

Electrical battery modeling for applications in wireless sensor networks and internet of things

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Article Info

Article history:

Received Nov 22, 2020
Revised Mar 25, 2021
Accepted Jun 11, 2021

Keywords:

Battery
Internet of things
Modeling
Wireless sensor networks

ABSTRACT

Modeling the behavior of the battery is non-trivial. Nevertheless, an accurate battery model is required in the design and testing of systems such wireless sensor network (WSN) and internet of things (IoT). This paper presents the one resistive-capacitance (IRC) battery model with simple parameterization technique for nickel metal hydride (NiMH). This model offers a good trade-off between accuracy and parameterization effort. The model's parameters are extracted through the pulse measurement technique and implemented in a physical and dynamic simulator. Finally, the performance of the model is validated with the real-life NiMH battery by applying current pulses and real wireless sensor node current profiles. The results of the voltage response obtained from both the model and experiments showed excellent accuracy, with difference of less than 2%.

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1. INTRODUCTION

Batteries are used in almost every part of our lives. Increasingly, it is finding its utility in new application areas such as hybrid electric cars, personal mobile devices, micro energy harvesting system and so on. There are extensive research efforts in many areas of the battery technology [1]-[5]. One of the important area is in the modeling of the battery because this allows researchers, designers and engineers to evaluate various design choices in a timely and cost effective manner. However, most of the work has been focused on Li-ion batteries due to their application in hybrid electric cars [6]-[11]. On the other hand, in the rapidly emerging areas of wireless sensor network (WSN) and internet of things (IoT), there has been less attention for the smaller capacity nickel metal hydride (NiMH) batteries. Therefore, this work endeavours to address this gap by developing a simple but accurate NiMH battery model.

WSN and IoT are experiencing an explosive growth due to their wide applicability across many industries. In order to enable the continuous and perpetual operation of WSN and IoT, micro energy harvesting system has emerged as a promising solution. A micro energy harvesting system consists of energy harvesting, energy storage and power management subsystems. The energy storage subsystem usually comprises a battery as a store of energy as renewable energy source. Since this energy source supplies in a non-constant manner, the system operation can be disrupted. Therefore, the battery is a key component in the micro energy harvesting system.

The ability of a battery model in simulating its behaviour under various conditions not only reduces time but also cost when compared to building a hardware prototype. Various tests can be performed and their results obtained in a timely manner [12]. In the literature, a large variety of models have been proposed,

which include electrical, electrochemical, analytical, and stochastic models. Among them, the electrical models are preferred due to its good trade-off between accuracy and simpler parameterization effort. Furthermore, these models also take into account both the complexity and non-linearity of the battery [13]. In contrast, electrochemical models require the solving of partial differential equations, which is much more complex. Therefore, the electrical models offer good usability and accuracy [14].

The electrical battery model comprises of an equivalent circuit with voltage source, resistance and capacitance. Its variants include one resistive (1R), one resistive-capacitance model (1RC) and two resistive-capacitance (2RC) models. The 1R model is represented by only series resistance with a voltage source. On the other hand, 1RC and 2RC have an additional single RC branch and double RC branch, respectively. Among them, the 1RC offers the best trade-off between accuracy and parameterization effort [15].

The accuracy of the model is highly dependent of the parameterization, which is basically to determine the values of the resistors and capacitors that should be used in the corresponding model. Two main techniques used for parameterization are the pulse measurement and optimization. A rectangular current pulse is applied to obtain the voltage response of the battery in both techniques. For the optimization technique, the values of resistance and capacitance are optimized by matching the produced voltage response against the measured voltage response. This process has a higher complexity and involves significant efforts. In the pulse measurement technique, the values of the resistance and capacitance are obtained through mathematical equations from the measurement of the voltage response [16], which is much simpler. Among the pulse measurement based parameter extraction techniques, one of the best was proposed Einhorn *et al.* in [15]. It consists of simple equations that can be applied with the pulse measurement procedures. The parameter extraction technique has been applied and tested on Li-ion battery, with very high accuracy. However, it has not been applied on the NiMH battery.

Although limited, there are several recent works in NiMH battery modeling. Cruz-Manzo *et al.* and Zhu *et al.* in [17], [18], electrochemical models were proposed with the objectives of obtaining new understanding in the interpretation of battery electrochemical mechanisms and to study the battery capacity degradation effects. These models are complicated and its integration with other electronic components' models is also not straightforward. An investigation into the tradeoff between accuracy and simplicity was undertaken in Fotouhi *et al.* [19] based on the electrical model and optimization-based parameterization. The study yielded very accurate results in terms of state of charge (SoC) and state of health (SoH). Meng *et al.* in [20], an accurate SoC estimator for design of battery management system (BMS) was proposed for battery lifetime extension. It worked very well in the specific application of electric boats that were to be used for scenic tours in caves. A enhancement to an existing analytical based battery model by taking into account the temperature effect was undertaken Rodrigues *et al.* in [21]. It provided an accurate estimation of the battery lifetime at different temperatures. However, in these works, the detailed voltage response results were not provided.

