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Battery performance models in ADVISOR

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Abstract

This paper summarizes battery modeling capabilities in ADVISOR—the National Renewable Energy Laboratory's advanced vehicle simulator written in the Matlab/Simulink environment. ADVISOR's Matlab-oriented battery models consist of the following: (1) an internal resistance model, (2) a resistance–capacitance (*RC*) model, (3) a PNGV capacitance model, (4) a neural network (nnet) lead acid model, and (5) a fundamental lead acid battery model. For the models, the electric schematics (where applicable), thermal models, accuracy, existing datasets, and sample validation plots are presented. A brief summary of ADVISOR's capabilities for co-simulation with Saber is presented, which links ADVISOR with Saber's lead acid battery model. The models outlined in this paper were presented at the workshop on 'Development of Advanced Battery Engineering Models' in August 2001.

Keywords: Battery model; Lithium ion; Nickel-metal hydride; Lead acid; Vehicle simulations

1. Introduction

The National Renewable Energy Laboratory's (NREL) advanced vehicle simulator (ADVISOR [1]) predicts battery and vehicle performance for conventional (e.g. non-electrified vehicles on the road today), hybrid, electric, and fuel cell vehicles as they vary with drive cycle. The purpose of battery models in ADVISOR is to aid in answering systems-level questions as follows.

- Is it better to regenerate electrical energy at a high or low current to maximize regenerative braking and improve energy efficiency in the overall vehicle system?
- How can a control strategy optimally heat or cool the batteries to get their best performance?
- If a vehicle's destination and route were known (e.g. via GPS), how would the battery be best used?

In order to answer these vehicle systems questions, ADVISOR's battery models must be accurate, predict the battery's voltage, current, temperature, and state-of-charge (SOC), and interface with or be written in the Matlab/Simulink environment. The battery models must be robust and accurately model the battery chemistries to be used in the vehicle, including lithium ion (Li-ion), nickel-metal hydride (NiMH), and lead acid (PbA).

Various battery modeling approaches are available in ADVISOR, including (1) equivalent circuit models coded in Matlab/Simulink and Saber, (2) a neural network model, and (3) an electrochemical equation model. Five models are Matlab-based and the Saber model is accessed via co-simulation of ADVISOR and Saber. Saber is a mixed-signal and mixed-technology simulation tool by Avant! Corporation [2] (soon to be Synopsys). These battery models are shown schematically in Fig. 1.

The five Matlab-based battery models available in ADVISOR are the following:

1. an internal resistance model (Rint),
2. a resistance–capacitance model (*RC*),
3. a partnership for a new generation of vehicles (PNGV) capacitance model (PNGV model),
4. a neural network (nnet) lead acid model (PbA nnet), and
5. a fundamental lead acid battery model (PbA fund).

The Saber model is an equivalent circuit *RC* model characterized for a lead acid battery.

This paper gives the equations or equivalent circuit models for the battery models and presents the accuracy of the models using data taken from battery tests that simulate actual driving cycles.

2. Internal resistance model

The internal resistance battery model (Rint) was implemented in ADVISOR in 1994. A schematic of the electrical model is shown in Fig. 2. The electrical model consists of a

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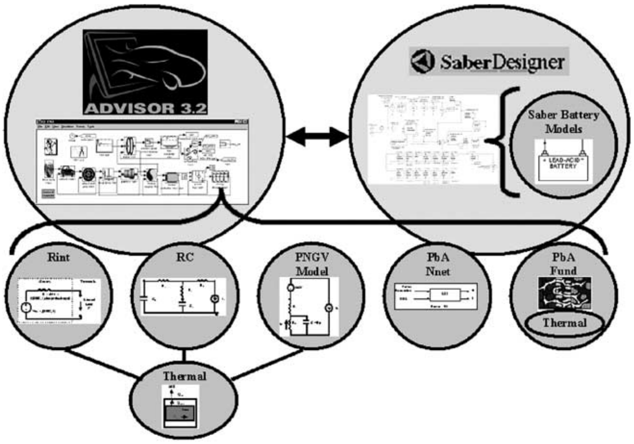


Fig. 1. Outline of ADVISOR battery models.

voltage source (open-circuit voltage, or OCV) and a resistor (internal resistance, or R). The parameters vary with SOC, temperature (T), and the direction of current flow (e.g. if the battery is charging or discharging). The thermal model is a lumped capacity model with air cooling, shown in Fig. 3, and detailed further in [3].

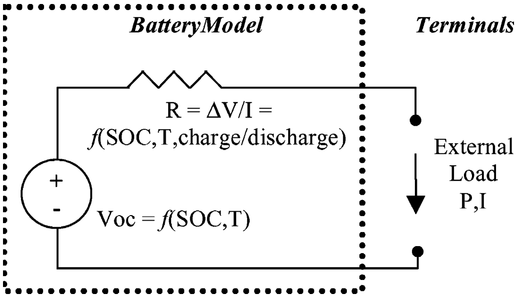


Fig. 2. Internal resistance electrical schematic.

