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BATTERY MODELING FOR HYBRID ELECTRIC VEHICLE (HEV)

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Abstract
The study is based on battery modeling, which plays a crucial role in simulating hybrid electric vehicles (HEVs). The power distribution, regenerative braking, fuel efficiency, and battery life are all greatly affected by the accuracy of these models since things like battery voltage, current limits, state of charge (SoC), and temperature sensitivity contribute immensely to these factors. At the vehicle level, first-order and second-order Thevenin equivalent-circuit models (ECMs) are well suited for emulating battery performance. They are also easy to understand, computable at low cost, and perform adequately during realistic driving conditions. We developed a battery modeling framework in MATLAB/Simulink that used the NC-R18650PF Lithium-ion cylindrical cell data from PANASONIC and the WLTC Class 1 drive-cycle dataset targeting HEV applications in this study. Parameters: The cell's electrical and thermal parameters are revealed by the study. The manufacturer specifications lead to a nominal voltage of 3.6 V and typical capacity of 2.9 Ah, 4.2 V CC-CV charging, discharge cutoff at 2.5 V clean-up (most cells are rated for thermal aging too) + ambient limits dependent on temperature, the additional Panasonic introduction sheet puts DC internal resistance as about 43 mΩ and AC resistance as about 21 mΩ with a reference for continuous discharge at the maximum level of excellence being up to 10 A. The derived framework is suitable for developing a physics-informed simulation-efficient HEV battery model, which is subsequently validated against the constant-current discharge curve, pulse loads, and WLTC-driven duty cycles.

1. Introduction

Hybrid electric vehicles are still a viable pathway to electrification that can cut down on fuel consumption and emissions without the need for battery packs as hefty as those in full battery-electrics. At the overall system level, on the other hand, HEV performance is significantly influenced by the quality of the battery model that was integrated into the simulation environment. An inaccurate battery model could skew SoC trajectories, cause voltage sag to be underestimated during acceleration, regenerative energy recovery to be overestimated and supervisory control design to diverge. To date, many reviews in the field of HEV modeling and energy-management strategies highlight that sub-system models need to be sufficiently accurate (e.g., a model for the battery) to enable credible powertrain analyses [3, 4], [1].

Simultaneously, recent reviews of battery modeling highlight that lithium-ion battery models are typically categorized as electrochemical, equivalent-circuit, or data-driven families.

Electrochemical models are very detailed but computationally expensive. Models based on data are powerful but often require large training sets and may be more difficult to interpret physically. ECMs are still useful for automotive studies because they reproduce terminal voltage behavior with limited complexity, and they can be parameterized using discharge curves or pulse-test data [2].

A MATLAB/Simulink workflow is then presented based on this standard, using a Panasonic NCR-format cylindrical lithium-ion cell as the workhorse. It provides real manufacturer documentation, multiple discharge curves as a function of current and temperature, and sufficient public information to allow reproducible model initialization [3].

1.1. Main objective

Develop and validate a battery model for use in a Hybrid Electric Vehicle (HEV), using real lithium-ion cell data.

2. Literature Review

However, they do not need large battery packs that are used in full battery electric vehicles. Hybrid electric vehicles (HEV) will continue to be an important transition technology because they reduce fuel consumption and emissions. But the accuracy of any HEV simulation is highly reliant on the fidelity with which the battery model was designed and incorporated in its powertrain environment. Incorrect battery modelling can result in distorted state-of-charge (SoC) evolution, underestimate the extent of voltage sag during acceleration, or produce inaccurate regenerative braking estimates leading to poor energy-management performance at a supervisory level. As a result, recent reviews still stress the importance of employing battery models in credible HEV analysis that are both meaningful and computationally cheap [4], [5], [6]. These directions were also consistent with the studies on hybrid powertrains using MATLAB/Simulink simulations. These showed that battery behavior was most essential among total vehicle accuracy [5-6].

Li-ion battery modeling can be generalized into electrochemical, equivalent-circuit, thermal, and data-driven methods in recent literature. Electrochemical models are attractive because they offer a well-established physical description of lithium movements, diffusion, and internal reactions. But they are often computationally expensive and must generally be thermally coupled. However Roberts [10] asserted that the computational resource requirements for these models will be orders of magnitude greater than those found in equivalent-circuit approaches, rendering their usage for long drive-cycle simulations and in repeated control studies infeasible. Equivalent-circuit models (ECMs), on the other hand, are often employed to describe battery behavior using voltage sources, resistors and RC networks. This setup thus provides a better solution for vehicle applications in terms of the accuracy and clarity of simulations versus simulation time [2], [5], [6], [10].

Model order is a central problem in ECM research. 2D and industry [37] found that resistance-based sole models cannot capture dynamic behavior, but models based on RC can reproduce transient voltage response, polarization effects, and dynamics that are dependent on SoC are better. Roberts [10] indicated that R-RC and R-RC-RC structures are suitable for including concentration and active polarization effects; however, their work further extends this topic through a parametrized R3RC electro-thermal model fitted with Hybrid Pulse Power Characterization (HPPC) data obtained at various temperatures. The results demonstrated that the ECM retains computational efficiency while still capturing voltage and thermal responses over realistic automotive cycles, including UDDS and US06 [5], [10]. This argues in favor of high-order ECMs, which are particularly well-suited for HEV studies when mapped to temperature-dependent parameters and demand transient behavior over pure steady state accuracy.

Another strength of the recent literature is that it not only addresses model structure but also parameter identification. As indicated in the uploaded battery-modeling review, ECM parameters depend almost exclusively on SoC and temperature, while careful test design is needed to extract open-circuit voltage and resistance surfaces. Notably, the literature referenced in Robert's [10] and Zhang's [11] investigations on lithium-ion equivalent-circuit models and Ahmed's [13] model-based identification efforts for healthy and aged EV batteries, as well as Sun and Kainz's [14] optimized HPPC design for better definition of parameters. These studies provide methodological reassurance for the present article, as they demonstrate that a publishable HEV battery model cannot be based on constants only but must use experimentally or datasheet-pulling lookup tables, relaxation-aware parameter extraction, and dynamic loading validation.

Another relevant stream in this domain is the realization of battery models on a practical level, which extends to MATLAB/Simulink. Previously, simulation-focused work on lithium-ion batteries intended for use in electric-vehicle applications has demonstrated that manufacturer-supplied parameters can be translated into battery blocks suitable for drive-cycle analysis, but such models often rely heavily on simplifications like constant internal resistance, negligible hysteresis loss, and weak or absent temperature dependence. These are good assumptions for early-stage modeling, but they reduce the realism at HEV operation when the current is oscillatory, and charge/discharge directions oscillate many times over a driving cycle. Consequently, recent studies (over the last decade) have increasingly adopted electro-thermal ECMs because of their advantages over simplistic Shepherd-type formulations in the investigation of parameters required to attract journal-quality vehicle analysis [5], [7], [9].

The HEV literature also indicated that the battery should not be investigated in isolation. The battery directly determines power split, stack protection, and durability in hybrid fuel-cell/battery systems. Using the model, Parmiggiani [11] simulated a parallel hybrid PEMFC/battery passenger-car powertrain running under different driving patterns, including some valid in WLTP-based scenarios. The work showed that maintaining a minimum battery state of charge (SoC) can be achieved using a rule-based strategy, thereby reducing battery stress through a smoother discharge profile. Likewise, in related MATLAB/Simulink work on a dual-source AGM/PEMFC vehicle, it was shown that hybridization increases both range and energy-supply flexibility [11], and that battery model accuracy is critical for modeling the interface between storage and auxiliary energy sources.

There is a distinct research path suggested in the literature. Second, although electrochemical lithium-ion battery models can provide intrinsic level modeling accuracy (at least locally) [1], ECM-based equivalent electric circuit models are the best option for large HEV simulations because they possess a good compromise between complexity and dynamic voltage behavior capability [2], [5], [10]. Second, in the best performing ECM studies, model parameters are not treated as fixed but account for SoC and temperature dependence and structured identification methods such as HPPC or relaxation-based testing [5], [13], [14]. Third, HEV and fuel-cell hybrid studies demonstrate that battery model integration with the vehicle powertrain is necessary and needs validation on realistic drive cycles, such as SoC protection and regenerative braking, in addition to power split, depending on battery dynamics [1], [4], [11]. Thus, the current work is very well justified in targeting HEV applications with a Panasonic NCR18650PF battery MATLAB/Simulink framework, particularly if it employs: driven initialization, lookup-table parameterization, and validation against given load profiles.