Therefore, this paper will present the 1RC NiMH battery model with the simple parameterization technique. This is followed by its implementation in a physical and dynamic simulator. Experiments with NiMH batteries using both current pulses and real wireless sensor node current profiles will be performed to test and validate the model's accuracy. The percentage difference between the model and experiment is less than 2%. The proposed parameterization technique shows a high accuracy with NiMH battery compared to the previous works, which only tested with Li-ion batteries. Following is the organization of the paper. The methodology for 1RC battery model parameterization is presented in section 2. The results are shown and discussed in section 3, while section 4 concludes the paper.

2. METHODOLOGY

2.1. 1RC electrical battery model

The battery modeling along with its parameter extraction technique is presented. The model is relatively simple and requires minimum parameters from the datasheet. 1RC electrical battery model consists of a voltage source V , series resistance R_s and a parallel RC branch connected in series is shown in Figure 1. The model is capable of predicting the battery performance and SoC estimation better than the typical analytical and electrochemical battery models. The model components are:

- V is the voltage source and it represents the open circuit voltage (OCV) of the battery
- R_s is the series resistance of electrolyte.
- R_p, C_p is the RC network and represents the transient response of the battery electrodes.

Parameterization is to extract the values of model parameters such as R_s, R_p and C_p . The 1RC battery model is dynamic in nature and the parameter values are varying with the change in SoC. Therefore, the important part is to get the correct parameters of the model when they are varying with SoC. The 1RC electrical battery model parameters are:

- C_N , the nominal capacity of a battery.
- R_s , the series resistance of electrolyte at SoC=0.
- R_p , the resistance of electrodes at SoC=0.
- C_p , the capacitance of electrodes at SoC=0.

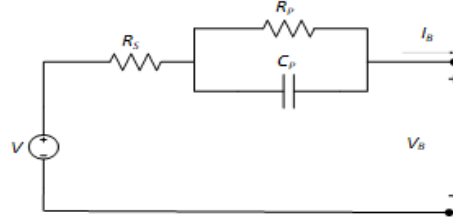


Figure 1. 1RC battery model

The SoC can be obtained by integrating the current over time. The SoC varies between 0 and 1. The SoC vs OCV curve provides the change in SoC of the battery with voltage. It is determined when there is no load attached to the battery and is shown in Figure 2. To extract the parameters of 1RC battery model, an experiment procedure to obtain the pulse measurement is required. Firstly, the battery is fully discharged to 0% SoC followed by a rest period. The rest period is to ensure the accurate measurement of the OCV after obtaining the thermodynamic stability [22]. After the rest period, a current pulse is applied for a certain duration to obtain the voltage response of the battery. The cycle of charging and resting period is repeated until the SoC reaches 100%. This whole procedure will provide the SoC vs OCV curve. Alternatively, this procedure can also be performed on a fully charged battery by applying discharging current pulses with the following rest periods. Hence, after obtaining the SoC vs OCV curve, the parameters can be extracted using the equations provided Hentunen *et al.* in [23].

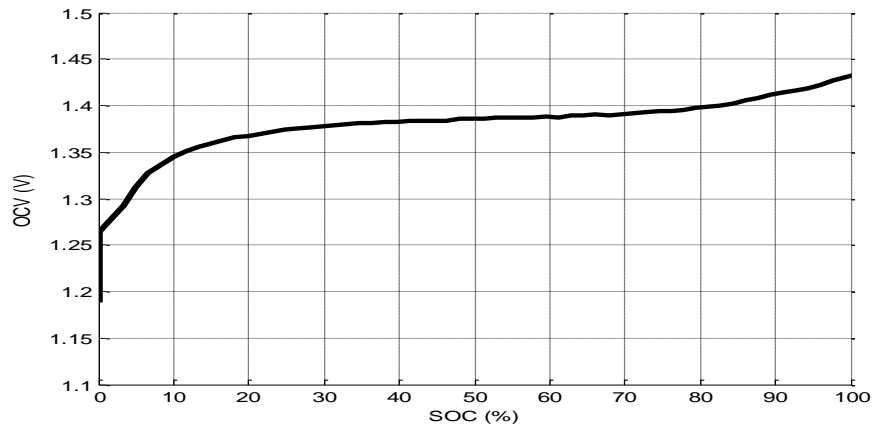


Figure 2. SoC vs. OCV curve of NiMH battery

2.2. Parameterization of the 1RC electrical battery model

The manufacturer provides the nominal capacity, C_N , of the battery in the datasheet. The values of R_s , R_p and C_p are obtained by applying a current pulse and measuring the voltage response. The parameterization technique is following the approach of [15]. The state of charge of the battery is represented in (1):