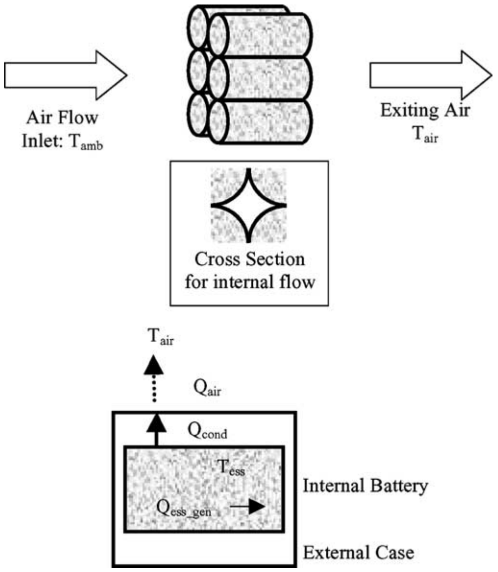


Fig. 3. Baseline thermal model of a battery in ADVISOR.

Table 1
Public datasets characterized for the Rint model

Chemistry	Capacity (Ah)	Manufacturer	Number of data sets
Lithium-ion	6	Saft	1
NiMH	6–93	Ovonic Panasonic	6
Lead acid	12–104	Hawker, Optima, JCI, Horizon, GNB	8
Ni–cadmium	102	Saft	1
Ni–Zn	22	Evercel	1
Ultra-capacitor	2.1	Maxwell	1

The SOC for the Rint model was estimated by performing amp counting, including Coulombic efficiency losses when charging, as shown in Eq. (1).

Idaho National Engineering and Environmental Laboratory (INEEL) [4] originally developed the electrical schematic for the Rint model. NREL development on the model included addition of parameter temperature variation, voltage limits, SOC estimator, and the thermal model.

Rint SOC estimator:

$$\mathrm{SOC} = \frac{Ah_{\max} - Ah_{\text{used}}(\eta_{\text{Coulomb}})}{Ah_{\max}} \tag{1}$$

where

$$Ah_{\text{used}} = \int_0^t \begin{cases} A, & \text{for } A > 0\,\text{discharge}, \\ \eta_{\text{coulomb}} A \, \mathrm{d}t, & \text{for } A < 0\,\text{charge}. \end{cases}$$

ADVISOR has many Rint parameter sets for various battery chemistries. Data sources for these parameter sets include NREL tests, other national laboratories, manufacturer data, published sources, and university tests. Table 1 details the datasets available in ADVISOR.

To characterize parameters for the Rint model for a given battery, three tests are run: (1) capacity tests, (2) open-circuit voltage tests, and (3) internal resistance tests. Figs. 4–6 show the model generation from test results for these three tests. NREL performs these tests over a temperature range from 0 to 40 °C to determine the parameter variation with temperature.

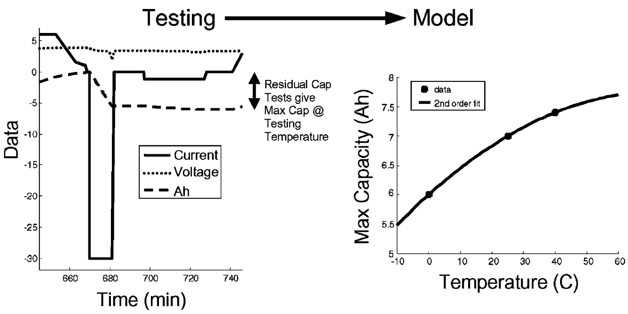


Fig. 4. Capacity tests for Rint model.

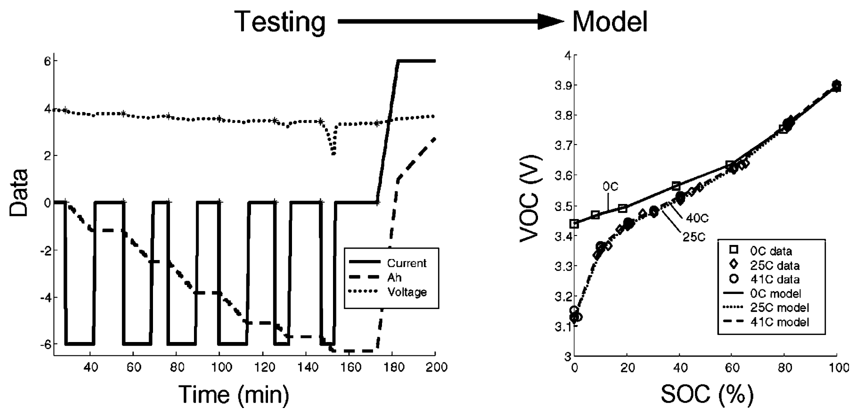


Fig. 5. Open-circuit voltage tests for Rint model.