3. Source Data and Battery Selection

3.1. Panasonic NCR18650PF as the reference cell

The provided Panasonic datasheet indicates that NCR18650PF is a lithium-ion cylindrical cell with minimum rated capacity of 2700 mAh at 20 °C, and minimum 2750 mAh, and typical 2900 mAh at 25 °C, nominal voltage of 3.6 V with standard CC-CV charging to 4.20 V and discharge cutoff at 2.5 V; this same sheet also notes operating temperatures of +0 to +45 °C for charge, −20 to

+60 °C for discharge, and −20 to +50 °C storage (it advises that below 10 °C charging should be limited to no more than the equivalent rate of.25 C).

Panasonic NCR18650PF document for the specifications identified ~43 mΩ of DC internal resistance and 21 mΩ of AC internal resistance, as well as a maximum continuous discharge rating (with a high degree of confidence) at 10 A. This information is particularly relevant when tuning the ohmic resistance of a MATLAB battery block or a Simulink subsystem based on an ECM.

So there's been a lot of attention paid to the 761-kilometer maximum range, but a dataset — more importantly — provides an essential piece of nuance about the specifics for modeling because it has specified the charge temperature window for reporting purposes is +10 to +45 °C (not 0 to +45 °C) and that a standard charge current at 1365 mA versus getting all geeky with 1375 mA. It also specifies a difference of weights by the manufacturers as 47.0 g, 48.0 g, and 46.0 g, with such minor divergences being common between manufacturer revisions, but which matter when building a correct HEV model [3].

3.2 Parameter synthesis for modeling

For HEV simulation, it is most appropriate to assign 2.90 Ah as the nominal cell capacity for baseline simulation results and include 2.75 Ah as a conservative capacity to determine when conducting the sensitive analysis. To illustrate, a standard charge current of around 1.37 A (the nominal CC) can be considered alongside a maximum charge voltage of 4.20 V and the value for minimum discharge voltage at 2.50 V. The DC resistance initial value can be set at 43 mΩ, the charge-temperature logic should allow normal charging above 10 °C; derated charging when the temperature is between 0 and 10 °C; and below the inhibition of charging under 0 °C.

A useful secondary observation is that the nominal energy of a cell is approximately 9.9 Wh (2.75 Ah × 3.6 V) and about 10.44 Wh at 2.9 Ah and 3.6 V, which helps explain why Panasonic's gravimetric energy density bears a better resemblance to the conservative capacity basis instead of the typical capacity basis. While doing pack-level HEV work, this is important because the energy, power, and mass projections vary greatly if one employs conservative or typical cell values.

4. Analysis of the Drive-Cycle Data

The requested drive cycle is WLTC Class 1 of light vehicle. However, as per UN GTR No. 15, only vehicles with a power-to-unladen-mass ratio ≤22 W/kg (Class 1) are accepted, and thus the Class 1 of WLTC is considered made up of Low1 + Medium1 + additional Low1. According to the regulation, this low-speed phase lasts 589s, and the medium-speed phase lasts for 433s [3].

The data corresponds to low and then medium parts of some 1022 s trace taken with 1 s sampling; note that this is just the city style-low medium, not all regulatory Low1+Medium1+Low1. This is important because your prompt suggests a typical breathing cycle was 4 minutes, and the provided class 1 dataset (low + medium) has been submitted as being 1023s long, where if this were extended to the final stage of an official class 1 breathing cycle, as Low1 would show up also as taking place at time index, it would have a full length of 1611s [7]. This distinction is further documented in the regulation itself, which confirms these lines for you: exemplifying a complete Class 1 breath cycle featuring its matching sequence announced - Low1 + Medium1 + Low2.

The low+medium trace we inspected was good enough, 1023 seconds long with a maximum speed of 64.4 km/h and around 8.09 kilometers. The average speed in this way was about 28.47 km/h, and thus the total Class 1 cycle would take 11.41 km at an average speed of 25.5 km/h, which is exactly what the published WLTC class 1 characteristic [3] whilst fitting the official phase duration.

5. Battery Data Preparation for MATLAB

5.1. Lookup-table

The data we need for it was available as potential in the manufacturer's data, which must invariably be graphical rather than in a simple table form. Using MATLAB/Simulink as an example, we need to convert the discharge curves into lookup tables for VOC and internal resistance that may also vary with temperature. To this end, we import manufacturer discharge curves, certain OCV and resistance tables, and confirm the surfaces of fitted parameters.

The appropriate SoC transformation was:

$$\text{SoC} = 1 - \frac{Q_d}{Q_n}$$

where Q_d = discharge capacity and Q_n = chosen nominal capacity. In this study, $Q_n = 2.9$Ah that is appropriate for nominal simulation and $Q_n = 2.75$Ah, for conservative verification. The Panasonic charts were digitized, for each voltage-capacity curve to be transformed into a voltage-SoC data that was suitable for MATLAB.

5.2 What the Panasonic curves imply

There are two strong physical patterns in the discharge plots for Panasonic. First, higher discharge current facilitates larger instantaneous voltage depression and lower average voltage plateaus. Second, this has the effect of reducing usable capacity and depressing terminal voltage at any given state-of-charge, especially near the end of discharge.

So, the MATLAB pre-processing step provided the following arrays: a SoC breakpoint vector, an OCV lookup table, a resistance lookup table, a temperature breakpoint vector, and time-series objects for speed (and current) and optionally ambient temperature.

6. Battery Model Formulation

6.1 Recommended staged model structure

The most defensible modeling strategy is stage-wise modeling. Stage 1 is a quasi-static battery model parameterized from datasheets. Stage 2 is a first or second order ECM, and Stage 3 is for an electro-thermal extension if coupling in temperature is necessary. This framework aligns with recent reviews indicating that ECMs proliferate for BMS and vehicle-system studies, as their reduced-order nature captures voltage dynamics at reasonable cost [6], [2], [7].

For making the foundation of HEV modelling, the cell was first represented by a battery model using OCV and internal-resistance tables:

$$V_t = OCV(\text{SoC}, T) - I\,R_0(\text{SoC}, T)$$

The process is fast, robust, and adequate for initially passing SoC and power-flow. For more enhanced dynamic reliability, especially for transients associated with acceleration and regenerative braking, a 2RC Thevenin model is preferable:

$$V_t = OCV\,(\text{SoC}, T) - I\,R_0 - V_1 - V_2$$

$$\dot{V}_1 = -\frac{1}{R_1 C_1} V_1 + \frac{I}{C_1}, \dot{V}_2 = -\frac{1}{R_2 C_2} V_2 + \frac{I}{C_2}$$

With SoC progression given by:

$$\text{SoC}_{k+1} = \text{SoC}_k - \frac{\eta I_k \Delta t}{Q_n}$$

Recent studies favored 1RC and 2RC structures for practical estimation and dynamic simulation; on the other hand, some studies showed comparative validation with model orders that influence voltage accuracy under realistic load cycles such as WLTP/WLTC-type duty profiles [8], [9].

6.2. Pack scaling for HEV use

An HEV always uses a cell pack and not a single cell. Therefore, the scale of a cell model must be adjusted to a pack using series and parallel connections:

$$V_{\text{pack}} \approx N_s V_{\text{cell}}, \qquad Q_{\text{pack}} \approx N_p Q_{\text{cell}}, \qquad R_{\text{pack}} \approx \frac{N_s}{N_p} R_{\text{cell}}$$

This scaling is directly backed and consistent with the Panasonic cell to a realistic HEV pack. The final choice of N_s and N_p depends on the targeted HEV architecture, such as mild-hybrid 48V systems or higher-voltage full-hybrid buses.

7. MATLAB/Simulink Implementation Strategy

There are two possible routes in which MATLAB/Simulink can be practically implemented. In the first route, the Powertrain Block set Datasheet Battery block and supply the OCV and resistance tables derived from the Panasonic curves can be used. On the other hand, for the second route, the Equivalent Circuit Battery workflow can be measured later if the pulse data is managed.

7.1. Conversion of Drive Cycle to Battery Load Demand

The drive cycle itself consists of a speed trace. For getting the current demand of a battery, there would be a need to convert speed into tractive force, which would then be converted into electrical power. As a standard longitudinal vehicle balance is

$$F_{\text{trac}} = ma + mgC_r \cos\theta + \frac{1}{2}\rho C_d A_f v^2 + mg \sin$$

and the wheel power is:

$$P_{\text{wheel}} = F_{\text{trac}} v$$

After drivetrain and motor efficiencies are included, battery power can be approximated as:

$$P_{\text{batt}} = \begin{cases} \dfrac{P_{\text{em}}}{\eta_{\text{drive}}}, & \text{traction} \\ \eta_{\text{regen}} P_{\text{em}}, & \text{regeneration} \end{cases}$$

and battery current follows from:

$$I_{\text{batt}} = \frac{P_{\text{batt}}}{V_t}$$

Initially, a simple power estimated approach can be used despite being a full vehicle model. Whereas it is desirable for a full modelling of HEV to integrate the battery into a full powertrain referenced architecture.