$$SOC = \frac{C_N - Q}{C_N} \quad (1)$$

where, Q is the charge of the battery at time to given as shown in:

$$Q = \int_0^{t_0} I_B(t) dt \quad (2)$$

The series resistance of the electrolyte can be approximated with (3):

$$R_s = \frac{V_i}{I} \quad (3)$$

where, I is the height of the pulse current and V_i is the initial voltage response. While resistance of electrodes are shown in (4):

$$R_p = \frac{V_f}{I} - R_s \quad (4)$$

where, V_f is the final voltage response. Both V_i and V_f are shown in Figure 3. The curve is obtained by applying a rectangular current pulse of 1.5A to the battery.

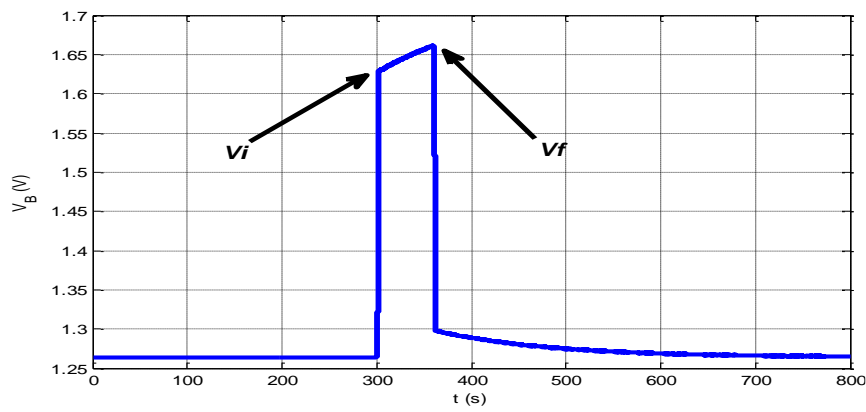


Figure 3. Battery voltage response

The step current of the pulse measurement technique includes a series of charge or discharge cycles followed by the rest period. The width of the pulse is normally from 1 minute to 5 minute. In this paper, the 1-minute pulse width is chosen to capture any abrupt change in the behaviour of the battery. A 1500 mAh NiMH battery is chosen to perform the tests. The step current of the pulse measurement technique is applied to the battery and the voltage response is obtained. The battery is initially discharged to 0% SoC and then subject to partial charge phase cycles until the SoC reaches 100%. After every charge cycle, a rest is given to the battery to stabilize the voltage. Therefore, at the end of one-hour cycle of rest period, the battery voltage is found stable to be considered a good estimate of the OCV. The SoC is determined based on the current gained or drawn from the battery at each cycle. This technique is also called coulomb counting. The capacitance of electrodes can be approximated as (5):

$$C_p = \tau \frac{R_s + R_p}{R_s R_p} \quad (5)$$

where, τ is the time constant of the exponential curve and is determined by (6):

$$\tau = Q(1 - 1/e) \quad (6)$$

where e is the Euler's number=2.71828. After obtaining the SoC vs. OCV curve by applying the step current of the pulse measurement technique, the parameters are extracted using (3)-(5).

2.3. Implementation of 1RC electrical battery model

The one diode PV panel model can be implemented through simple MATLAB equations. However, since the battery is dynamic, its model implementation requires both physical and dynamic simulators such as Simscape and Simulink. The model utilizes Simscape to build custom circuit elements such as source, resistor and capacitor which are dependent on SoC [24].

The 1RC NiMH equivalent circuit model system architecture is shown in Figure 4. The major building blocks are the signal builder, 1RC equivalent circuit model, ideal temperature source, convective heat transfer, voltage sensor, and the scope. The signal builder provides the pulse charging current. The ideal temperature source basically represents an ideal source of thermal energy that is able to maintain the specified temperature of the system. The convective heat transfer block simulates the heat transfer by convection. Furthermore, the voltage sensor block converts the voltage measured into a physical signal that can be captured and displayed.