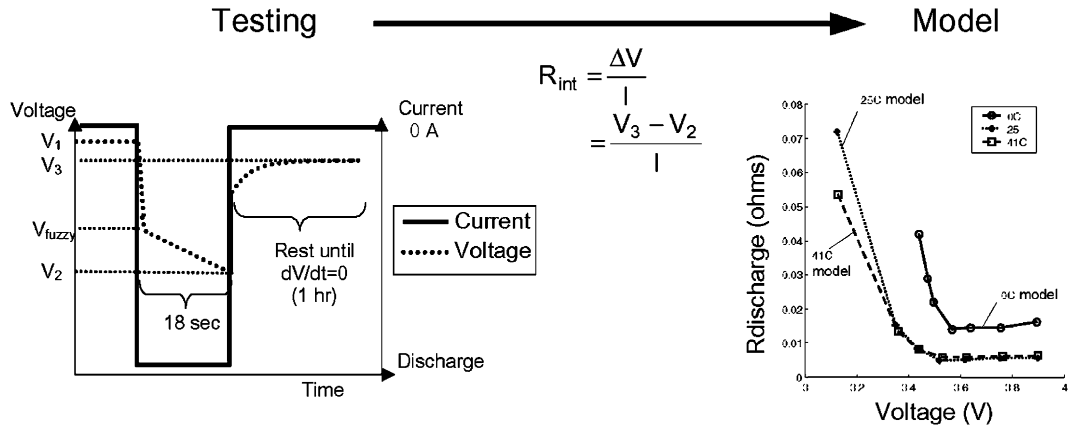


Fig. 6. Internal resistance tests for Rint model.

The Saft Rint model was validated in [5]. The Rint model's voltage predictions were accurate to within 3% over fifteen 100 s US06-derived power cycles, with a maximum error of 12%.

Observed limitations of the Rint model are that the model's voltage response to load changes is too responsive, and the internal resistance does not change as a function of the current magnitude. Test results for discharge resistance for a 1 Ah lead acid battery are given in Fig. 7. The data shows that the internal resistance can vary by eight times as the discharge rate varies from 1 to 100 A. As a result of these tests and observed limitations, NREL developed an improved battery model for ADVISOR that incorporated capacitance (the *RC* model).

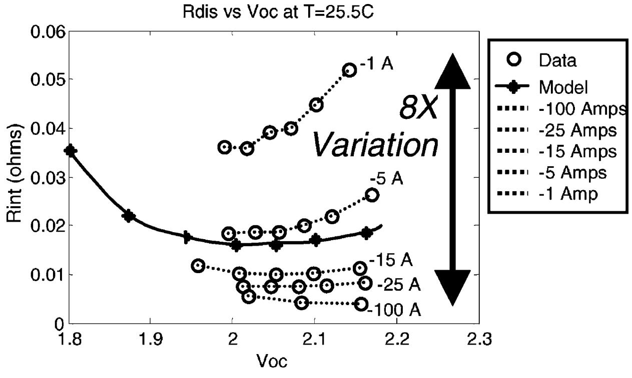


Fig. 7. Internal resistance variation with rate.

3. Resistance–capacitance model

The resistance–capacitance battery model (*RC*) was implemented in ADVISOR in 2001 [6]. A schematic of the electrical model is shown in Fig. 8. The electrical model consists of two capacitors (C_b and C_c) and three resistors (R_e, R_c, and R_t). The capacitor C_b is very large and represents the

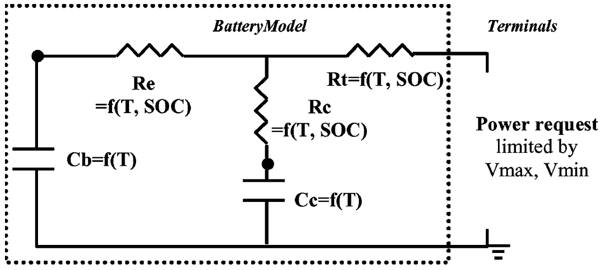


Fig. 8. Resistance–capacitance electrical schematic.

Table 2
Public datasets characterized for the *RC* model

Chemistry	Capacity (Ah)	Manufacturer	Number of data sets
Lithium-ion	6	Saft	1
NiMH	6	Panasonic	1

ample capability of the battery to store charge chemically. The capacitor C_c is small and mostly represents the surface effects of a cell, e.g. the immediate amount of current a battery can deliver based on time constants associated with the diffusion of materials and chemical reactions. The parameters vary with SOC and temperature (T). The thermal model is the same lumped capacity model used in the Rint model, shown in Fig. 3.

The SOC for the *RC* model was estimated by using the voltages of the two capacitors, given in Eq. (2). The estimator weighed V_{C_b} heavily as it represented the bulk energy in the battery.

RC SOC estimator:

$$\mathrm{SOC}_{RC} = \frac{1}{21}(20\mathrm{SOC}_{C_b} + \mathrm{SOC}_{C_c}) \qquad (2)$$

where $\mathrm{SOC}_{C_b} = \mathrm{SOC}(V_{C_b})$ and $\mathrm{SOC}_{C_c} = \mathrm{SOC}(V_{C_c})$.

The NREL *RC* model was based on Saft's two-capacitor battery model [5]. Enhancements were made to the model to include temperature and SOC parameter variation, voltage limits, an SOC estimator, and battery temperature as a function of time.

Battery models for the *RC* model that are currently available to the public in ADVISOR are given in Table 2.

