Prediction of Battery Discharge States Based on the Recurrent Neural Network

Yi-Zeng Hsieh[1,2,3], Shih-Wei Tan[1], Siang-Long Gu[1], Yu-Lin Jeng[4]

[1] Department of Electrical Engineering, National Taiwan Ocean University, Taiwan
[2] Institute of Food Safety and Risk Management, National Taiwan Ocean University, Taiwan
[3] Center of Excellence for Ocean Engineering, National Taiwan Ocean University, Taiwan
[4] Department of Information Management, Southern Taiwan University of Science and Technology, Taiwan
yzhsieh@mail.ntou.edu.tw, tanshwei@mail.ntou.edu.tw, long840321@gmail.com, jackjeng@stust.edu.tw

Abstract

The recurrent neural network can solve the time sequential problems and the battery discharge state is predicted based on the time sequential neural network. The main purpose is to predict the battery discharge condition with recurrent neural network, and then improve the traditional mathematical prediction method. Nowadays, prediction of the battery life cycle is more important. Compared with our models, there are the five fixing currents as testing experiments. The error rate has less than 2% and the prediction battery life is close to real data.

Keywords: Deep learning, Battery life prediction, LSTM, RNN, GRU

1 Introduction

Today's society mobile devices have become mainstream, and each mobile device requires a battery as its power supply equipment, so the condition of the battery will be very important. The battery discharge status directly affects the time a mobile device, so our paper will use recursive neural network (RNN [1], LSTM [2], GRU [3]) predicting battery discharge conditions.

In this study use the same type of battery, although the battery model is the same, but the characteristics of battery are not the same, so we use 30 batteries for voltage measurement. There is the method of constant current method for voltage data collection, such as 0.2c, 0.1c and 0.04c respectively. It had sampled every 5 seconds to the discharge end and there is a total of 810,000 sample points.

Traditional battery state predictions have been good results from [4]. The traditional mathematical model predicts the battery discharge state error as 2.87%, and the deep neural networks handle all types of problems can be effectively solved, so even significantly improved the prediction problem has been better. In this study, the RMSE (root mean square error) of our proposed Deep-LSTM [5] model can be less than 0.0003, and the Deep- RNN model RMSE can be less than 0.003 and the Deep- GRU model RMSE can be less than 0.002.

2 Related Works

2.1 Battery Equivalent Model

The establishment of the battery model is mainly for the calculation and analysis of circuit simulation. A good model should have the ability to simulate the actual situation. This paper proposed a new battery model to accurately estimate the battery capacity.

Generally, when we analyze the electrical characteristics of battery, the battery is usually regarded as an ideal voltage source. That is, the output voltage remains the same. However, the internal chemical properties of the battery are susceptible to many factors, making the battery not a simple voltage source.

When the battery is discharged, the terminal voltage of the battery does not maintain a constant value. For example, the constant current discharge is one case. The terminal voltage of the battery will continue to decrease. When the tolerance of battery terminal voltage drift is low and you use a simple battery model for circuit simulation, the real problem cannot be seen. However, if you use a model that can fully and realistically present battery characteristics, you can predict real problems. For example, a steady state circuit can be added across the battery terminal voltage.

So far, several battery models have been used such as ideal model, linear model, Thevenin equivalent model, and the equivalent capacitance model.

*Corresponding Author: Yu-Lin Jeng; E-mail: jackjeng@stust.edu.tw
DOI: 10.3966/160792642020012101011

2.1.1 Ideal Model [13]

The ideal model is shown in Figure 1. It is thought of the battery as a simple voltage source and output voltage is constant. It is completely ignoring the internal factors of the battery and does not reflect the characteristics of the battery. V_{bc} is the open circuit voltage of the battery, and E_{oc} is the terminal voltage of the battery. The equation can be derived from the equation as equation (1). Although this model is the simplest and roughest battery model, it is also the model that most people use in circuit simulation analysis.

$$V_{bc} = E_{oc} \tag{1}$$

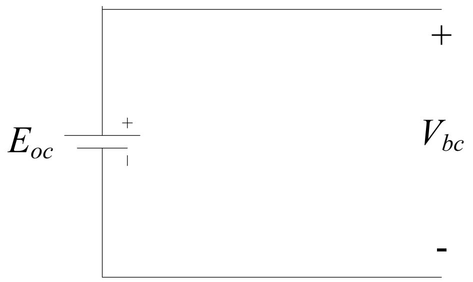

Figure 1. Ideal model

2.1.2 Linear Model [13]

The linear model consider the internal resistance of the battery, the open circuit voltage (E_{oc}) and the internal battery resistance (R_{in}) of the battery are all internal factors as shown in Figure 2. There is an internal resistance inside the battery. Consider the model of the internal resistance and the estimation of the true capacitance, and the better rise of the voltage rise and fall as the output current changing as shown in equation (2).