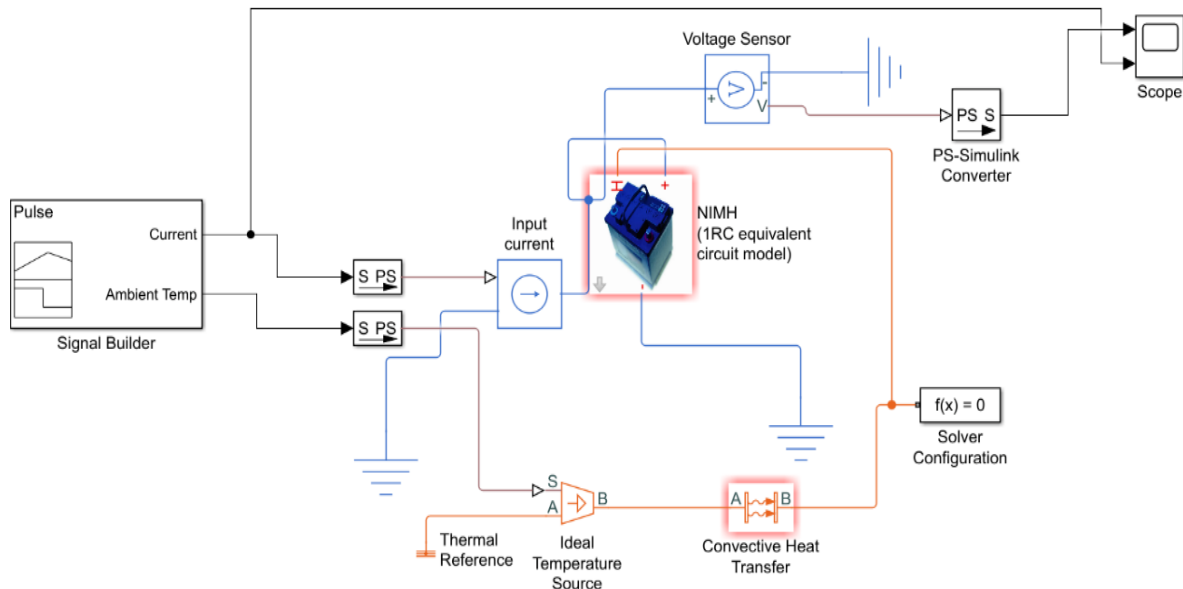


Figure 4. 1RC equivalent circuit model system architecture in Simulink and Simscape

The 1RC model is required to generate the simulation results which are later compared with the experiment to verify the accuracy of the model. The 1RC equivalent circuit model has four variable circuit elements that are SoC dependent. These variable circuit elements are open circuit voltage V_{oc} , series resistance R_s and RC network, R_p and C_p . These variable circuit elements are implemented through lookup table. An example of the lookup table is shown in Table 1. The built-in Simulink thermal model is used to model battery temperature. It is assumed that the heating is primarily from internal resistance and the cooling is primarily via convection. The model can be used to simulate various operating conditions by just changing the temperature and current profiles.

Table 1. Example of lookup table used in simscape model

SoC	OCV	R_s (Ohm)	R_p (Ohm)	C_p (F)
0.2	1.24	2.13	1.54	6134
0.4	1.27	2.15	1.65	6207
0.6	1.32	2.67	1.73	6398
0.8	1.38	2.45	1.43	6254
1.0	1.43	2.19	1.32	6243

3. RESULTS AND DISCUSSION

Validation of the model is carried out through experiments. The main component of the experimental setup is the ubiquitin like modifier activating enzyme 5 (UBA5) battery analyzer. The battery analyzer consists of charging/discharging and measurement subsystems. The former allows charging/discharging at constant voltage, constant current or constant power modes. The test cycle, which is user programmable, is used to control the charging and discharging of the battery. The latter includes a built-in measurement system that can allow simultaneous measurement of both the current and voltage. All of these subsystems are controlled by the battery analyzer and its associated software which is installed on a PC.

In the experiments, the battery analyzer is used to apply the required current profile and measure the corresponding voltage response [25]. The NiMH battery can be charged or discharged with a completely

programmable current profile. The NiMH battery with capacity of 1500 mAh from Energizer is used in the experiment. The battery is tested to verify the model's accuracy at room temperature. The block diagram of the experiment is shown in Figure 5.

The step current pulses of 1-minute width are applied to both the NiMH battery and the model. By using (3)-(5), the parameter of 1RC battery model can be obtained and apply to the Simulink. The comparison of the corresponding voltage responses obtained is shown in Figure 6 (a) and 6 (b). It can be seen that they are in excellent agreement. The difference between the two curves is less than 1.5%, which shows the high accuracy of the model.