The *RC* model's parameters are easily determined by collecting data from the battery using the hybrid power pulse characterization (HPPC) tests outlined in the PNGV Battery Test Manual [7]. The HPPC profile consists of an 18 s discharge, a 30 s rest, then a three stage charge profile of 2, 4, and again 4 s (Version 2 of the Manual), or an 18 s discharge, a 30 s rest, then a 10 s charge (Version 3, Fig. 9). In practice, open-circuit voltage tests (Fig. 5) are sometimes also run. As with the Rint tests, NREL performs these tests over a temperature range from 0 to 40 °C to determine each model's parameter variation as a function of temperature. Figs. 10 and 11 show Bat model, an automated data processing and optimization tool that allows the user to develop models based on actual data, and example *RC* model parameter variation with SOC.

The *RC* model's voltage predictions are accurate to within 1% over fifteen 100 s US06-derived power cycles, with a maximum error of 4%. Validated models for Li-ion and nickel-metal hydride chemistries can be found in [6]. Sample plots of the voltage, errors, and SOC comparison/validation for the Saft 6 Ah Li-ion battery are shown in Figs. 12 and 13. These validations show that the *RC* model has improved accuracy over Rint, and, therefore, better predictions than the Rint model. The SOC comparison in Fig. 13

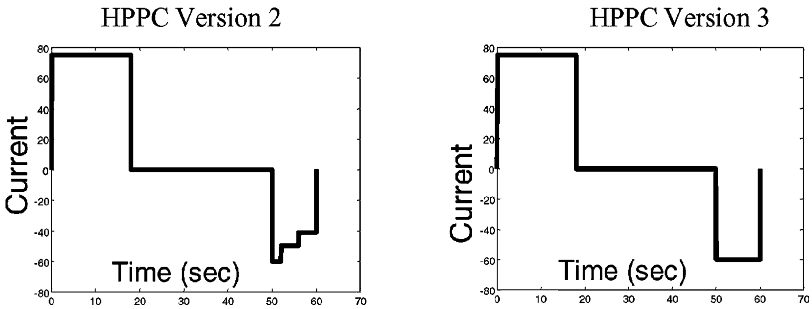
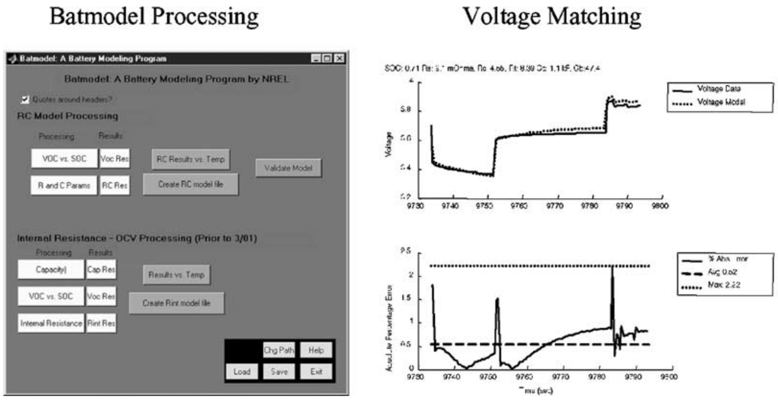

HPPC Version 2
HPPC Version 3

Fig. 9. HPPC profile for *RC* model testing.


Batmodel Processing
Voltage Matching

Batmodel: A Battery Modeling Program

Batmodel: A Battery Modeling Program by NREL

☑ Quotes around headers?

RC Model Processing

Internal Resistance - OCV Processing (Prior to 3/01)

Fig. 10. Automatic data processing and optimization.

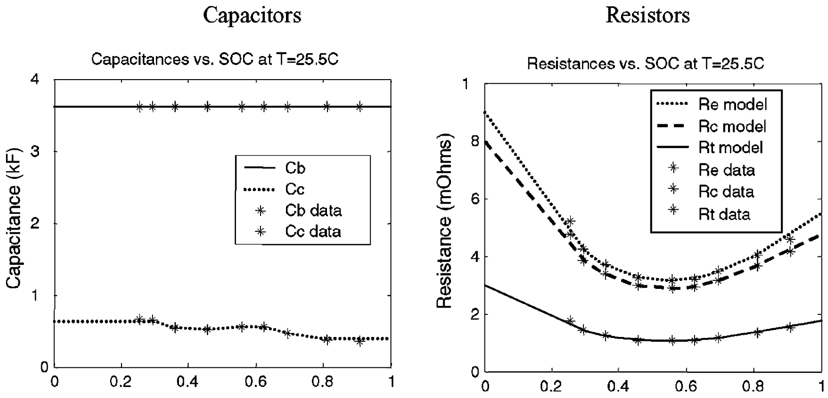
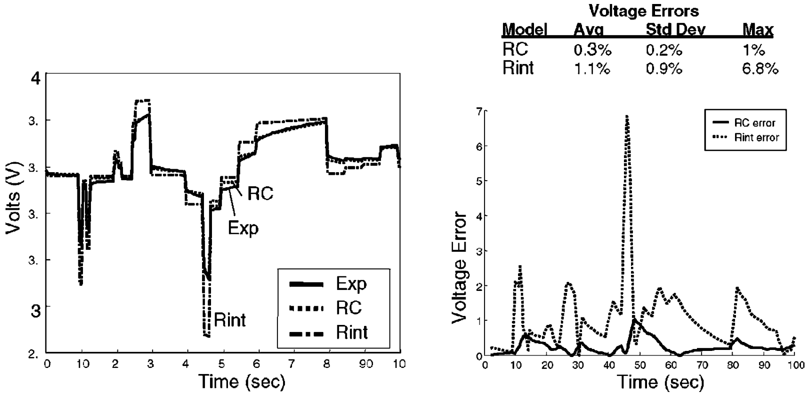


Fig. 11. *RC* parameters vary with SOC and temperature.