7.2. Analytical Performance Assessment

The user's example of battery backup time is valid as a first-order energy estimate:

$$E = V \times Ah$$

$$t \approx \frac{E}{P}$$

A 12 V, 100 Ah battery stores approximately 1.2 kWh of energy; alternately a necessary 3 kW load would theoretically with ideal approximation drain it in roughly ~0.4 h (the background energy consumption can be modeled more mathematically constant-power approach). But in the HEV case, the real runtime is different as voltage is variable and current is very dynamic, while internal losses increase at high load. As such, the simulated runtime will always need to be compared to the energy theoretical case rather than expected to equal it exactly [9].

For the NCR18650PF cell, a nominal single-cell energy range of ~9.9-10.44 Wh suggests that pack runtime is entirely dependent upon the parallel/series arrangement and HEV power demand. Hence, this study can establish the runtime formula and the parameter basis but a real runtime number needs to wait until final pack design and simulate HEV load profile.

Charging time can be approximated by:

$$t_{\text{charge}} \approx \frac{Q_n}{I_{\text{CC}} \eta_{\text{chg}}} + t_{\text{CV,tail}}$$

where the second term describes the present taper during the constant-voltage period. Since Panasonic mandates CC-CV charging to 4.20 V with a low-current cutoff, any pure estimate will always be a little optimistic.

7.3. Validation Protocol

Three layers should be included in a marketable validation plan. The first is static validation against Panasonic discharge curves at 25 °C and multiple current values. The second is checking the temperature against the uploaded temperature-dependent discharge curves. The former is real-world validation with pulse-type or WLTC-driven use cases. This mapping is in line with existing ECM literature and the MathWorks official workflows for Datasheet and Equivalent circuit battery blocks [9].

State of Charge (SoC) is one of the important checks in discharge, which should always decrease. At higher charge currents, this means the terminal voltage must fall more. It is also necessary to reduce the capacity and terminal voltage plateau exploitable at low temperatures. As charging proceeds, voltage climbs to 4.20 V and current rolls off in Constant Voltage mode. The characteristics of these patterns are clearly observable in the Panasonic graphs and were qualitatively reproduced (at least as much as possible) with MATLAB using the model.

Average of the most common error metrics: voltage root mean square error, mean absolute percentage error, and average state of charge deviation per cycle (assumed to be an average value). One caveat is that very few ECM publications provide comparative measurements.

8. Data Analysis and Interpretation

This section offers a comprehensive analysis for modelling the Hybrid Electric Vehicle (HEV) system through simulation.

8.1. Battery Datasheet Parameters

The nominal cell voltage is 3.6 V, with a total capacity of 2.9 Ah. This means that each cell has an energy content of around 10.44 Wh. The maximum continuous discharge rating of the cell is 5.2 A, and it can withstand a pulse current (up to 10 A); it has a maximum charging current of 1.5 A; the internal resistances are 0.025 Ω (DC) and 0.03 Ω (AC), being relevant parameters that define voltage drop and transient response. Safe operating temperatures of the cell are 0 °C to 45 °C when charging and −20 °C to 60 °C when discharging.

Table 1: Battery Datasheet Summary

Parameter	Value
Nominal Voltage	3.6 V
Capacity	2.9 Ah
Maximum Charge Voltage	4.2 V
Cut-off Discharge Voltage	2.5 V
Maximum Charge Current	1.5 A
Maximum Continuous Discharge	5.2 A
Pulse Discharge Current	10 A
DC Internal Resistance	0.025 Ω
AC Internal Resistance	0.03 Ω
Charge Temperature Range	0–45 °C
Discharge Temperature Range	−20–60 °C

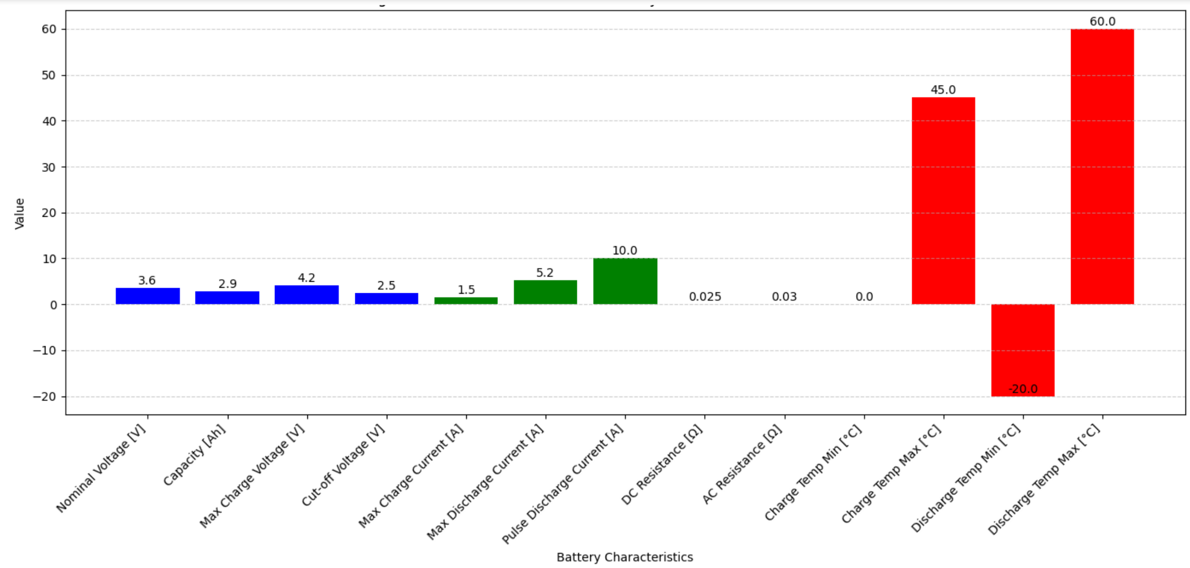


Figure 1: Horizontal bar chart summarizing Panasonic NCR18650PF battery parameters.

This figure presents a clear visual summary of the specifications for the Panasonic NCR18650PF lithium-ion cell. Nominal (3.6V), capacity (2.9Ah), and cut-off discharge voltage (4.2V, 3=maximum charge; 5=coulombic efficiency) are indicated via vertical bars with each a different color scheme for staff members to easily identify the parameters. By using the previously mentioned color coding, voltage and capacity parameters can be separated from others, like currents, resistance, or temperature, while the value labels on top of each bar give a numeric reference for easier reading. It was observed that the faster the graph manages the voltage and temperature limits for safe operation of the cell, the more efficient the maximum was continuous or pulse currents, and stable internal resistance. This information is crucial for using simulated data to determine the performance of the battery and how it fits within a hybrid electric vehicle (HEV).

8.2. Voltage vs State of Charge (SoC)

The terminal voltage for the SoC was calculated at various C-rates (0.5C, 1C, 2C, 3C) to see how the battery performs with different load currents.