$$V_{bc} = E_{oc} + V_{Rin} \tag{2}$$

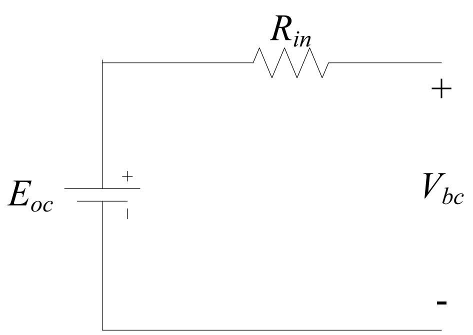

Figure 2. Linear model

2.1.3 Thevenin Equivalent Model [13]

The Thevenin equivalent model is shown in Figure 3. It considers the dynamic characteristics of the battery when it is charged. This battery model includes the unloaded voltage E_{oc} (ideal voltage source), the internal resistance R_{in}, the resistance R_{ov}(overvoltage resistance), and capacitor C_{ovv} (Overvoltage capacitance) are parallelly grouped. The state is to express the phenomenon of equivalent voltage overvoltage of the battery, so the model will be more realistic in the process of simulating the battery charging. This model improves the shortcomings of the linear model, and therefore it is more accurate than the linear model. The Thevenin equivalent model is superior to the above two battery models, but the phenomenon of self-discharge of the battery and the influence of temperature on the battery characteristics are still not considered.

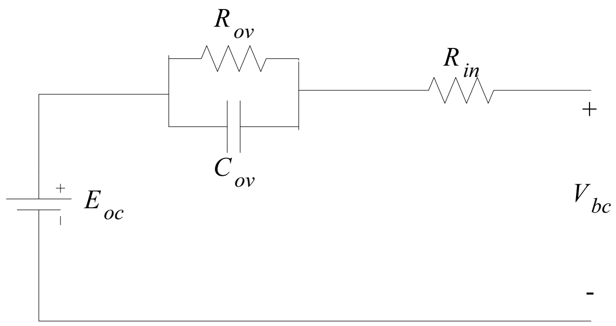

Figure 3. The thevenin equivalent model

2.1.4 Equivalent Capacitance Model [13]

This model corrects the absence of the Thevenin equivalent model, as shown in Figure 4. The equivalent capacitance model can exhibit self-discharge. R and C parallel circuit replaces the ideal voltage source in the Thevenin model. V_{bc} is the open-circuit voltage of the battery that is the terminal voltage when the battery is not connected to the load. R_{sd} is a self-discharge resistance, and its value is related to the battery terminal voltage, initial battery capacity, temperature, and it is very sensitive to temperature changes. When the battery is in an open state, the internal battery will still perform a slow discharge behavior inside due to the self-forming loop system. When the temperature rises, the chemical reaction will become intense, and the self-discharge condition will be more serious. The state of discharge is represented by the magnitude of the self-discharge resistance. Under normal conditions, the self-discharge resistance value is inversely proportional to the temperature, inversely proportional to the open circuit voltage of the battery, and inversely proportional to the remaining capacity of the battery. R_{in} is the internal resistance of the battery, and the concept is the same as the internal resistance in the Thevenin equivalent circuit. C_{bc} is battery capacitance, representative of the battery energy storage element. R_{ov} and C_{ov} are connected in parallel to express the over

-voltage effect of the battery, which can show the phenomenon that the terminal voltage rises and falls when the battery is charged and discharged, and V_{ov} is the voltage value of the over-voltage phenomenon.

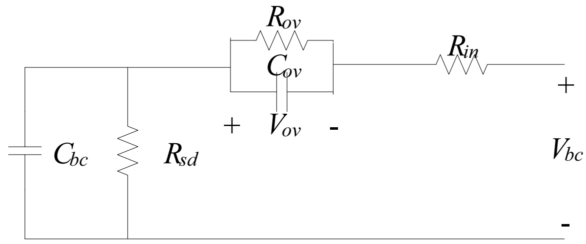

Figure 4. Equivalent capacitance model

2.2 Electricity Estimation Method

There are many ways to estimate the battery power. According to the accuracy requirements, there will be different measurement methods, and even more than two types of power estimation methods can be used to achieve higher accuracy and immediate measurement. The basic power estimation method is described as follows:

2.2.1 Discharge Test Method [14]

Completely discharge the fully charged battery and continuously detect the discharged electricity during the discharge process. Using this process, the amount of electricity contained in the battery can be calculated. This method is more suitable for calculating the initial capacitance, or on a device that is often used for a full charge and discharge cycle.