Voltage Errors

Model	Avg	Std Dev	Max
RC	0.3%	0.2%	1%
Rint	1.1%	0.9%	6.8%

Fig. 12. *RC* vs. Rint and validation: voltage and errors for one cycle.

shows that there is little difference in the various SOC predictors (Eqs. (1) and (2)) for the initial cycles (e.g. <200 s). After several cycles, the improved accuracy of the *RC* model allows the SOC to track the experimental estimate for SOC more closely than the Rint prediction. For these reasons, the *RC* model is the preferred model in vehicle simulations.

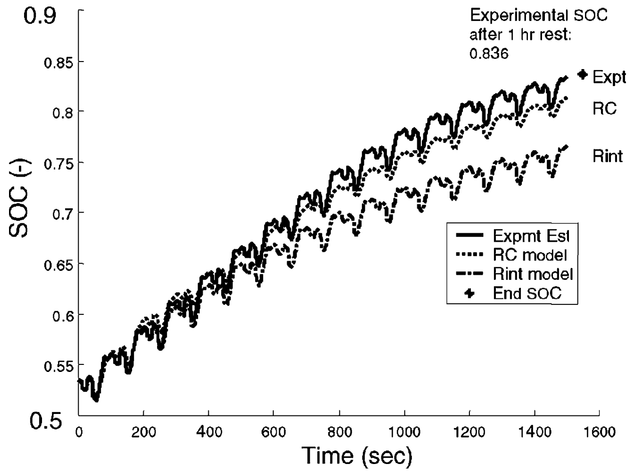


Fig. 13. *RC* vs. Rint and validation: SOC for 15 cycles.

4. PNGV model

The PNGV battery model (PNGV model) was implemented in ADVISOR in 2001. A schematic of the electrical model is shown in Fig. 14. The electrical model consists of a capacitor (C, modeled in parallel with a resistor, R_p), an internal resistance (R_0) an open-circuit voltage (OCV), and a small second capacitor to represent changing OCV with rate (1/OCV′). The parameters vary with SOC and temperature.

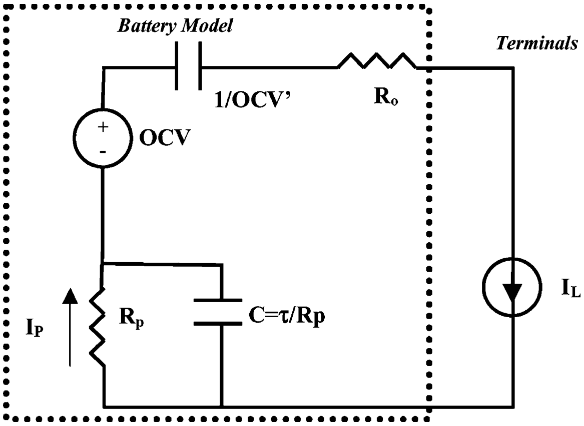


Fig. 14. PNGV model electrical schematic.

Table 3
Datasets characterized for the PNGV model

Chemistry	Capacity (Ah)	Manufacturer	Number of data sets
Lithium-ion	6	Saft	1
NiMH	6	Panasonic	1

The thermal model is the same lumped capacity model used in the Rint model, shown in Fig. 3.

SOC in the PNGV model was estimated by performing amp counting, including Coulombic efficiency losses when charging, equivalent to the Rint SOC predictor given in Eq. (1).

The PNGV team developed the PNGV model (PNGV Battery Test Manual [7]). The model was also implemented in the PNGV Systems Analysis Toolkit (PSAT 4.1 [8]). NREL development on the model included addition of temperature and SOC parameter variation, voltage limits, SOC estimator, and the thermal model.

As with the *RC* model, ADVISOR is currently building its set of parameters for multiple battery chemistries for the PNGV model. Table 3 details the datasets characterized in ADVISOR.

To characterize parameters for the PNGV model for a given battery, the same tests used for the *RC* model need to be run: the PNGV Battery Test Manual's HPPC tests [7] (Fig. 9).

An observed limitation of the PNGV model is that the change in OCV with time term (e.g. the $1/\mathrm{OCV}'$ term) was missing in Version 2 of the model. This was solved by including the $1/\mathrm{OCV}'$ term in Version 3.

The updated PNGV model is currently being characterized and validated and will be available in future releases of ADVISOR.

