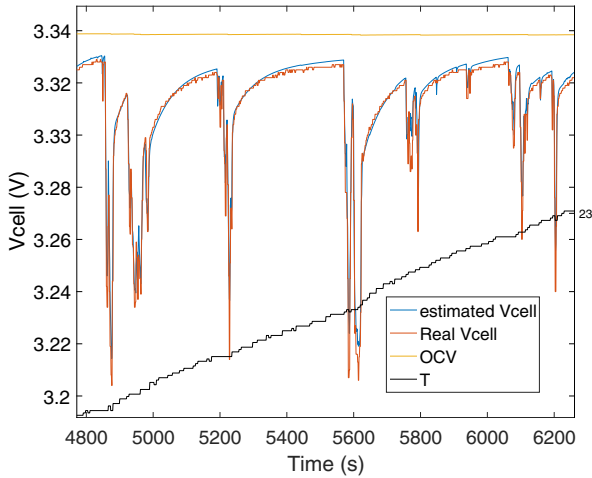


Fig. 7: Cell voltages comparison with driving cycle used for parameters identification

Tables I and II display the three average time constant values and their capacitance values for the driving cycle which was used for parameters identification. These tables also show the values of the constants in equations (4) and (5). The

time constants present three different values, 2 seconds to reproduce charge transfer and double layer effects, 66 seconds and 500 seconds to reproduce both diffusion phenomena and relaxation phases. Regarding relaxation phenomena, to be able to better reproduce it at best, others R/C circuits should be added with higher time constants up to several hours [19]. The Fig. 8 illustrates the evolution of the internal resistance R_{in} (which is the sum of the four resistances) versus the temperature.

TABLE I: Model parameters values and time constants for $20.5^{\circ}\text{C} < T < 24.5^{\circ}\text{C}$

Components	Values
τ_1	66 s
τ_2	2 s
τ_3	500 s
C_1	72000F
C_2	2700F
C_3	500000F
a	3.22 V
b	-0.001 V/ $^{\circ}\text{C}$
c	-0.0216 V
d	0.182 V
e	-0.0886 V
f	-0.0632 V
g	0.0778 V
h	-0.001 V
i	-0.5 $^{\circ}\text{C}^{-1}$

TABLE II: Model resistance coefficient values

Resistance	a_n	b_n
R_0	0.0003 Ω	-0.0753 $^{\circ}\text{C}^{-1}$
R_1	0.0010 Ω	-0.0052 $^{\circ}\text{C}^{-1}$
R_2	0.0013 Ω	-0.0301 $^{\circ}\text{C}^{-1}$
R_3	0.0010 Ω	-0.0025 $^{\circ}\text{C}^{-1}$

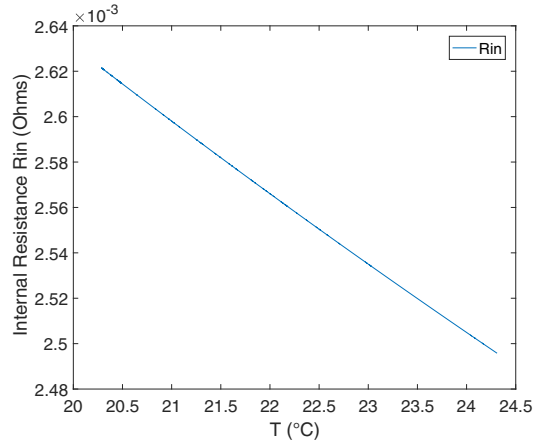


Fig. 8: Internal resistance evolution versus temperature

These results can lead to the following conclusion. The model is able to reproduce the voltage response of one driving

cycle by taking into account the dependencies on the temperature and on the state of charge with a good accuracy after having identified the parameters. Here results are illustrated with the driving cycle which has been used to identify the parameters, so the method is not validated and it must be verified that the parameters are able to reproduce all the driving cycles of this battery.

VI. VALIDATION

To validate this modeling and verify if the identified parameters are coherent, another driving cycle has to be reproduced to observe if the error remains low. To do that, a driving cycle where the temperature is between 5°C and 9°C was chosen. Figures 9 and 11 can validate the identified parameters as the model is able to adjust the voltage in function of the temperature range.

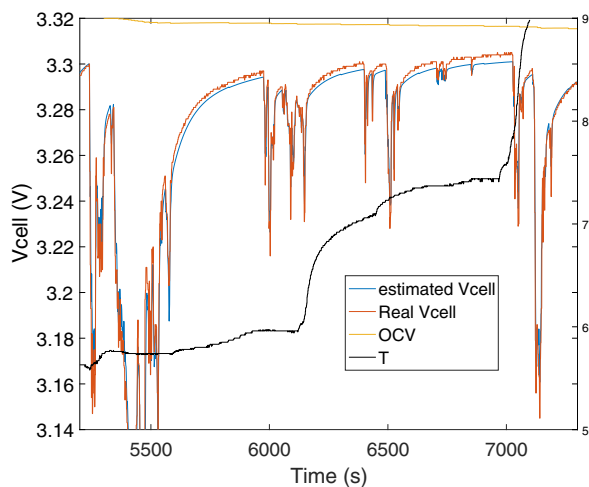


Fig. 9: Cell voltages comparison with driving cycle used for validation

VII. CONCLUSION AND PERSPECTIVES

In this study a battery model for one driving cycle taking into account dependency on temperature and state of charge has been deduced by using a Thevenin electrical equivalent circuit and data directly extracted from real driving cycle through an optimization algorithm. This method presents a good accuracy and efficiency as the computing time is few minutes and the NRMSE is low. Future works should aim at optimizing again the dependency on the temperature and on the SOC.