2.2.2 Coulomb Method

Using the principle that the outflow is equal to the incoming charge, continuously detecting the battery current to record the remaining battery power, this method requires an accurate current detector. When the battery is charging, it can be accumulated by the initial battery power and to get the battery power at any time of charging. When the battery is discharged, the ampere-hour method can also be used to reduce the initial charge of the battery. The battery level is expressed as equation (3):

$$C(t_n) = C(t_0) \pm \int i(t)\, d(\mathrm{t}) \quad \mathbf{(3)}$$

There is t as the current discharge time, t_0 as the initial time, and t_n as the current time, C(t_0) is the initial capacitance, C(t_n) is the current charge, and i(t) is the discharge current. Since the Coulomb method cannot detect the self-discharge of the battery and the power consumption caused by aging or other factors, if you want to reduce the cumulative error and improve the accuracy of long-term operation, it must be combined with other methods such as open circuit voltage method.

2.2.3 Open Circuit Voltage Method [15]

When the battery is charged and discharged and the load is changed, the terminal voltage that changes over a period of time will be gradually stable. As long as the battery is unloaded and stable, the measured open circuit voltage can be used to check the "open circuit voltage corresponding electricity" which is the curve data by finding the remaining maximum power. Since the battery terminal voltage drops and rises with time after the battery charging and discharging behavior is stopped, the tested battery needs to wait for a long static stabilization period before detecting. The lithium ion battery takes about 30 minutes. Therefore, it takes a long time to measure the curve data of the open circuit voltage corresponding to the power. The battery is continuously tested, and the battery is continuously recorded, waiting for the voltage to stabilize, or discharging, waiting for the voltage stability program to record the battery power. The drawback is that the battery cannot be measured during charging and discharging.

2.2.4 Linear Model [16]

The linear parameter of the battery voltage is calculated to the power with the least square method. To improve the accuracy, more data is needed to express the various operating conditions of the system, such as considering different discharge rates and temperatures and other factors. It must use more input and calculate a more complex linear model.

2.2.5 Impedance Spectrum [17]

Different signals are applied to the battery to analyze the response of the battery, and the internal resistance of the battery is measured to determine the current state of the battery. When charging, the internal resistance of the battery will increase as the battery is fully charged. When discharging, the internal resistance will decrease as the stored electricity in the battery is completely discharged. Therefore, when detecting the power, it is only necessary to judge the internal resistance of the battery. This method is applicable to a variety of batteries, but requires additional power to generate drive signals and expensive spectrum analysis, so it is not suitable for portable devices.

2.2.6 Recurrent Neural Network

Using the concept of a recurrent neural network [6-9], several input and output parameters are developed. The fuel gauge generates parameters through training and learning before using, and these parameters allow the fuel gauge to understand the characteristics of the battery. This method can be applied to a variety of batteries, the relative input and output parameters of what to use and how to train and learn is a university question, and the recurrent neural network algorithm is usually very complicated.

[20] aims at evaluating the effects of lithium-ion nickel manganese cobalt/carbon (NMC/C) battery state of health (SOH). [21] developed an effective health indicator to indicate lithium-ion battery state of health and moving-window-based method to predict battery remaining useful life. [22] proposed a semi-empirical lithium-ion battery degradation model that assesses battery cell life loss from operating profiles.

3 The Proposed Method

With the rapid development of deep learning, timing problems (translation, climate prediction, speech recognition, sensor network [18-19] and predict the charge and discharge) are to be an effective solution to these problems in recent years, the recursive neural network is as RNNs, LSTM, GRU. The research of many scholars has improved these related technologies and the accuracy is getting better. The sequential neural network is discussed as below.

3.1 RNN

The hidden layer of RNNs [10] is connected to the conventional neural network in the hidden layer node is no longer independent, so each layer RNNs parameters are shared between the output and input.

RNNs link the hidden layers of the neural network, so that the nodes in the hidden layer are no longer independent making the output and input related. Therefore, each layer parameter in the RNNs is shared.