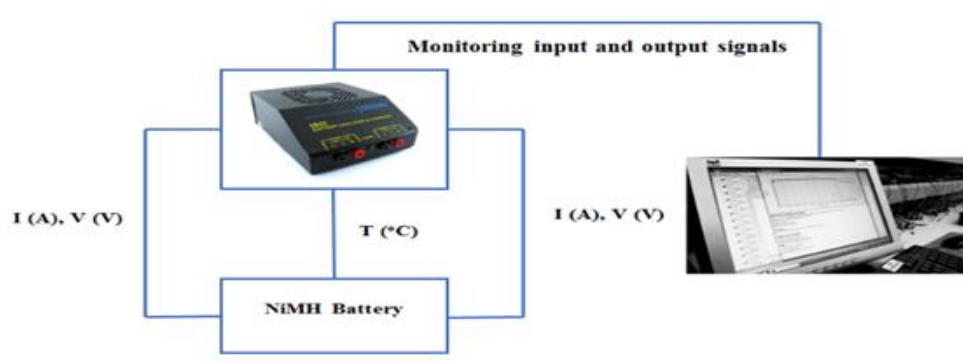


Figure 5. Block diagram of battery experiment

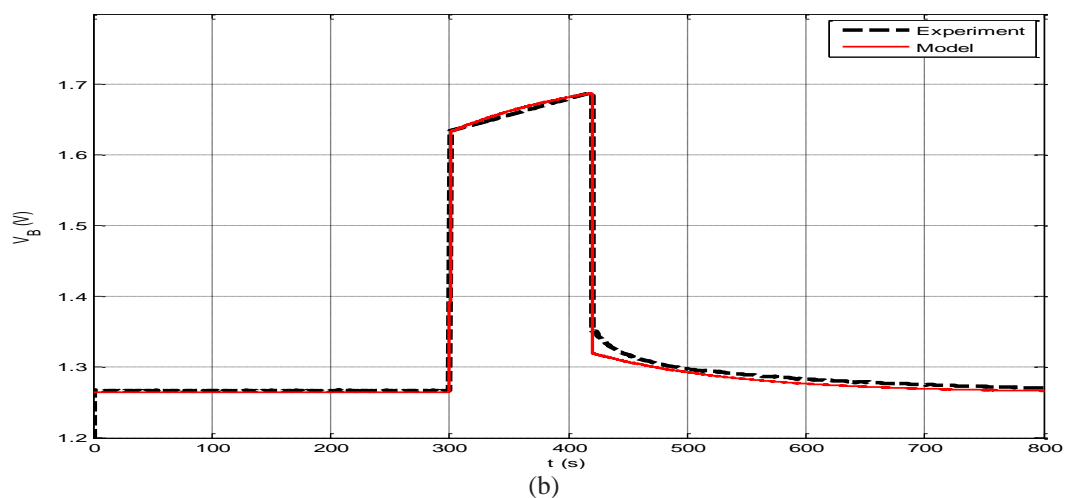
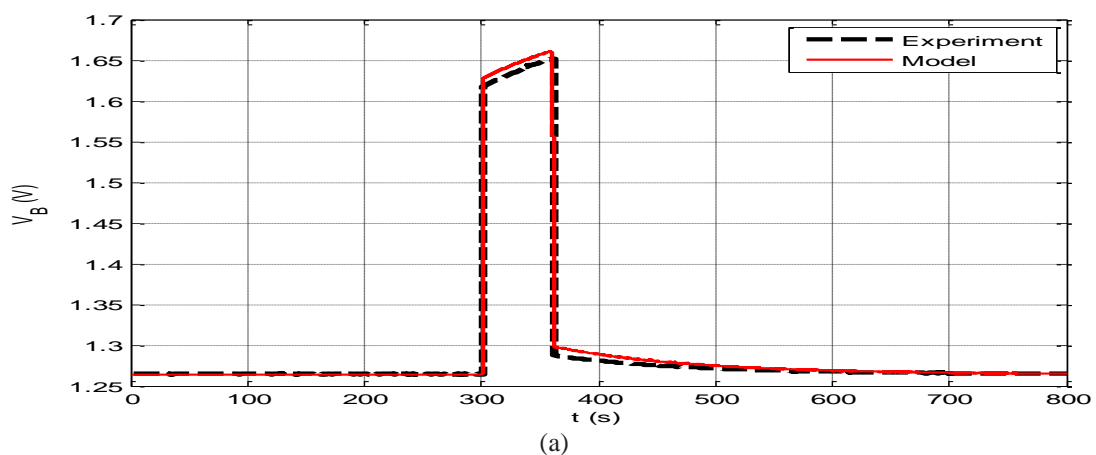


Figure 6. Voltage responses obtained from experiment and model with, (a) 1 minute pulse, (b) 2 minute pulse

The validation of the model is also performed for both 1 minute and 2-minute pulse width in order to test the accuracy of the model. The step current of 2 minute is applied to both NiMH battery and the model in order to validate its accuracy. The 2-minute pulse width is equivalent to 3.2% of the SoC of the battery. The percentage difference between the voltage response obtained from both model and NiMH battery is also less than 1.5% which is very accurate.