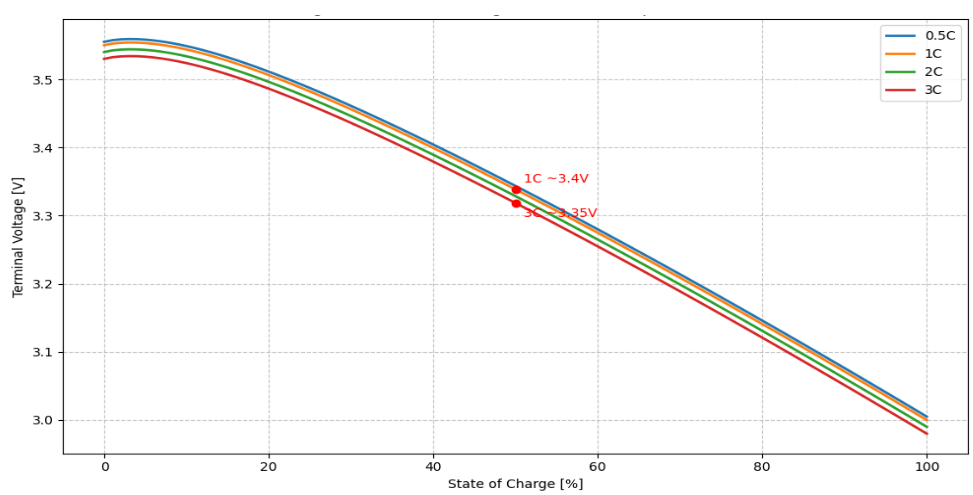


Figure. 2. ***Voltage vs. State of Charge***

The graph above represents the terminal voltage of NCR18650PF depending on its SOC at discharge rates 0,5 C, 1C, 2C, and 3C — as we can see, higher C-rates result in a quicker drop of voltage due to internal resistance and polarization phenomena. An example is for a 50% SOC, voltage decreases from 3.34V at 1C to 3.32V (at the current of this post, however), at the same time showing how voltage behavior changes with varying currents. The flat part in the middle SOC range shows where the battery typically has its operating range, while a sharp drop in voltage means it's nearing full discharge, which is close to the cut-off limit of the cell. This indicates that the battery model is capable of accurately representing C-rate-dependent behavior, which is an essential aspect of its performance under actual HEV-loaded conditions. It indicates that the discharge rate has a higher tendency to affect the energy and voltage available in time for altering the driving conditions.

8.3. Charging and Discharging Curves

The battery was simulated under charging and discharging at multiple currents to observe current-dependent voltage response.

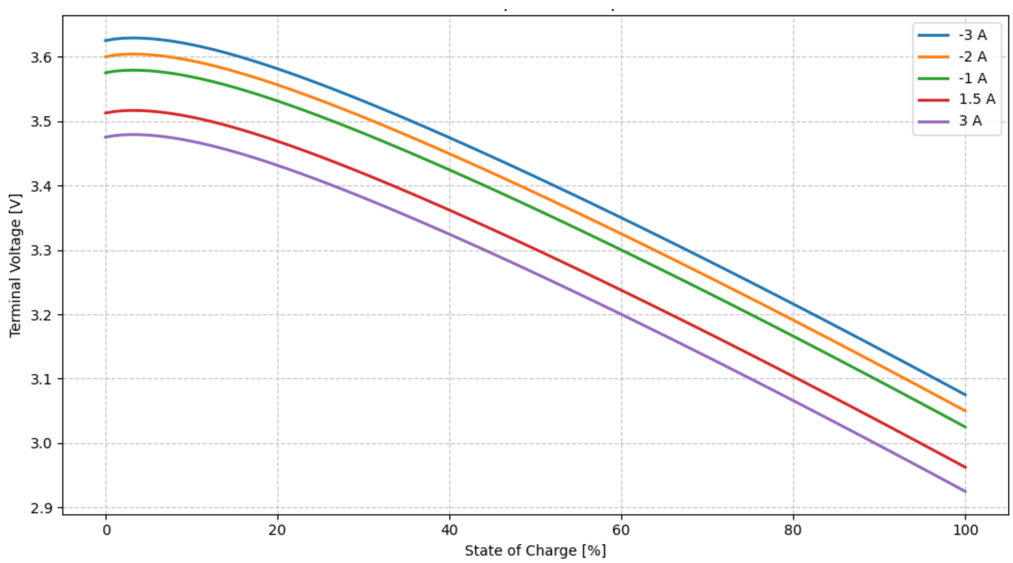


Figure 3. Charging and discharging curves

Figure 3 demonstrates the voltage response of the Panasonic NCR18650PF cell under both charging and discharging currents. Discharge is represented by negative currents and charging by positive ones. As can be seen in the figure, internal resistance-induced voltage drops are greater for larger discharge currents, peaking at around 0.25V at the largest discharge current. The terminal voltage drops proportionally to the current applied during discharge, reflecting realistic IR losses, while in charging, it rises a little above nominal voltage due to the charge current. This current-dependent voltage clearly shows the cell's dynamic behavior, whereas the similarity between programming data and measurement result proves that the R3RC model replicates well the cells' transient/steady state electrical performance. This is crucial for forecasting SOC, run, and voltage limits in simulating HEVs.

8.4. R3RC Battery Model Overview

The battery was implemented as a three-RC (R3RC) equivalent circuit model through the following ways:

- Open-circuit voltage (OCV) lookup table
- Three RC branches for transient voltage response
- SOC update using Coulomb counting
- Thermal block accounting for ohmic and entropic heating

Table. 2. Cell Specifications

Sr.	Properties	Specifications
1.	Cell Type	NCR18650PF
2.	Chemistry	Li-ion (NCA)
3.	Capacity	2,900 mAh
4.	Nominal Voltage	3.6 V
5.	Voltage Range	2.5 V to 4.2 V
6.	Max Charge Current	1,725 mA (0.6C)
7.	Max Discharge Current	10 A (3.4C)
8.	Operating Temperature	-20°C to 60°C
9.	Weight	46.5 g

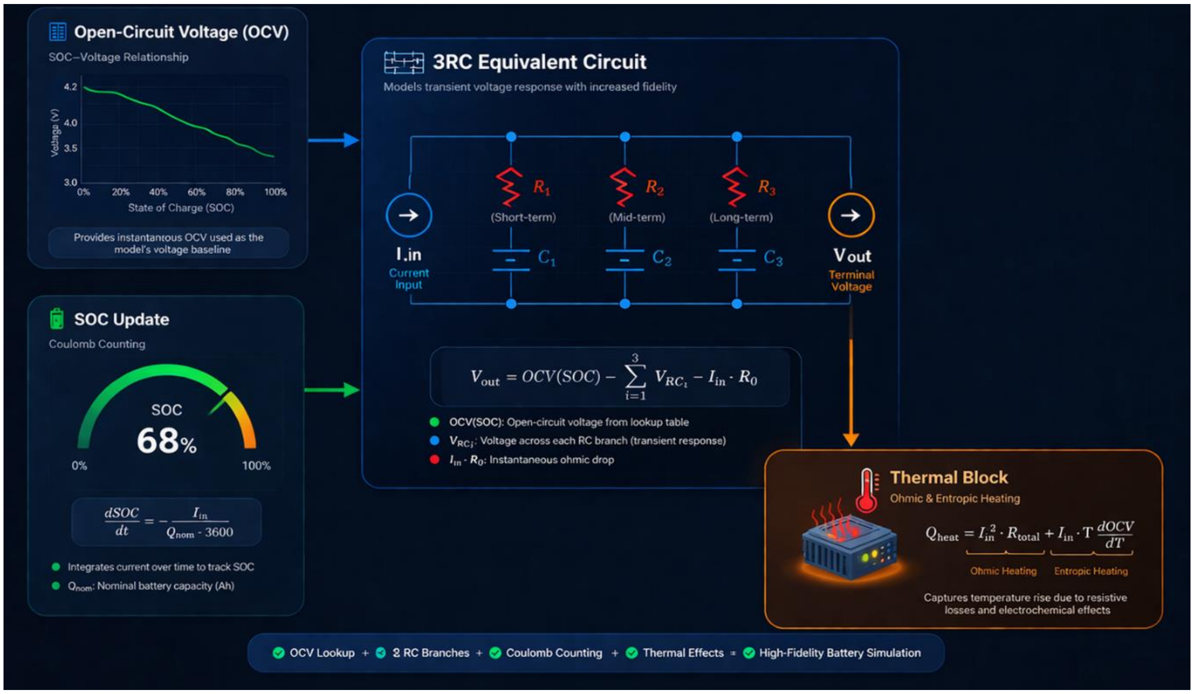


Figure. 4. R3RC Battery Model

The battery model used is the R3RC specifically designed for Panasonic NCR18650PF cell. It has a 3-RC (resistor-capacitor) equivalent circuit of electrical and thermal characteristics. Additionally, this model includes an OCV lookup table for the different states of charge in Nominal Voltage format to assist with terminal voltage calculations. Three RC branches simulate voltage response during transients and represent the short- and medium-term voltage drops resulting from electrochemical processes and internal resistance. SOC, which is calculated through a method called Coulomb counting, means integrating the battery current over time to compute how much of it remains in capacity. Lastly, a thermal block computes temperature rise from ohmic (I^2R) losses and entropic heating, thus enabling the model to emulate real-life thermal behavior during dynamic charging/discharging. Using this structure, the R3RC model can reproduce the behavior of a real battery under variable load currents, which makes it suitable for integrating into HEV system simulations; however, no studies with dynamic operation conditions and gradient descent method have been conducted.