From Figure 5, the equation (4) indicates that the hidden vector h_t of each layer completes the memory chain by the product of the hidden vector of the previous state (t-1) and the input [11]. The σ() is activation function.

$$h_t = \sigma(U_h \times X_t + W_h + h_{t-1} + b_h) \quad \textbf{(4)}$$

h_t is the hidden layer activations in time t.
X_t is the input vector.
U_h is the weight of input vector.
W_h is the weight of hidden layer activations.
b_h is the bias.

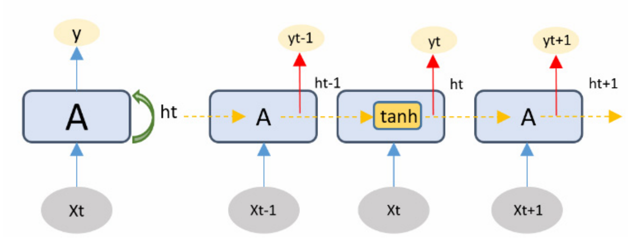

Figure 5. The architecture of RNN

3.2 Long Short Term Memory

The LSTM is recurrent network and it has “LSTM cells”. There are an internal recurrence (a self-loop) in the cells. In addition, it is the outer recurrence of the RNN. There is the same inputs and outputs for each cell. There are more parameters to control the flow of information [24].

There are three gates of long short term memory as shown in Figure 6.

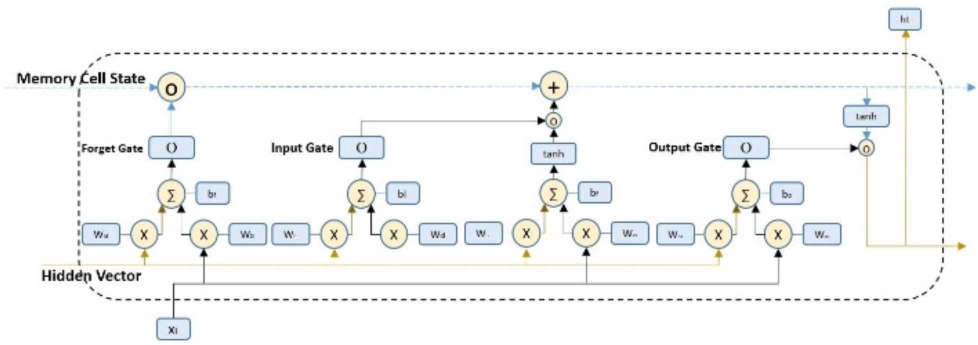

Figure 6. The architecture of LSTM

Forgotten gate. There are an internal recurrent (a self-loop) in the LSTM cells and the forgotten gate control it. It is useful for the forgotten gate to forget the old state [24]. The forgotten gate is input by the hidden vector of the previous state (t-1) and the current state (X_t) as equation (5).

$$f_t = \sigma(W_{xf} \times X_t + W_{hf} \times h_{t-1} + b_f) \quad \textbf{(5)}$$

f_t is the current forgotten gate.
X_t is the current input vector.
W_{xf} is the current weight of input vector.
W_{hf} is the weight of the hidden vector.
h_{t-1} is the weight of hidden vector in time t-1.
b_f is the bias.

Input gate. To Update s_t via input gate, the input gate is also the same as the forgotten gate. It is related with the hidden vector and the current state (X_t) input of the previous state (t-1) as equation (6). The function of forgotten gate is to forget important information, and then update the storage unit by the input gates as equation (7). The activation function is *tanh*(). The equation (7) is internal state as following.

$$i_t = \sigma(W_{xi} \times X_t + W_{hi} \times h_{t-1} + b_i) \quad \textbf{(6)}$$

i_t is the external input gate.

$$s_t = i_t * \sigma(W_{xs} \times X_t + W_{hs} \times h_{t-1} + b_s) + f_t * s_{t-1} \quad \textbf{(7)}$$

s_t is the internal state.

Output gate O_t. The purpose of the output gate can be calculated h_t for the next state (t+1) as equation (8) and (9).

$$O_t = \sigma(W_{XO} \times X_t + W_{ho} \times h_{t-1} + b_o) \quad \textbf{(8)}$$

$$h_t = O_t \times tanh(s_t) \quad \textbf{(9)}$$

O_t is the output gate.
h_t is the output.