Furthermore, the NiMH battery model is also tested with the real wireless sensor node current profiles obtained from [26]. The current profile of the WSN node includes the sleep, wakeup and ON conditions of both the micro-controller unit (MCU) and the radio. Both the current profiles during transmission and reception are considered. The current profile during transmission is shown in Figure 7 (a). It can be seen that the highest current consumption of the wireless sensor node occurs during the radio transmission mode. The current profile in reception is also similar to the transmission mode. There are sudden changes in the current profile of the wireless sensor node when transitioning from one state to another. The NiMH battery model should be able to allow for these sudden changes of the current profile and reflect them accurately in the output battery voltage.

The current profiles are applied to the battery model and the corresponding output voltages of the battery are obtained. Furthermore, the same current profiles are also applied to the real NiMH battery. The comparison of the output battery voltages of transmission is shown in Figure 7 (b). The percentage difference between the output battery voltages of model and experiment is less than 2% which is highly accurate. This compares well with works on Li-ion batteries, where the accuracy reported ranges from 2%-5% [15], [22]. After testing and validating the model with the real current profile of the wireless sensor node, it can be concluded that the model can be adopted for any sophisticated current profiles of the wireless sensor networks (WSNs) and IoT devices.

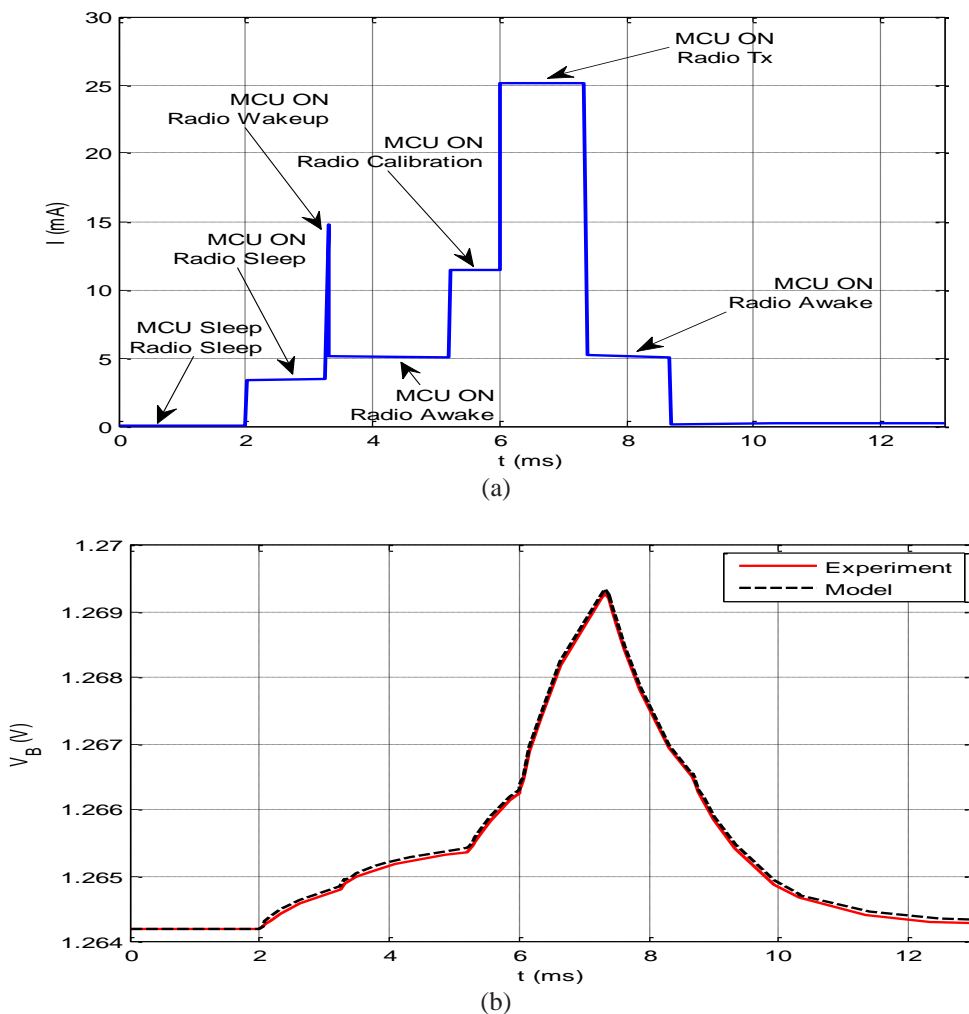


Figure 7. These figures are; (a) current profile of wireless sensor node in the transmission mode, (b) comparison of voltage response obtained from NiMH battery and model