5. Neural network model

The neural net (nnet) battery model was implemented in ADVISOR in 1999 [9]. A block diagram of the model is shown in Fig. 15. The model is a two layer neural network that takes requested power and SOC as inputs and gives available current and voltage as outputs. The model was characterized for a 12 V lead acid module. Battery test data at an operating temperature of 25 °C was used to train the neural network model. Due to the limited temperature range of test data available at the time of the training of the model, the model did not show a sensitivity to temperature. Therefore, no thermal model is used in the nnet model.

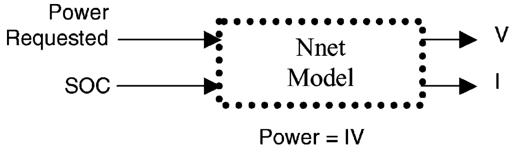


Fig. 15. Neural network block diagram.

Table 4
Public dataset characterized for the nnet model

Chemistry	Capacity (Ah)	Manufacturer	Number of data sets
Lead acid	12	Hawker	1

SOC in the nnet model was estimated by performing amp counting, including Coulombic efficiency losses when charging, equivalent to the Rint SOC predictor given in Eq. (1).

Professor R. Mahajan in the mechanical engineering department at the University of Colorado developed the nnet model under subcontract with NREL.

The advantage of nnet models of batteries is that virtually any test data can be used to characterize the model. The most applicable tests would be those that used the battery over its intended operating range. ADVISOR has a single lead acid battery characterized for the nnet model, shown in Table 4.

The nnet model was validated over multiple US06 drive cycles. The voltage predictions are accurate to within 5%.

One limitation of the nnet model is that the model is only valid over the training data's range. The Hawker test data ranged from a SOC of 27–74% and a power request of 1200 W discharge to 750 W charge. Additionally, the nnet model needed overriding at the zero power request case. The nnet model is characterized for a lead acid battery, but the technique could be applied to other chemistries. Future enhancements of nnet battery modeling would train the nnets over a broad range of temperatures, and therefore have temperature as an additional input. A second thermal neural network could be trained to represent the thermal aspects of the battery heating and cooling, or the lumped capacity thermal model (Fig. 3) could be used.

6. Fundamental lead acid model

The fundamental lead acid (fund) battery model was implemented in ADVISOR in 1999 [10]. A diagram of the model is shown in Fig. 16. The model is based on

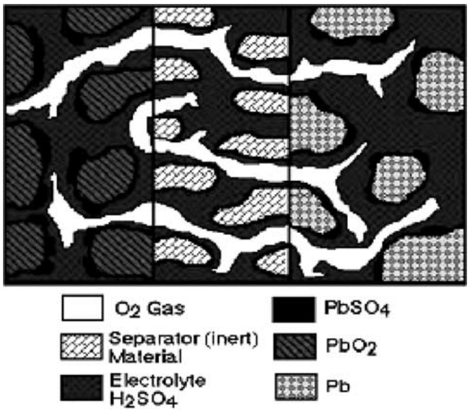


Fig. 16. Fundamental lead acid diagram.

physical and chemical reactions for a plate (one-dimensional), such as those given in Eq. (3). The model includes performance and material property variation with temperature. The thermal aspects of the model include Joule heating in the electrolyte and energy dissipated in the electrode overpotentials. SOC in the fund model was estimated by determining the relative amount of charge available at the limited electrode. The model's code was written in Fortran and was compiled to a dynamic-linked library (dll) to link it with ADVISOR.

Fundamental lead acid reactions:

$$\mathrm{PbO_2(s)+3H^+ + HSO_4{}^- + 2e^-} \underset{\text{charge}}{\overset{\text{discharge}}{\rightleftarrows}} \mathrm{PBSO_4(s)+2H_2O}$$

$$\mathrm{Pb(s)+HSO_4{}^-} \underset{\text{charge}}{\overset{\text{discharge}}{\rightleftarrows}} \mathrm{PBSO_4(s)+H^+ + 2e^-} \qquad (3)$$

Professor John Harb in the chemical engineering department at Brigham Young University developed the fundamental model under subcontract with NREL.

The input parameters for the fund model are multiple and fall into four categories:

1. physical parameters (e.g. cathodic charge transfer coefficient for the Pb electrode, or ratio of gas to liquid volume fractions in the electrode),
2. numerical parameters (e.g. number of computational nodes in the positive electrode),
3. battery characteristics (e.g. initial concentration of sulfuric acid, or thickness of the separator), and
4. external limits (e.g. minimum operating battery voltage).

The model was characterized for two 12 V modules, shown in Table 5.

Table 5
Public dataset characterized for the fund model

Chemistry	Capacity (Ah)	Manufacturer	Number of data sets
Lead acid	16 scaleable	Optima Generic	2 1

The fund model was validated over a variety of conditions. The model showed good agreement with constant current charges and discharges, as well as over a hybrid drive cycle (voltages were within 3%). The model showed great temperature agreement with test data.

One limitation of the fund model is that good parameter values are needed for accurate results. The fund model is of course only valid for lead acid chemistries; however, the fundamental model shows that ADVISOR can link to more complex battery codes than equivalent circuit models if the user desires.