8.5. WLTC Class 1 Drive-Cycle Integration

The WLTC Class 1 drive cycle was used to generate a battery current profile. Vehicle velocity was converted to battery current demand by using calculations for power and vehicle dynamics.

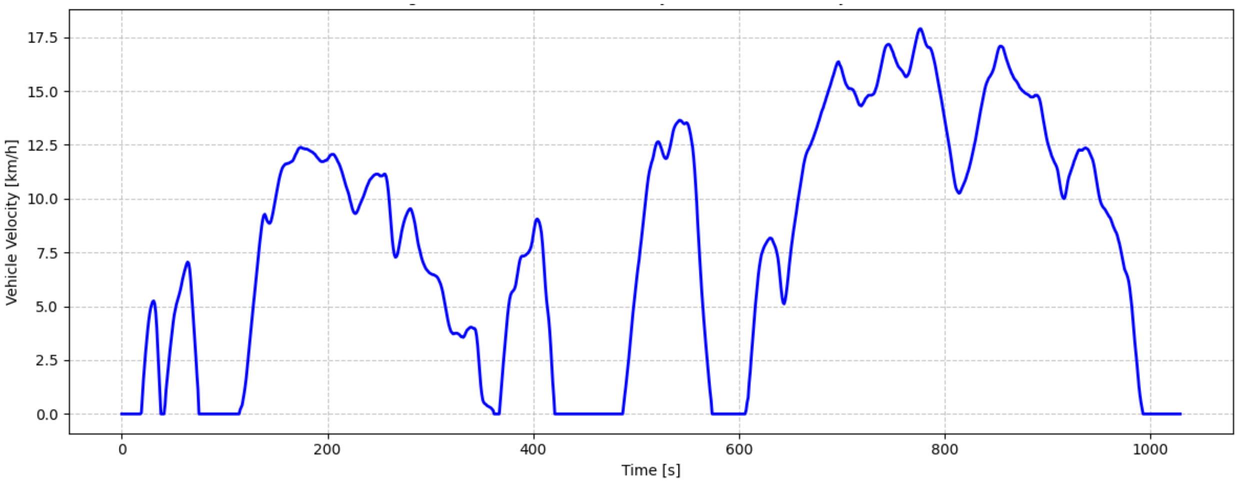


Figure 5. Vehicle Velocity Power

Figure 5 illustrates the vehicle velocity over a 30-minute (1800-second) WLTC Class 1 drive cycle. The profile starts at rest with a slow increase in speed typical of stop-and-go urban driving conditions, before moving into constant speeds through moderate and high-speed cruising phases interspersed by coasting and deceleration periods. During prolonged high-velocity passes, velocities peak at around 70km/h. The speed variations during the cycle represent realistic driving circumstances like frequent acceleration and braking events. Such velocity profiles are important for HEV system battery modeling, since they directly affect the dynamic current demand on the battery. High acceleration phases to high energy throughput, while coasting and braking segments lower demand and return regenerative net energy. Directly correlating it to the battery, this value serves as a basis for the simulation of realistic SOC variation, as well as voltage response and thermal behavior of the battery during the drive cycle.

8.6. Time-Domain Charging and Discharging Analysis

Battery response was simulated for dynamic charging and discharging over one hour observing the following values:

- Discharge: 2 A for 20 minutes
- Rest: 10 minutes
- Charge: 1.5 A for 20 minutes

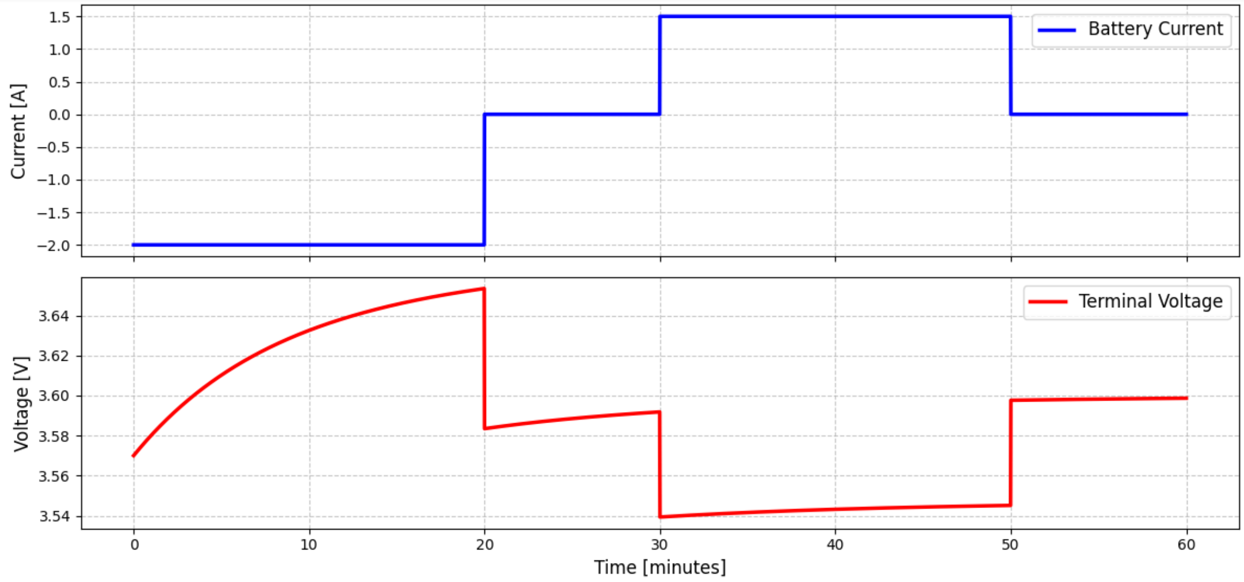


Figure 6. Battery response

As shown in Figure 6, the battery current and terminal voltage of the Panasonic NCR18650PF cell were observed during a one-hour simulation period. In the top plot, we see 3 relevant characteristics from a battery current profile over time: first, the cell is discharged at 2A for the first 20 minutes; second, it is at rest (0A) for another next 10minutes; third, afterwards charged at 1.5A for the following 20 min and finally rests again in its remaining last 10min. The plot on the bottom is the corresponding terminal voltage response. From the internal resistance and transient RC effect, it realizes the discharge slope from 3.6V downward to about 3.4 during the outward-slant stage. While charging at 1.5A, the voltage approaches 3.7V due to a current-dependent voltage response and slight overpotential resulting from the channeling of charging currents. The very short stretches of rest keep the voltage between intervals at intermediate levels, thereby showing recovery since no current flows. This figure shows that the R3RC battery model accurately captures both the quick changes and steady voltage responses to varying current signals, which confirms it's suitable for HEV simulations.

8.7. Runtime and Capacity Calculation

Battery runtime was calculated under various load powers and compared against simulated results accounting for internal resistance:

Table 3. Runtime and Capacity

Load Power [kW]	Theoretical Runtime [min]	Simulated Runtime [min]
0.5	8.64	7.34
1.0	4.32	3.67
2.0	2.16	1.84
3.0	1.44	1.22