3.3 Gated Recurrent Unit [12]

Update gate. To update gate (Z_t) [9] is a state information for the degree of influence on the determination of the current state. It is like the forget gate and input gate of LSTM, but the update gate of GRU is simpler to make convergence efficiently as shown in Figure 7.

$$Z_t = \sigma(W_z \times X_t + W_z \times h_{t-1} + b_z) \quad \textbf{(10)}$$

Z_t is the update gate.

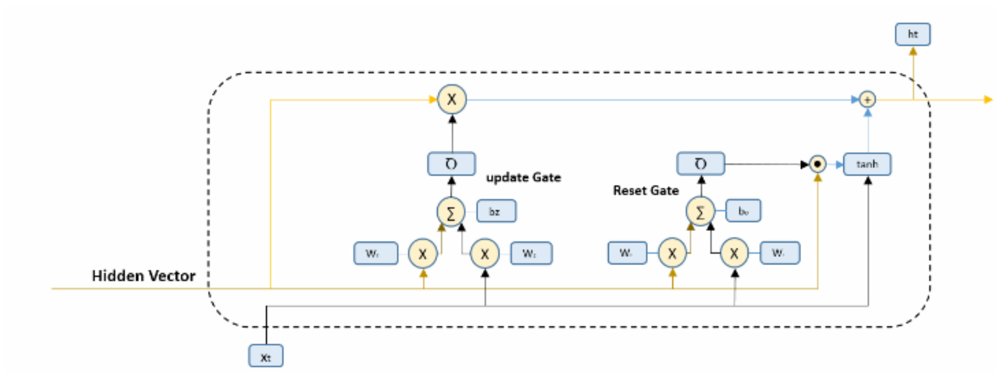

Figure 7. The architecture of GRU

Reset gate. The reset gates control which parts of the state get used to compute the next target state, introducing an additional nonlinear effect in the relationship between past state and future state [24]. Reset gate (R_t) for ignoring previous state is compared to the extent of the update information as equation (11).

$$R_t = \sigma(W_r \times X_t + W_r \times h_t - 1 + b_r) \quad \textbf{(11)}$$

R_t is the reset gate.

Candidate activation. When R_t approaches zero, reset gate is off. Then, the gate will forget information of the last state [9].

$$\widetilde{h_t} = tanh(W_h \times X_t + R_t \odot h_t - 1) \quad \textbf{(12)}$$

$$h_t = (1 - Z_t) \times h_t - 1 + Z_t \times \widetilde{h_t} \quad \textbf{(13)}$$

3.4 Our Experiment of Dataset

Our collected dataset is total of 30 batteries at a constant current, and the sampling rate is 5 seconds, so we have collected 810000 data samples. To avoid overfitting, we separate the dataset to 10 as training set, 10 as validation set and 10 as testing set. The 10-fold cross validation is adopted. Recursive neural network is very sensitive to the value of information, and it can speed up the convergence between normalized to 0 to 1. The tools python-sklearn is efficient with our information and the data is normalized to between 0 and 1.

3.5 Network Architecture

In this study we can know that the recursive network has better results in the deep model, so we try to establish a deep network architecture to more fit battery life circle. The recurrent neural network architecture is as shown in Figure (4). The recurrent model of our proposed network architecture is the same with architecture of the LSTM, RNN and GRU as shown in Figure 8.

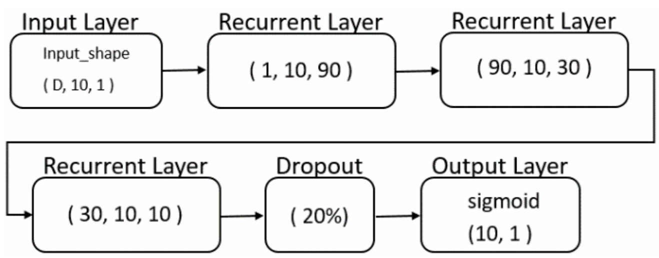

Figure 8. Our neural network architecture

The Multi-Layer Perceptron (MLP) is adopted to compare with our recurrent model. There is input-output relationship of the MLP network and it can define a mapping from an m-dimensional Euclidean input space to an M-dimensional Euclidean output space. It can also define infinitely continuously differentiable when the activation is likewise [23]. The architecture of MLP is as shown in Figure 9, and the output layer of MLP is one output for function approximation. The model of MLP network including a nonlinear activation function, and it can be differentiable. There are also one or more layers to connect the both input and out nodes [23]. The first hidden layer is 60 neurons, and the second hidden layer is 30 neurons, and the third hidden layer is 10 neurons. The activation function of each layer is sigmoid. The loss function adopts root mean square error (RMSE), and the optimized algorithm is Adam.