7. ADVISOR–Saber co-simulation

Co-simulation between ADVISOR and Saber for a conventional (non-hybrid) vehicle was implemented in ADVISOR in 2001 [11,12]. Simulation of the mechanical side of a conventional vehicle stayed in ADVISOR (Matlab), while Saber gave extended functionality by simulating the electrical side of a vehicle. ADVISOR–Saber co-simulation was a joint project with Delphi Automotive: first to address single- and dual-voltage (see Fig. 17) conventional vehicle systems (2001) and second to address hybrid vehicles (2002). Through the link with Saber, ADVISOR gained the use of an additional lead acid battery model whose electrical schematic is shown in Fig. 18. The model is a lead acid plate model, characterizable, and includes self-discharge behavior [13]. With respect to a thermal model, the Saber model's performance varies with input temperature, but there is no transient thermal model to predict the

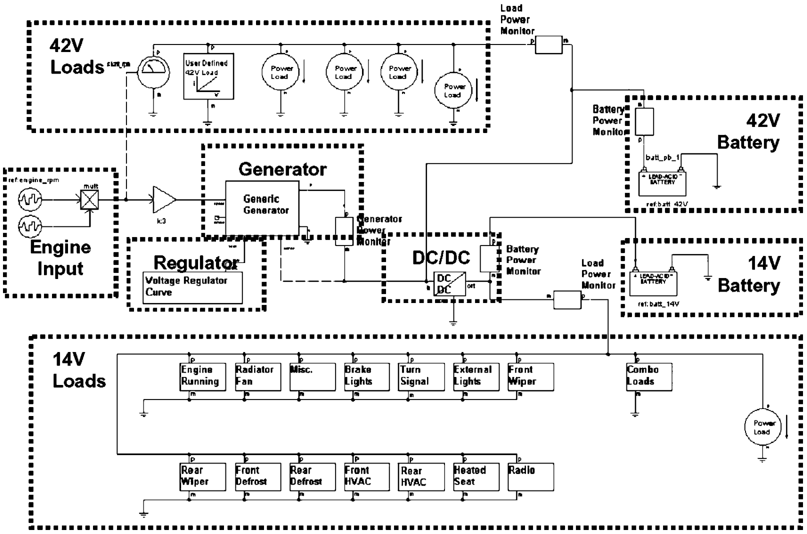


Fig. 17. Saber dual voltage schematic used in ADVISOR–Saber co-simulation.

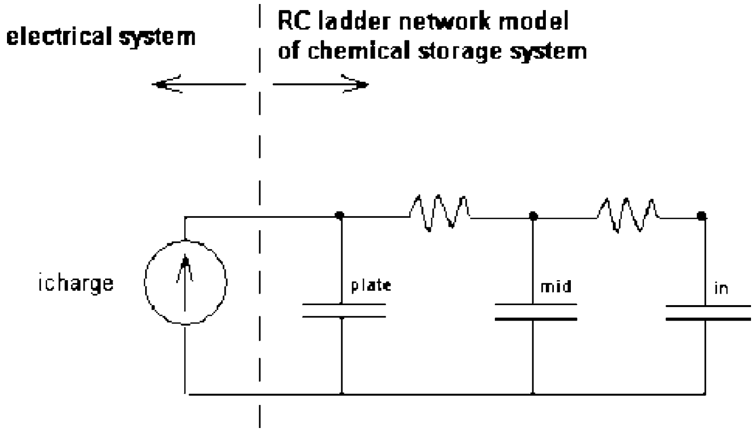


Fig. 18. Saber lead acid battery model.

battery's changing temperature. Currently, SOC is estimated by using the specific gravity at the plate. The Saber model was created by Dan Herbison at Avant!.

The link between ADVISOR and Saber was completed recently (2001), and co-simulation of hybrid configurations is currently under development (2002). Therefore, much of the future work related to co-simulation involves using Saber's advantages as a mixed-signal and mixed-technology simulation tool to answer questions as follows.

- How do cell by cell performance variations affect pack performance?
- Does cell by cell balancing pay off in the overall fuel economy of a vehicle?
- What benefit is there to having a multiple energy storage battery pack?

ADVISOR–Saber co-simulation capabilities can be used to answer these questions using Saber's Monte Carlo analysis feature and the advantages of Saber's underlying structure. Monte Carlo analysis with varying parameters is easily run in Saber, to aid in cell-by-cell analysis. Cells are easily connected in the Saber framework as in the physical world, as the system state equations are assembled by Saber. Using this feature, the control of each cell can be specified to study cell-by-cell balancing, or an ultra-capacitor can be used with conventional batteries to determine multi-energy storage battery pack tradeoffs.

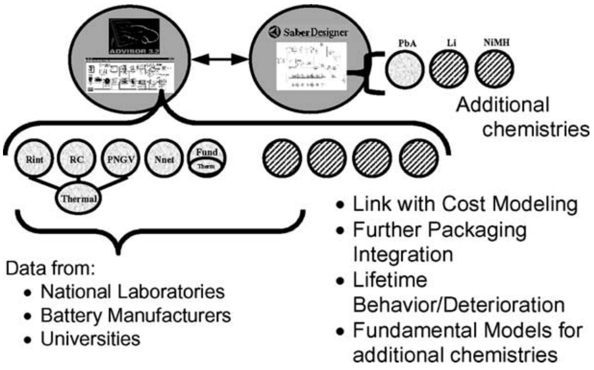


Fig. 19. Summary and future direction of ADVISOR battery modeling (diagonal fill represents future opportunities).