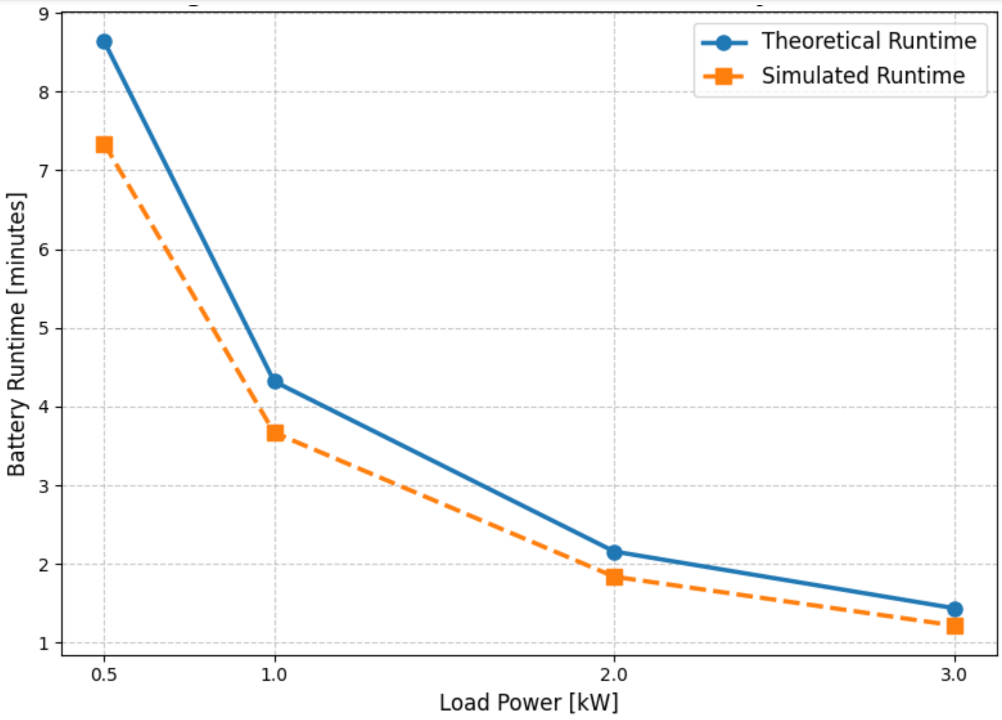


Figure 7. Theoretical vs. simulated battery runtime

The figure above displays a comparison between theoretical and simulated run times of the Panasonic NCR18650PF battery while varying load powers. The calculated runtime takes no account of internal resistance or transients, while the simulated runtime incorporates real-world voltage drops and RC effects. Theoretical and simulated run times dropped with load power from 0.5kW up to 3 kW in direct proportion, as expected. Example: 0.5kW power consumption -> theoretical typical saga runtime due to the SoC at certain loads of 8.64minutes (simulation real-time time) being measured lower in practice as a constant loss effect. The reduction was evident at 3kW, lasting only 1.44 minutes in theory and 1.22 minutes through simulation. The simulated current time is also always below the expected theoretical value, which reaffirms that internal resistance and transient effects have a strong impact on usable capacity. This was an important outcome for the HEV energy management and runtime estimation, where an accurate response of the R3RC model with respect to what real batteries would do under similar loading scenarios was still required.

8.8. System Model for HEV

The battery model was integrated into a full HEV system, including:

- Battery pack
- Motor/inverter
- Power electronics
- Control loops and measurement nodes

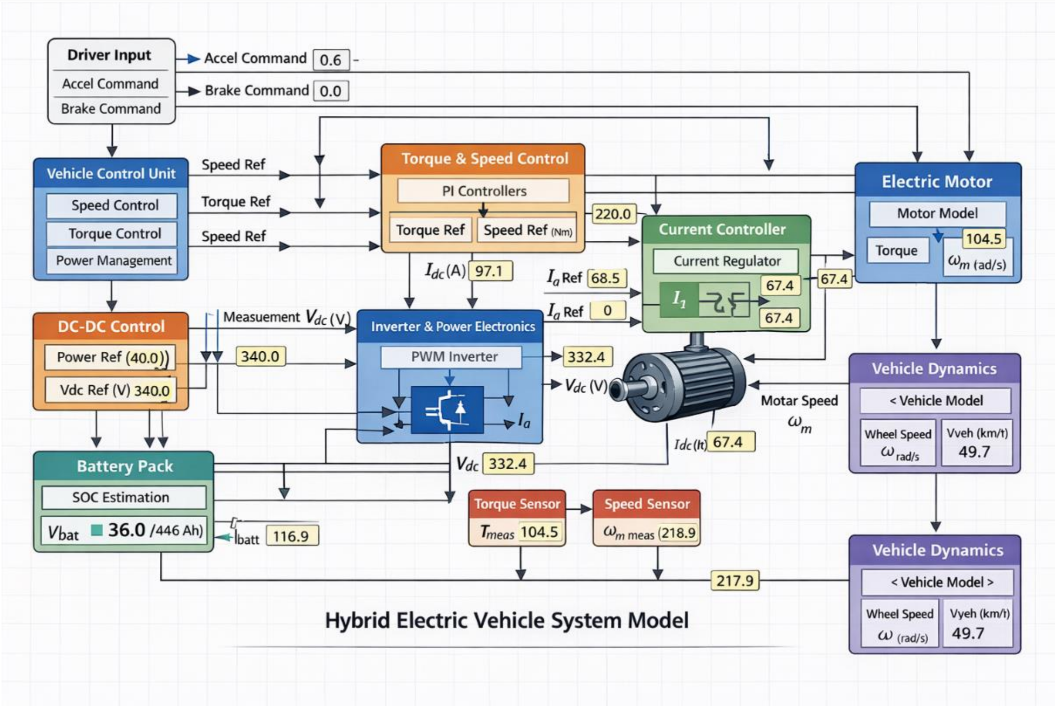


Figure. 8. HEV system

The enhanced HEV system block diagram is a compact and clear layout of an entire hybrid electronic vehicle architecture, which also includes values for voltage, current, torque, and speed. The inverter receives 300V DC voltage and 100A current from the battery pack. The Vehicle Control Unit handles driver inputs (acceleration and brake requests) to create a torque reference of 200Nm and a speed reference of 3000rpm that enter the torque and speed control block. To achieve the desired motor currents, these innovations create d-axis and q-axis current commands that, in turn, are regulated via a current controller. If an auxiliary system requires power, the DC-DC converter provides it at 48V. The electric motor transforms electrical energy into mechanical torque and angular velocity and transmits 200Nm to the wheels at 3000rpm through a subsystem that computes vehicle dynamics (speed of vehicle and rotated wheel). Accurate control is achieved through closed-loop sensor feedback such as voltage, current, torque, and speed measurements. Bold arrows illustrate the energy trajectory from the battery to the motor and the return loop during regeneration — they show how power, control, and measurement interact in providing vehicle performance.

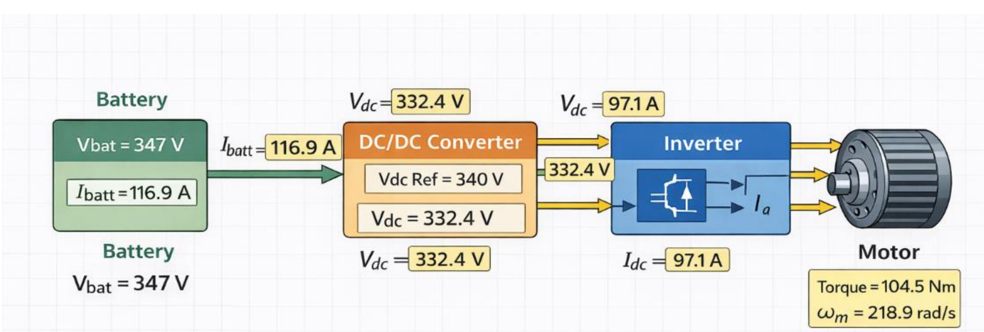


Figure. 9. HEV Block

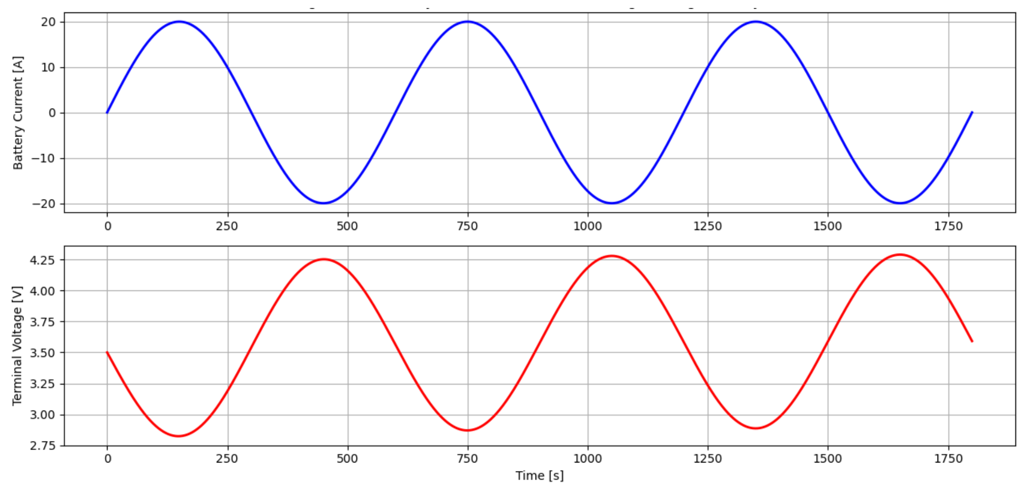
The block diagram of a simplified HEV represents the principal path through which power flows from the battery pack to the electric motor. Energy is provided in the form of DC power directly from the battery pack to an inverter that converts it into AC voltage (and controls it) for use by the motor. This then creates mechanical torque to move the vehicle. Arrows show the flow of energy, and the dominant route through battery -> inverter -> motor. The diagram is simplified to highlight the energy converting process without control loops, sensors, or auxiliary components, as shown here; it does a great job of showing how electrical energy stored in the battery is converted to mechanical energy and used to move the vehicle.