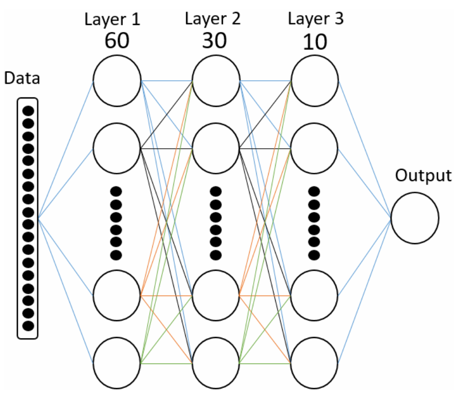

Figure 9. Our MLP architecture

5 Experiment Result

Our method compared with predictions of a mathematical model closer to real data. The error can be well controlled, and it can be seen that the deep learning algorithm have very significant effects in data analysis.

In the Figures 10-13, red is the prediction result. The blue is the original data. There is the y- axis as the voltage, the x- axis as the number of data, and the Figure 10 is the voltage prediction of our proposed LSTM. The testing of RMSE error is about 0.01. Figure 11 is the voltage prediction of our proposed GRU. The testing of RMSE is about 0.009. Figure 12 is the voltage prediction of our proposed RNN, and the testing of RMSE is about 0.02. Figure 13 is the voltage prediction of our proposed MLP. The voltage testing of RMSE is approximately 0.013. Table 3 shows the average RMSE of the four algorithms and we can find the average RMSE of GRU is better than the other algorithms.

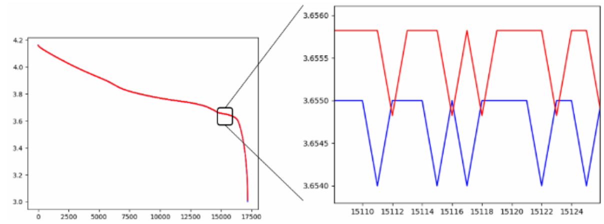

Figure 10. Deep LSTM

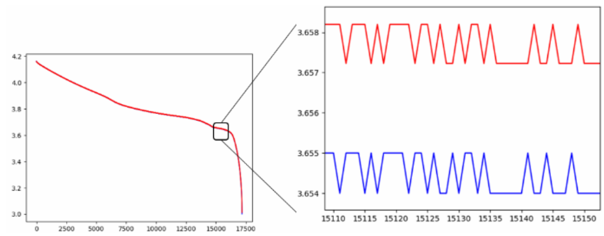

Figure 11. Deep GRU

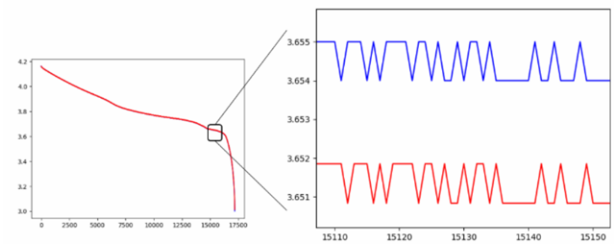

Figure 12. Deep RNN

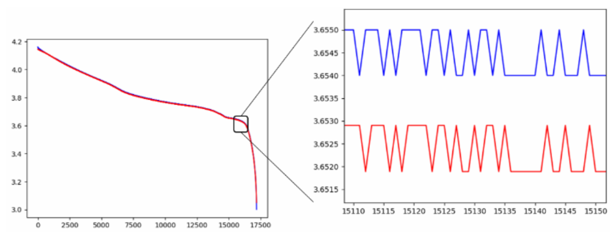

Figure 13. MLP

Table 1. The RMSE of training data

	Training data number	LSTM Training RMSE	GRU Training RMSE	RNN Training RMSE	MLP Training RMSE
0.1c-1	7046	0.006418	0.002214	0.0096685	0.05896
0.1c-2	6681	0.000533	0.002135	0.002106	0.003060
0.1c-3	6936	0.001008	0.003187	0.003354	0.002188
0.1c-4	7606	0.001732	0.003445	0.004102	0.003120
0.2c	3538	0.000546	0.00732	0.001690	0.002299
0.04c-1	17849	0.00059	0.011352	0.001069	0.001158
0.04c-2	17152	0.000223	0.002058	0.001792	0.003066
0.5c	1442	0.044898	0.006253	0.074581	0.010544
1.5c	473	0.042234	0.006834	0.060140	0.023545
1c	727	0.010549	0.003599	0.086205	0.015128