8. Summary and future work

This paper summarized the battery modeling capabilities in ADVISOR, NREL's advanced vehicle simulator. Battery models in ADVISOR predict current, voltage, SOC, and temperature of the battery and integrate with the vehicle system by using power request as an input. The models presented were:

- an internal resistance model,
- a resistance–capacitance model,
- the PNGV model,
- a lead acid neural network model,
- a fundamental lead acid model, and
- Saber's lead acid electrical *RC* model.

The first five models were Matlab-based and the last model was linked to ADVISOR through Saber co-simulation. For the models, where applicable, the paper showed the electrical models, thermal models, SOC predictors, origins, existing datasets, testing, validation, and limitations of the models. The models represented a range of chemistries (e.g. lead acid, nickel-metal hydride, Li-ion) and a range of approaches (e.g. electrical representation, neural networks, fundamental models). Table 6 gives a summary of the models.

Future directions of ADVISOR battery modeling include expanding the library of batteries for the existing models, adding new models (electrical or fundamental), characterizing additional chemistries in Saber, and linking with other related models (e.g. cost modeling, packaging, lifetime behavior). Fig. 19 shows a summary of existing battery modeling capabilities and the future direction of ADVISOR battery modeling.

Table 6
Summary of ADVISOR battery models

Chemistry	Capacity (Ah)	Maker	Model	Number of data sets	Voltage accuracy	Thermal model	Software	Model status
Lithium-ion	6	Saft	Rint	1	3% average + S.D., 12% maximum	Lumped capacity	Matlab/Simulinnk	In ADVISOR
	6	Saft	*RC*	1	1% average + S.D., 4% maximum	Lumped capacity	Matlab/Simulinnk	In ADVISOR
	6	Saft	PNGV	1	In progress	Lumped capacity	Matlab/Simulinnk	In future releases
NiMH	6–93	Ovonic Panasonic	Rint	6		Lumped capacity	Matlab/Simulinnk	In ADVISOR
	6	Panasonic	*RC*	1		Lumped capacity	Matlab/Simulinnk	In ADVISOR
	6	Panasonic	PNGV	1	In progress	Lumped capacity	Matlab/Simulinnk	In future releases
Lead acid	12–104	Hawker Optima JCI Horizon GNB	Rint	8		Lumped capacity	Matlab/Simulinnk	In ADVISOR
	12	Hawker	nnet	1	5%	None	Matlab/Simulink	In ADVISOR
	16 scaleable	Optima Generic	Fund	2	3%	Joule heating, electrode over-potentials	Matlab/Simulink through Fortran dll	In ADVISOR
	Scaleable	Generic	3-cap	*N*	Unknown	None	Saber	In Saber
Ni–cadmium	102	Saft	Rint	1		Lumped capacity	Matlab/Simulinnk	In ADVISOR
Ni–Zn	22	Evercel	Rint	1		Lumped capacity	Matlab/Simulinnk	In ADVISOR
Ultra-capacitor	2.1	Maxwell	Rint	1		Lumped capacity	Matlab/Simulinnk	In ADVISOR

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References

[1] Advanced Vehicle Simulator (ADVISOR), Version 3.2, http://www.ctts.nrel.gov/analysis/.

[2] Avant! at http://www.avanticorp.com/.

[3] Wipke, et al., ADVISOR 3.2 Documentation, see www.ctts.nrel.gov/analysis/advisor_doc, August 2001.

[4] Simplev Manual, http://ev.inel.gov/simplev/.

[5] V. Johnson, A. Pesaran, T. Sack, Temperature-dependent battery models for high-power lithium-ion batteries, in: Proceedings of the 17th Electric Vehicle Symposium, Montreal, Canada, October 2000.

[6] V. Johnson, M. Zolot, A. Pesaran, Development and validation of a temperature-dependent resistance/capacitance battery model for ADVISOR, in: Proceedings of the 18th Electric Vehicle Symposium, Berlin, Germany, October 2001.

[7] PNGV Battery Test Manual, Revision 2, August 1999, Revision 3, February 2001.

[8] B. Larson, A. Rousseau, et al., in: Proceedings of the Joint ADVISOR/PSAT Vehicle Systems Modeling User Conference on Argonne's Hybrid Electric Vehicle Technology Development Program, August 2001.

[9] S. Bhatikar, R. Mahajan, K. Wipke, V. Johnson, Artificial neural network based energy storage system modeling for hybrid electric vehicles, in: Proceedings of the FutureCar Congress, 2000.

[10] J.N. Harb, Development and integration of a fundamentally-based battery model for low-emission vehicle simulations, NREL Report, June 1999.

[11] J. Conover, V. Johnson, Co-simulation of electrical and propulsion systems, in: Proceedings of the SAE Future Transportation Technology Conference, August 2001.

[12] V. Johnson, A. Brooker, K. Wipke, ADVISOR–Saber co-simulation for single-voltage and dual voltage conventional vehicles, NREL Report, June 2001.

[13] SaberDesigner Documentation, Version 5.1.