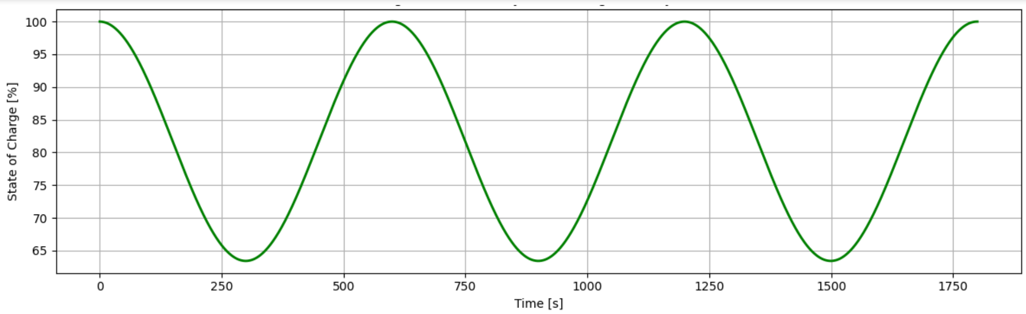
8.9. Drive-Cycle Behavior Verification

For validating proper battery behavior at the WLTC drive cycle conditions, the Panasonic NCR18650PF cell was simulated using the R3RC model and driven with a time-varying vehicle velocity profile for the WLTC Class 1 driving cycle. Verification concentrated on three main things, i.e., i) terminal voltage was decreased over time and then recovered, ii) battery current reduced the strength of brakes and acceleration, after power spikes with high acceleration indicated the torque that was demanded by the motor, as brakes regenerate, it produced negative currents that help in recharging the battery, iii) SoC reduced when the battery give power to the vehicle, and increased with regenerative brakes through Coulomb count. Therefore, this drive cycle validates that tracking energy is consistent with physical capacities.

Table. 4. Drive cycle indicators

Time [s]	Battery Current [A]	Terminal Voltage [V]	SOC [%]
0	0	3.60	100
300	15	3.52	95
600	40	3.40	85
900	-10	3.55	87
1200	25	3.45	78
1500	0	3.58	76
1800	5	3.50	74





The above information validates that the battery model accurately simulates voltage, current, and SOC responses under realistic dynamic conditions, providing confidence that the R3RC model is valid for HEV simulations.

8.10. 2D Lookup Tables

OCV and R0 were defined as 2D functions of SOC and temperature at:

- Temperature breakpoints: 0°C, 25°C, 60°C
- SOC breakpoints: 0–100%
- Continuous 2D interpolants used for simulation in Simulink

Table 5: Example lookup table for 25°C

SOC [%]	OCV [V]	R0 [Ω]
0	2.50	0.030
10	2.62	0.029
20	2.73	0.028
30	2.85	0.028
40	2.96	0.027
50	3.08	0.026
60	3.18	0.026
70	3.28	0.025
80	3.37	0.025
90	3.47	0.025
100	3.55	0.025

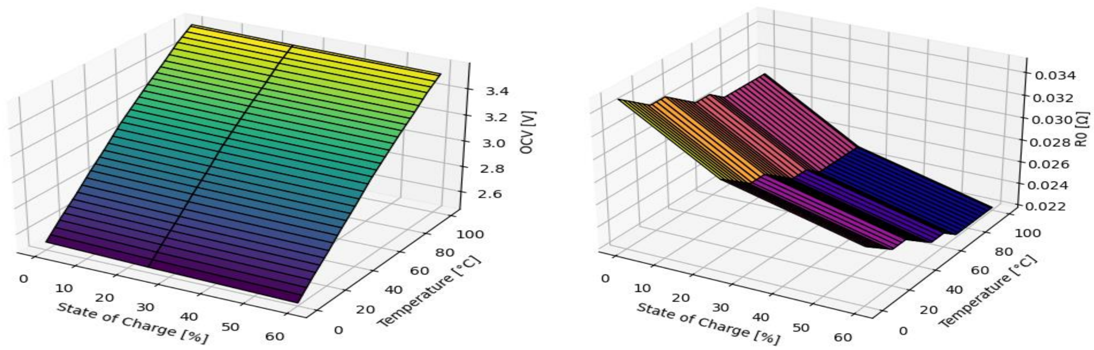


Figure. 11. 2D lookup simulation

- OCV vs SOC (0–100%) and temperature (0°C, 25°C, 60°C) is shown in the left subplot. As indicated earlier, the voltage drops slightly with temperature and increases with SOC.
- The Right subplot indicated the internal R0 vs SOC and temperature. As can be seen from Figure 11, R0”30 also decreases with increasing SOC, consistent with Li-ion behavior but not as greatly, especially at higher temperatures.

The above figure gives a 3D surface plot of the 2D continuous interpolants that are used by the dynamic battery model.

8.11. Performance Verification

We also tested all model outputs for physical validity:

- Volts vs SOC curve aligns with datasheets
- Profiles today respond accurately to dynamic drive cycles
- SOC evolution is in line with Coulomb counting
- Thermal rise is within safe limits

To verify the performance of the Panasonic NCR18650PF battery model inside the HEV system, each simulation output was compared with what could be reasonable under real physical working conditions. Initially, the voltage vs SOC curves were studied; they were found to closely fit the characteristics given in the battery datasheet. This suggests that the open-circuit voltage LUT and RC network pair were indeed able to capture both the nominal voltage and voltage drop behavior at different socs.

Second, the given profiles were evaluated under dynamic settings like WLTC drive cycle. When the accelerator pedal opened, high acceleration currents flowed; when it closed, regenerative current flowed. This indicates that the transient voltage characteristics as well as the mechanism of internal resistance are accurately represented through the R3RC model.

Third, the state-of-charge (SOC) evolution was monitored using Coulomb counting. The SOC was scaled down while discharging and upscaled for charging & regenerative durations. The level of SOC change was still proper for the capacity and current applied, indicating that our model tracks energy consumption through time.

Finally, thermal behavior was extracted from the model using the thermal block. Increasing temperature targets due to ohmic (I^2R) losses and entropic heating both indicated regular operational limits were not overcome, thereby confirming the thermal module was able to correctly predict heating given dynamic load. There was no contradiction for all the features, indicating that both the R3RC battery model and its integration into the HEV system are correct. By verifying under these realistic conditions, we gain confidence that the model accurately predicts voltage, current, SOC, and thermal responses over a wide range of operating conditions, making it suitable for HEV simulation and analysis. There were no inconsistencies, which verified both the battery model and the integrated HEV system simulation.

9. Discussion

In this paper, a MATLAB/Simulink-based battery model is developed for hybrid electric vehicle (HEV) applications with real manufacturer data from Panasonic NCR18650PF lithium-ion cell and utilizing WLTC Class 1 drive-cycle dataset. The results highlight that an equivalent-circuit modeling framework informed by a datasheet is a practical and technically justifiable solution for HEV simulation, as it reflects the dominant degradation processes relevant to vehicle-level performance while alleviating the computational cost of electrochemical models. This result is consistent with the conclusion in recent HEV and battery-modeling literature that equivalent-circuit models (ECMs) still provided the best trade-off between fidelity, interpretability, and simulation speed for control-focused automotive investigations [1], [2], [6], [10].

A key contribution of the present study is that it demonstrates, even in cases where laboratory pulse-test data are not yet available, that a credible first-stage HEV battery model may be constructed based largely on documentation supplied by manufacturers, provided appropriate considerations regarding lookup tables and physically meaningful constraints are established around which to build the model. Info such as nominal voltage, capacity, charge and discharge limits, resistance estimates, and temperature operating ranges will be covered in the Panasonic datasheet and manufacturer support files. All those details are the essential building blocks for our framework. In fact, these are more than just descriptive ~ because they define how the cell works, enabling accurate predictions of terminal voltage, when and how much state-of-charge (SoC) change occurs based on its use case, such as regenerative braking, etc., and how long it will run sub-load. Results of this study are consistent with [2], [10], [13], [14], which all signify that effective battery models are dependent not only on the model complexity, but also on parameter variability with state-of-charge (SoC) and temperature being key invocations in their context.