Table 2. The RMSE of testing data

	Testing data number	LSTM Testing RMSE	GRU Testing RMSE	RNN Testing RMSE	MLP Testing RMSE
0.1c-1	3800	0.007053	0.002384	0.010138	0.06228
0.1c-2	2900	0.000641	0.002633	0.002259	0.003569
0.1c-3	3400	0.001193	0.003532	0.003916	0.002761
0.1c-4	2460	0.001961	0.003779	0.004274	0.003598
0.2c	7700	0.000676	0.00945	0.001835	0.002783
0.04c-1	1500	0.00131	0.012847	0.001394	0.001688
0.04c-2	1100	0.000676	0.002428	0.002975	0.003169
0.5c	3020	0.071206	0.011955	0.074168	0.012782
1.5c	3680	0.042356	0.031265	0.06041	0.024701
1c	3340	0.022374	0.018815	0.083041	0.017021

Table 3. The average RMSE

	Data number	LSTM RMSE	GRU RMSE	RNN RMSE	MLP RMSE
Training	69450	0.010873	0.0048397	0.0244705	0.0123068
Testing	32900	0.0149446	0.0099088	0.024441	0.0134352

4 Conclusion

From the Table 1 and Table 2, we can see that the results of our proposed recurrent model (LSTM, GRU, RNN) prediction rate is better than the results of the MLP. To predict the discharge state of battery, there is a good performance. In the testing data, experiments have shown that the effect of increasing the number of sampling points back to the network. Finally, the deep learning method is efficient to the battery discharge life cycle, and according to the prediction method development can solve many problems in the real world, and the battery devices have become an essential item for everyone. The evaluation of battery power is an important issue. In the future, we will further analyze the battery aging research with data, and believe that deep learning can bring us a more convenient life.

Acknowledgments

This paper was partly supported by the University System of Taipei Joint Research Program, USTP-NTUT-NTOU-106-02, USTP-NTOU-TMU-108-01 and USTP-NTOU-TMU-108-0, and Ministry of Science and Technology, Taiwan, R.O.C, under grants MOST 107-2221-E-019-039-MY2, MOST 108-2634-F-019-001-, MOST 108-2634-F-008-001-.

References

[1] A. Graves, M. Liwicki, S. Fernández, R. Bertolami, H. Bunke, J. Schmidhuber, A Novel Connectionist System for Unconstrained Handwriting Recognition, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 31, No. 5, pp. 855-868, May, 2009.

[2] S. Hochreiter, J. Schmidhuber, Long Short-Term Memory, *Neural Computation*, Vol. 9, No. 8, pp. 1735-1780, November, 1997.

[3] K. Cho, B. Van Merrienboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, Y. Bengio, Learning Phrase Representations Using RNN Encoder-decoder for Statistical Machine Translation, *Conference on Empirical Methods in Natural Language Processing (EMNLP 2014)*, Doha, Qatar, 2014, pp. 1724-1734.

[4] Y. Wang, C. Liu, R. Pan, Z. Chen, Modeling and State-of-charge Prediction of Lithiumion Battery and Ultracapacitor Hybrids with a co-estimator, *Energy*, Vol. 121, pp. 739-750, February, 2017.

[5] R. G. Hefron, B. J. Borghetti, J. C. Christensen, C. M. S. Kabban, Deep Long Short-term Memory Structures Model Temporal Dependencies Improving Cognitive Workload Estimation, *Pattern Recognition Letters*, Vol. 94, pp. 96-104, July, 2017.

[6] Z. Wu, S. King, Investigating Gated Recurrent Networks for Speech Synthesis, *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Shanghai, China, 2016, pp. 5140-5144.

[7] K. Cho, B. van Merrienboer, D. Bahdanau, Y. Bengio, On The Properties of Neural Machine Translation: Encoder-Decoder Approaches, *Proceedings of SSST-8, Eighth Workshop on Syntax, Semantics and Structure in Statistical Translation*, Doha, Qatar, 2014, pp. 103-111.

[8] S. Lin, G. C. Runger, GCRNN: Group-Constrained Convolutional Recurrent Neural Network, *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 29, No. 10, pp. 4709-4718, October, 2018.

[9] J. Chung, C. Gulcehre, K. H. Cho, Y. Bengio, Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling, *NIPS 2014 Workshop on Deep Learning*, Montreal, Canada, 2014, pp. 1-9.