4. CONCLUSION

IRC electrical battery model with simple parameterization for NiMH battery has been presented in this paper. The parameters are obtained through the pulse measurement technique which includes applying a series of charge cycles followed by the rest periods. Subsequently, the model is implemented in the physical and dynamic simulator. To determine the accuracy of the model, two step currents and the real current profiles of the wireless sensor node are applied to both real-life NiMH battery and the model. Compared to the previous works, which parameterized Li-ion batteries only, the resulting NiMH voltage responses obtained from the proposed model show that they are in very good agreement with difference of less than 2%. It can be concluded that the presented model is simple and can be applied to any sophisticated real-life current profiles of the WSN and IoT, with excellent accuracy. Moreover, the validation of proposed model with different types of battery chemistry is also recommended.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the support for this research from the Malaysian Ministry of Higher Education (MOHE) under the fundamental research grant scheme FRGS/2/2014/TK03/UTP/02/2 and Yayasan Universiti Teknologi PETRONAS under grant 015LC0-023.

REFERENCES

- [1] M. Souaihia, B. Belmadani, and R. Taleb, "A robust state of charge estimation for multiple models of lead acid battery using adaptive extended Kalman filter," *Bulletin of Electrical Engineering and Informatic*, vol. 9, no. 1, pp. 1-11, February 2020, doi: 10.11591/eei.v9i1.1486.
- [2] E. Martinez-Laserna, *et al.*, "Technical Viability of Battery Second Life: A Study From the Ageing Perspective," in *IEEE Transactions on Industry Applications*, vol. 54, no. 3, pp. 2703-2713, May-June 2018, doi: 10.1109/TIA.2018.2801262.
- [3] M. Rao, *et al.*, "Investigation of lithium content changes to understand the capacity fading mechanism in LiFePO₄/graphite battery," *Journal of Electroanalytical Chemistry*, vol. 853, no. 1, pp. 1-12, November 2019, doi: 10.1016/j.jelechem.2019.113544.
- [4] M. Al-Zareer, I. Dincer, and M. A. Rosen, "Comparative assessment of new liquid-to-vapor type battery cooling systems," *Energy*, vol. 188, no. 1, pp. 116010, December 2019, doi: 10.1016/j.energy.2019.116010.
- [5] P. He, *et al.*, "Building better zinc-ion batteries: A materials perspective," *EnergyChem*, vol. 1, no. 3, p. 100022, November 2019, doi: 10.1016/j.enchem.2019.100022.
- [6] J. Du, *et al.*, "Impact of high-power charging on the durability and safety of lithium batteries used in long-range battery electric vehicles," *Applied Energy*, vol. 255, p. 113793, December 2019, doi: 10.1016/j.apenergy.2019.113793.
- [7] A. Sarkar, P. Shrotriya, A. Chandra, and C. Hu, "Chemo-economic analysis of battery aging and capacity fade in lithium-ion battery," *Journal of Energy Storage*, vol. 25, p. 100911, October 2019, doi: 10.1016/j.est.2019.100911.
- [8] X. Han, *et al.*, "A review on the key issues of the lithium ion battery degradation among the whole life cycle," *eTransportation*, vol. 1, p. 100005, August 2019, doi: 10.1016/j.etrans.2019.100005.
- [9] M. Xu, B. Reichman, and X. Wang, "Modeling the effect of electrode thickness on the performance of lithium-ion batteries with experimental validation," *Energy*, vol. 186, p. 115864, November 2019, doi: 10.1016/j.energy.2019.115864.
- [10] X. Dang, L. Yan, H. Jiang, X. Wu, and H. Sun, "Open-circuit voltage-based state of charge estimation of lithium-ion power battery by combining controlled auto-regressive and moving average modeling with feedforward-feedback compensation method," *International Journal of Electrical Power & Energy Systems*, vol. 90, pp. 27-36, September 2017, doi: 10.1016/j.ijepes.2017.01.013.
- [11] R. Ahmed, *et al.*, "Model-based parameter identification of healthy and aged Li-ion batteries for electric vehicle applications," *SAE International Journal of Alternative Powertrains*, vol. 4, no. 2, pp. 233-247, July 2015.
- [12] J. H. Meng, G. Z. Luo, M. Ricco, M. Swierczynski, D. I. Stroe, and R. Teodorescu, "Overview of lithium-ion battery modeling methods for state-of-charge estimation in electrical vehicles," *Applied Sciences*, vol. 8, no. 5, p. 659, April 2018, doi: 10.3390/app8050659.
- [13] A. Nikolian, *et al.*, "Lithium Ion Batteries-Development of Advanced Electrical Equivalent Circuit Models for Nickel Manganese Cobalt Lithium-Ion," *Energies*, vol. 9, no. 5, p. 360, May 2016, doi: 10.3390/en9050360.
- [14] Y. Cao, R. C. Kroeze, and P. T. Krein, "Multi-timescale Parametric Electrical Battery Model for Use in Dynamic Electric Vehicle Simulations," in *IEEE Transactions on Transportation Electrification*, vol. 2, no. 4, pp. 432-442, December 2016, doi: 10.1109/TTE.2016.2569069.
- [15] M. Einhorn, F. V. Conte, C. Kral, and J. Fleig, "Comparison, Selection, and Parameterization of Electrical Battery Models for Automotive Applications," in *IEEE Transactions on Power Electronics*, vol. 28, no. 3, pp. 1429-1437, March 2013, doi: 10.1109/TPEL.2012.2210564.
- [16] V. Knap, D. Stroe, R. Teodorescu, M. Swierczynski, and T. Stanciu, "Comparison of parametrization techniques for an electrical circuit model of Lithium-Sulfur batteries," *2015 IEEE 13th International Conference on Industrial Informatics (INDIN)*, 2015, pp. 1278-1283, doi: 10.1109/INDIN.2015.7281919.