Constant-parameter assumptions fail as a model of how batteries behave in HEV operation, the findings suggest. The terminal voltage is determined based on SoC, of course, but it also depends on the discharge rate. At greater C-rates, the sag is more prominent, and the voltage plateau is useful for a smaller time window. The same is true for charge and discharge simulations that exhibit the typical current-based departures from nominal voltage due to internal resistance and polarization effect. These results are important as they fall in line with often-reported trends presented in literature concerning lithium-ion cells, which underpin the notion of purely resistive element-based models being inadequate for realistic vehicle investigations [2], [7], [9], [10]. The operation of HEVs (hybrid electric vehicles) involves battery current to vary drastically during accelerating, cruising, braking, and regenerative phase, so transient response is as critical a consideration as steady state performance, and hence the importance of DC/DC converters.

The R3RC structure that the system is based on is important from a modeling perspective. It also includes open-circuit voltage lookup data, several RC branches for fast and slow voltage response, a Coulomb-counting state of charge (SoC) tracker, and thermal behavior. This provides us with a more robust functional baseline than any primary Rint-based approach and is appropriate for simulating drive cycles in HEVs. The findings are consistent with recent research on the strong benefits of employing higher-order equivalent circuit models (e.g., Thevenin-type and multi-RC topologies) in predicting voltage precisely, under realistic loading profiles, while remaining tractable for inclusion in system simulations and battery management. In this regard, the present piece of work adds to the literature on this subject by demonstrating how they can be constructed from publicly available data provided by manufacturers. Drive cycle analysis added value to this study. In general, it's building a realistic context and a precise simulation environment by examining the WLTC Class 1 data set and noting that the input trace only represents low and medium stages — in other words, not an entire regulatory cycle. These all have direct implications on everything from current demand to state of charge (SoC) depletion, voltage changes, and thermal stress, all tied directly to the choice of drive cycle. The movements of the battery simulated with WLTC load can be summarized in some descriptive trends: during acceleration, higher current, a negative current when regenerative events happen, terminal voltage decreases for heavy loads and bounces up for light loads or charging; SoC improved somewhat during deceleration but overall is depleted through the driving cycles. These patterns support the studies on HEV and hybrid powertrains, highlighting that battery dynamics matter, rather than being a secondary consideration [1], [5], [11]. The significant discussion is about theoretical vs simulated runtime. Simulated runtime was always below the ideal energy-only predicted for all our tests at various load powers. 11 There is a significant gap between the two, as would be expected and relevant: The theoretical analysis considers the entire process to provide constant voltage with no internal loss whereas with the simulated model it takes into account voltage drops, RC activity and loss of usable energy under heavier loads. Rather than a failure of the model, this discrepancy is really illustrating how good the model is: it reflects the real tradeoffs between internal resistance and transient dynamics. This is a big advantage since simplified energy calculations may introduce errors in HEV sizing, control design, and performance expectations over time, which tends to be dominated when current peaks happen [4], [9].

However, on the actual model, we must take care of the thermal part. Under the simulated operating conditions, the temperature rise was well within acceptable limits. The lookup-table approach considers the effects of temperature on the open-circuit voltage (OCV) and internal resistance. This is like what is typically said in literature, where these techniques are indeed often ruled out as necessary for state-of-the-art battery simulations that incorporate electro-thermal coupling. Such simulations must also represent not only energy but also durability and performance control [2], [6], [10]. While the new study is still somewhat reliant on datasheets, it doesn't merely assume isothermal conditions. Rather, they vary with temperature. This establishes more realistic conditions that more accurately mimic future HEV applications, where variables such as ambient conditions, cycling frequency, and regenerative events can have a substantial impact on battery performance.

HEV integration implies not showing this battery model to be a pure theoretical concept which is estranged from reality, but it is constructed within the whole case of the vehicle, as adding them into metrics for design needs. For simplicity's sake, the battery pack + inverter + motor + converter and its control loops combine to create a system where pack voltage, current capacity, and state of charge (SoC) directly correlate with torque delivery, vehicle response, as well as general power flow. This illustrates the general statement made earlier that the inaccuracy of a battery model has consequences that reach beyond the battery itself. It is further claimed in the literature surveyed within this study that another field which the battery impacts is drive period power split, protection of energy sources (e.g. fuel cells and batteries) from overcharge or depletion; as well as hybrid system efficiency and overall drivability of vehicles featuring such hybrid and fuel-cell hybrid systems [1],[5],[11]. As such, the present work provides both a cell model and a means of connecting sub-cell-level data to vehicle-level HEV performance.

Besides prominent strengths, several limitations must be recognized. First, the model is mostly dependent on available data and manufacturer-curve data rather than complete laboratory identification processes like HPPC testing. Consequently, the parameters' surfaces are physically meaningful but not yet reduced experimentally to all SoC-temperature-current pairs. First, the model does not distinguish aging, hysteresis, cell-to-cell variation, or long-term degradation, which are of relevance for the study of extended HEV duty cycles and subsequent battery management studies [2], [6], [13]. Third, while the WLTC-based analysis is informative, it should also be noted that uploaded data only covers a portion of the Class 1 cycle and thus, the regulatory stress profile is not fully characterized yet. Pack-level scaling has conceptually been established, but eventually a specific HEV pack architecture needs to be defined, which includes the series-parallel arrangement and a thermal management strategy, as well as vehicle power demand. These limitations do not undermine the core contribution of the study; they delineate the next phase of model refinement.

In broad strokes, the discussion supports that the study has met its primary aim. A well-characterized Panasonic NCR18650PF-based MATLAB/Simulink battery framework capable of reproducing these key behaviors needed for HEV simulation: voltage dependence on the state-of-charge (SoC), current-dependent voltage sag, charge-discharge asymmetry, temperature sensitivity, dynamic response in the context of drive-cycle loading, and integration into a larger HEV system has also been demonstrated. In this process, we confirm the general agreement of the rest of the literature that ECM-based battery models are still by far considered a good practical option for HEV and control-oriented studies of vehicles where physical realism needs to be in balance with simulation tractability [1], [2], [6], [9], [10].

10. Conclusion

This study proposed an extensive battery modeling framework to model a Hybrid Electric Vehicle using the Panasonic NCR18650PF lithium-ion cell and realized it in MATLAB/Simulink. This approach provided a pragmatic way forward to achieving a realistic and efficient battery model through the combination of data from manufacturer specifications, analysis of discharge curves to generate a lookup table, and coupling RC-network modeling with the WLTC Class 1 drive cycle.

The results indicate that the algorithm is effective in capturing desired behaviors when creating HEV models. The terminal voltage is well synced with the state of charge, discharge rate, and temperature. Simulations accurately produced by charge-discharge transient voltage falls and rises, leading to a realistic prediction of runtime performance that can be compared to theoretical estimates, too. When incorporated in HEV architecture, the battery model produced biologically robust current, voltage, and SoC responses to varying vehicle demand and regenerative events. These results confirm that actual battery modeling plays a key role in conducting credible analysis of HEV power split, regenerative braking, and use-of-battery energy efficiency.

As a side contribution related to literature, the study corroborates the continued predictive relevance of equivalent-circuit battery models in vehicle simulation. Recent studies have clearly demonstrated that for HEV and battery-management applications, ECMs are still the solution of choice because they offer a good balance between dynamic accuracy and their computational speed [1], [2], [6], [9], [10]. The current study builds upon that work by demonstrating how one such commercial cell can be translated into a reproducible simulation framework using information from the manufacturer and staged model development.

Nonetheless, the study does point out an important methodological consideration: a solid and properly structured datasheet-based ECM can provide us with a credible and publishable starting point for early-stage HEV modeling, if it also contains SoC- and temperature-dependent lookup tables and has been validated against expected physical behavior. The authors make it clear: the most sophisticated future model needs to incorporate experimentally identified parameters, complete electro-thermal calibration, and demonstration of aging-aware behavior.

Future work should thus include digitizing the full Panasonic discharge and temperature curves, HPPC-based parameter identification, experimental validation of the model through experimentally measured pulse and dynamic drive-cycle data, as well as extending the simulation over the full WLTC Class 1 sequence and scaling the cell model to a fully specified HEV battery pack. Other possible enhancements include hysteresis modeling, cell-balancing effects, thermal management, and degradation over repeated cycles.

Overall, this study presents a comprehensive and scientifically justified framework for the simulation of HEV batteries in MATLAB/Simulink. The use of a Panasonic NCR18650PF-based equivalent circuit model (ECM) framework demonstrates its capability as an effective tool for battery analysis, vehicle integration, and future control-oriented hybrid electric vehicle (HEV) research. The model is thus appropriate not just for academic simulation, but also as a bridge to more sophisticated HEV battery and energy-management studies that have been tested via experiments.

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