VIII. ACKNOWLEDGMENT

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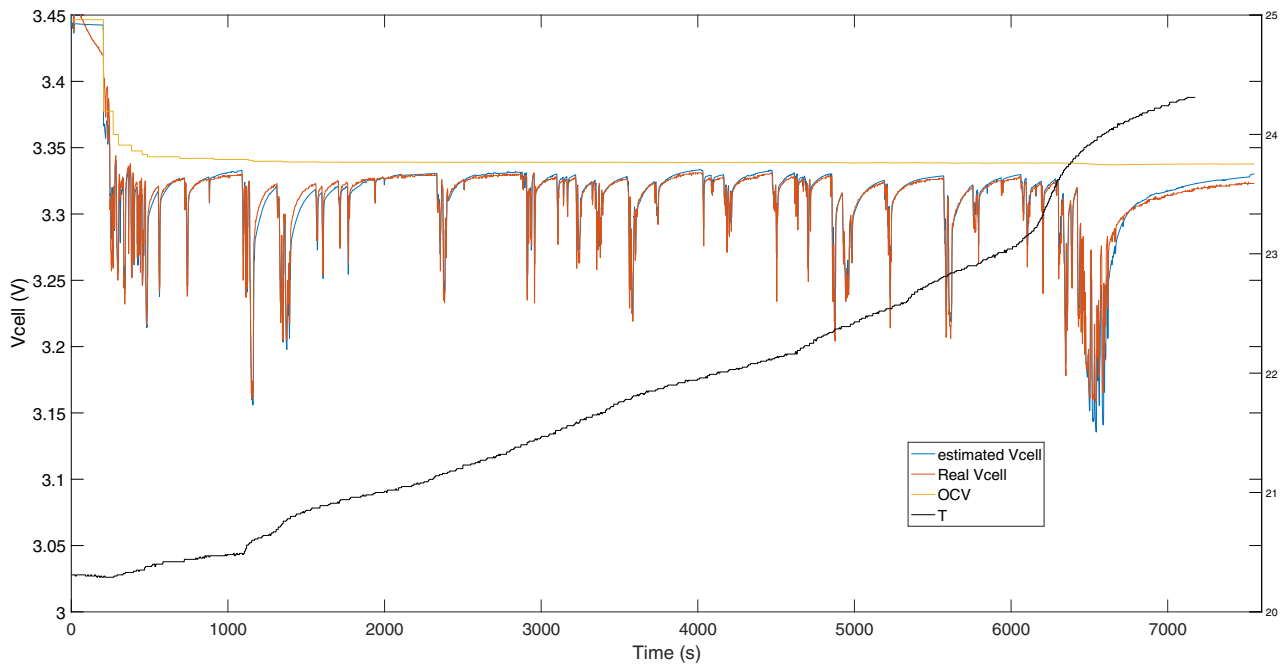


Fig. 10: Cell voltages comparison with entire driving cycle used for parameters identification

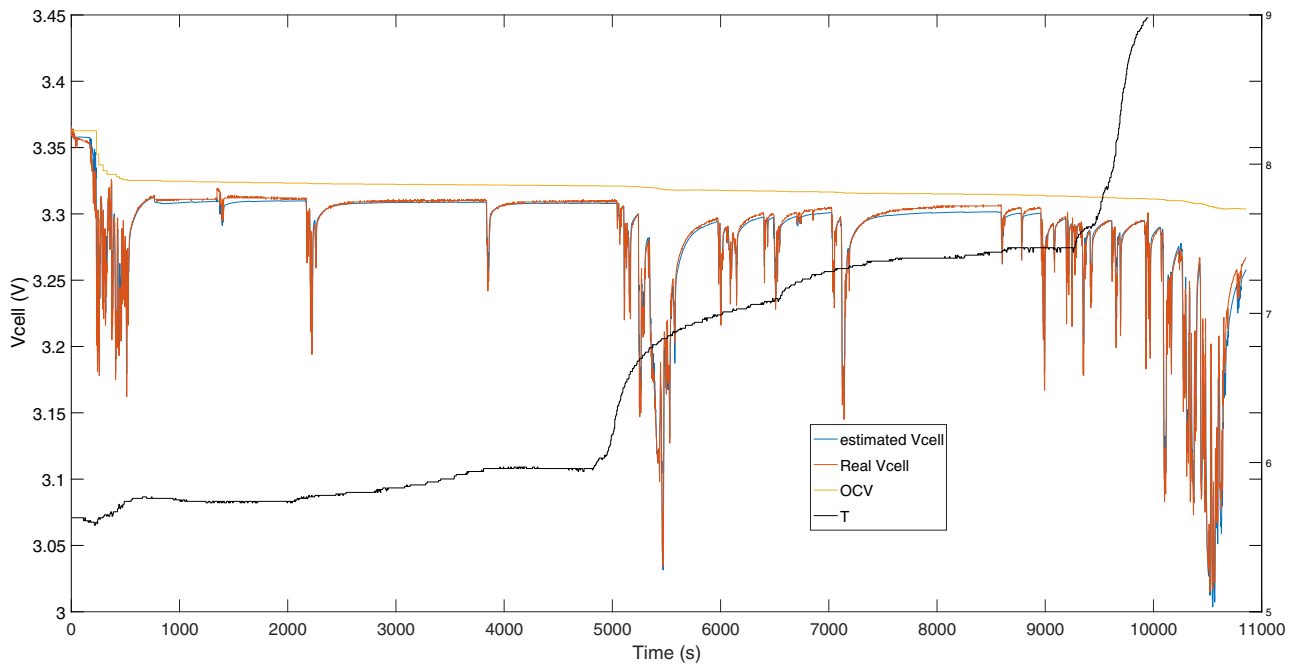


Fig. 11: Cell voltages comparison with entire driving cycle used for validation