- [17] S. Cruz-Manzo, P. Greenwood, and R. Chen, "An Impedance Model for EIS Analysis of Nickel Metal Hydride Batteries," *Journal of the Electrochemical Society*, vol. 164, no. 57, pp. A1446-A1453, May 2017.
- [18] Y. Zhu, W. H. Zhu, Z. Davis, and B. J. Tatarchuk, "Simulation of Ni-MH Batteries via an Equivalent Circuit Model for Energy Storage Applications," *Advances in Physical Chemistry*, vol. 2016, no. 1, pp. 1-11, January 2016, doi: <http://dx.doi.org/10.1155/2016/4584781>.
- [19] A. Fotouhi, D. J. Auger, K. Propp, and S. Longo, "Accuracy Versus Simplicity in Online Battery Model Identification," in *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 48, no. 2, pp. 195-206, February 2018, doi: 10.1109/TSMC.2016.2599281.
- [20] B. Meng, Y. Wang, J. Mao, J. Liu, G. Xu and J. Dai, "Using SoC Online Correction Method Based on Parameter Identification to Optimize the Operation Range of NI-MH Battery for Electric Boat," *Energies*, vol. 11, no. 3, p. 586, March 2018, doi: 10.3390/en11030586.
- [21] L. M. Rodrigues, C. Montez, R. Moraes, P. Portugal, F. Vasques, "A temperature-dependent battery model for wireless sensor networks," *Sensors*, vol. 17, no. 2, p. 422, February 2017, doi: 10.3390/s17020422.
- [22] Daniel-Ioan Stroe, M. Swierczynski, Ana-Irina Stroe and S. K. Kaer, "Generalized Characterization Methodology for Performance Modelling of Lithium-Ion Batteries," *Batteries*, vol. 2, no. 4, pp. 37-58, December 2016, doi: 10.3390/batteries2040037.
- [23] A. Hentunen, T. Lehmuspelto, and J. Suomela, "Time-Domain Parameter Extraction Method for Thévenin-Equivalent Circuit Battery Models," in *IEEE Transactions on Energy Conversion*, vol. 29, no. 3, pp. 558-566, September 2014, doi: 10.1109/TEC.2014.2318205.
- [24] Mathworks, "Model and simulate multidomain physical systems", 2019. [Online]. Available: <http://www.mathworks.com/products/simscape/>.
- [25] B. Homan, M. V. T. Kortenaar, J. L. Hurink, and G. J. Smit, "A realistic model for battery state of charge prediction in energy management simulation tools," *Energy*, vol. 171, pp. 205-217, March 2019, doi: 10.1016/j.energy.2018.12.134.
- [26] A. Moschitta and I. Neri, "Power consumption assessment in wireless sensor networks," *ICT-Energy-Concepts Towards Zero-Power Information and Communication Technology*, Croatia, 2014, pp. 203-224, doi: 10.5772/57201.

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