[10] S. Squartini, A. Hussain, F. Piazza, Preprocessing Based Solution for the Vanishing Gradient Problem in Recurrent Neural Networks, *2003 International Symposium on Circuits and Systems (ISCAS'03)*, Bangkok, Thailand, 2003, pp. 713-716.

[11] Z. C. Lipton, J. Berkowitz, C. Elkan, *A Critical Review of Recurrent Neural Networks for Sequence Learning*, https://arxiv.org/abs/1506.00019.

[12] R. Dey, F. M. Salem, Gate-Variants of Gated Recurrent Unit (GRU) Neural Networks, *2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS)*, Boston, MA, USA, 2017, pp. 1597-1600.

[13] H. L. Chan, D. Sutanto, A New Battery Model for Use with Battery Energy Storage Systems and Electric Vehicles Power Systems, *2000 IEEE Power Engineering Society Winter Meeting*, Singapore, 2000, pp. 470-475.

[14] S. J. Lee, J. H. Kim, J. M. Lee, B. H. Cho, The State and Parameter Estimation of an Li-Ion Battery Using a New OCV-SOC Concept, *2007 IEEE Power Electronics Specialists Conference*, Orlando, FL, USA, 2007, pp. 2799-2803

[15] S. Piller, M. Perrin, A. Jossen, Methods for State-of-charge Determination and Their Applications, *Journal of Power Sources*, Vol. 96, No. 1, pp. 113-120, June, 2001.

[16] C. Ehret, S. Piller, W. Shroer, A. Jossen, State-of-charge Determination for Lead-acid Batteries in PV-applications, *16th European Photovoltaic Solar Energy Conference*, Glasgow, Scotland, 2000, Vol. 3, pp. 2486-2489.

[17] F. Huet, A Review of Impedance Measurements for Determination of the State-of-charge or State-of-health of Secondary Batteries, *Journal of Power Sources*, Vol. 70, No. 1, pp. 59-69, January, 1998.

[18] H. W. Wang, P. J. Chen, The Performance Optimization of Energy-Efficient Scheduling Algorithm for Cluster-Based Wireless Sensor Networks, *Journal of Internet Technology*, Vol. 18, No. 2 , pp. 361-370, March, 2017.

[19] K. T. Kim, H. Y. Youn, A Dynamic Level-Based Routing Protocol for Energy Efficiency in Wireless Sensor Networks, *Journal of Internet Technology*, Vol. 18, No. 1, pp. 11-21, January, 2017.

[20] E. Martinez-Laserna, E. Sarasketa-Zabala, I. V. Sarria, D.-I. Stroe, M. Swierczynski, A. Warnecke, J.-M. Timmermans, S. Goutam, N. Omar, P. Rodriguez, Technical Viability of Battery Second Life: A Study from the Ageing Perspective, *IEEE Transactions on Industry Applications*, Vol. 54, No. 3, pp. 2703-2713, May-June, 2018.

[21] R. Xiong, Y. Zhang, J. Wang, H. He, S. Peng, M. Pecht, Lithium-ion Battery Health Prognosis Based on a Real Battery Management System Used in Electric Vehicles, *IEEE Transactions on Vehicular Technology*, Vol. 68, No. 5, pp. 4110-4121, May, 2019.

[22] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, D. Kirschen, Modeling of Lithiumion Battery Degradation for Cell Life Assessment, *IEEE Transactions on Smart Grid*, Vol. 9, No. 2, pp. 1131-1140, March, 2018.

[23] S. Haykin, *Neural Networks and Learning Machines*, Pearson, 2008.

[24] I. Goodfellow, Y. Bengio, A. Courville, *Deep Learning*, The MIT Press, 2017.

Biographies

Yi-Zeng Hsieh received the B.S., M.S. and Ph.D. degree in computer science and information engineering from National Central University, Tao-yuan, Taiwan in 2004, 2006 and 2012, respectively. He is currently an associate professor of electrical engineering, National Taiwan Ocean University. His current research interests include deep learning, pattern recognition, image processing and machine learning.

Shih-Wei Tan is currently an associate professor of electrical engineering, National Taiwan Ocean University. His current research interests include Solar photovoltaic, Organic optoelectronic technology, Nano semiconductor communication components.

Siang-Long Gu is currently a master student of electrical engineering, National Taiwan Ocean University. His current research interests include machine learning.

Yu-Lin Jeng is currently an associate professor at the Department of Information Management, Southern Taiwan University of Science and Technology. He is actively involved in industrial projects and his research interests include e-learning system, cloud software applications and mobile software development.