Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

Haejoong Lee

Sogang University, EE

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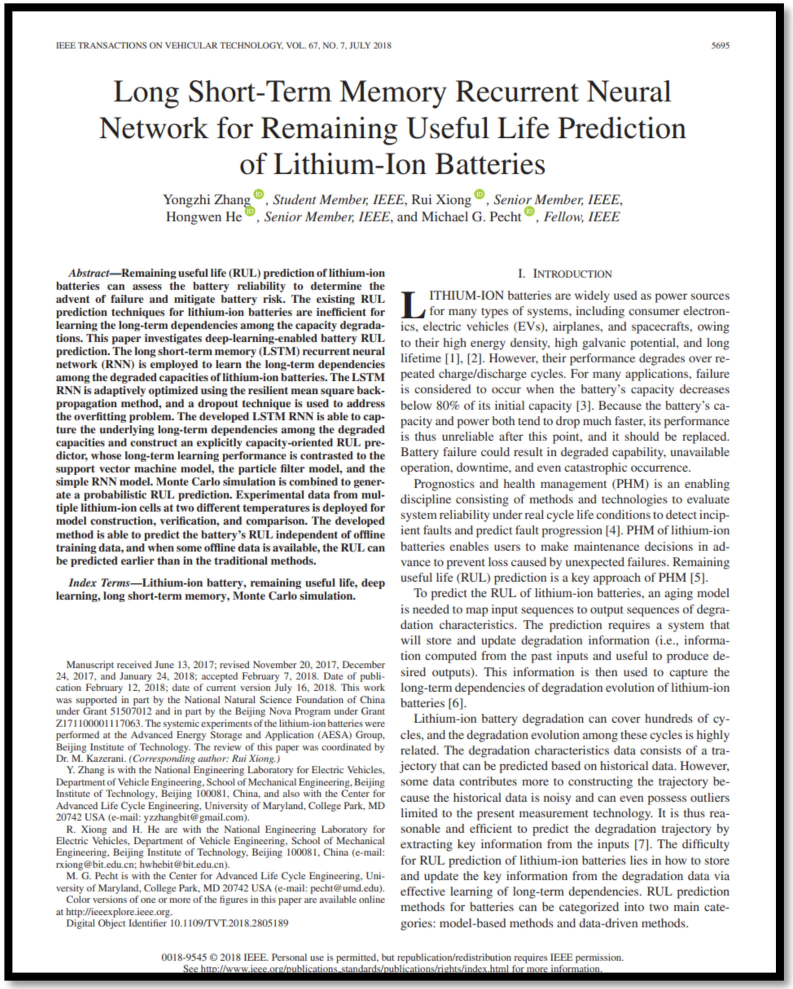

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

Yongzhi Zhang, *Student Member, IEEE*, Rui Xiong, *Senior Member, IEEE*, Hongwen He, *Senior Member, IEEE*, and Michael G. Pecht, *Fellow, IEEE*

***Abstract*—Remaining useful life (RUL) prediction of lithium-ion batteries can assess the battery reliability to determine the advent of failure and mitigate battery risk. The existing RUL prediction techniques for lithium-ion batteries are inefficient for learning the long-term dependencies among the capacity degradations. This paper investigates deep-learning-enabled battery RUL prediction. The long short-term memory (LSTM) recurrent neural network (RNN) is employed to learn the long-term dependencies among the degraded capacities of lithium-ion batteries. The LSTM RNN is adaptively optimized using the resilient mean square back-propagation method, and a dropout technique is used to address the overfitting problem. The developed LSTM RNN is able to capture the underlying long-term dependencies among the degraded capacities and construct an explicitly capacity-oriented RUL predictor, whose long-term learning performance is contrasted to the support vector machine model, the particle filter model, and the simple RNN model. Monte Carlo simulation is combined to generate a probabilistic RUL prediction. Experimental data from multiple lithium-ion cells at two different temperatures is deployed for model construction, verification, and comparison. The developed method is able to predict the battery's RUL independent of offline training data, and when some offline data is available, the RUL can be predicted earlier than in the traditional methods.**

***Index Terms*—Lithium-ion battery, remaining useful life, deep learning, long short-term memory, Monte Carlo simulation.**

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Y. Zhang is with the National Engineering Laboratory for Electric Vehicles, Department of Vehicle Engineering, School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China, and also with the Center for Advanced Life Cycle Engineering, University of Maryland, College Park, MD 20742 USA (e-mail: yzzhangbit@gmail.com).

R. Xiong and H. He are with the National Engineering Laboratory for Electric Vehicles, Department of Vehicle Engineering, School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China (e-mail: rxiong@bit.edu.cn; hwhebit@bit.edu.cn).

M. G. Pecht is with the Center for Advanced Life Cycle Engineering, University of Maryland, College Park, MD 20742 USA (e-mail: pecht@umd.edu).

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I. Introduction

LITHIUM-ION batteries are widely used as power sources for many types of systems, including consumer electronics, electric vehicles (EVs), airplanes, and spacecrafts, owing to their high energy density, high galvanic potential, and long lifetime [1], [2]. However, their performance degrades over repeated charge/discharge cycles. For many applications, failure is considered to occur when the battery's capacity decreases below 80% of its initial capacity [3]. Because the battery's capacity and power both tend to drop much faster, its performance is thus unreliable after this point, and it should be replaced. Battery failure could result in degraded capability, unavailable operation, downtime, and even catastrophic occurrence.

Prognostics and health management (PHM) is an enabling discipline consisting of methods and technologies to evaluate system reliability under real cycle life conditions to detect incipient faults and predict fault progression [4]. PHM of lithium-ion batteries enables users to make maintenance decisions in advance to prevent loss caused by unexpected failures. Remaining useful life (RUL) prediction is a key approach of PHM [5].

To predict the RUL of lithium-ion batteries, an aging model is needed to map input sequences to output sequences of degradation characteristics. The prediction requires a system that will store and update degradation information (i.e., information computed from the past inputs and useful to produce desired outputs). This information is then used to capture the long-term dependencies of degradation evolution of lithium-ion batteries [6].

Lithium-ion battery degradation can cover hundreds of cycles, and the degradation evolution among these cycles is highly related. The degradation characteristics data consists of a trajectory that can be predicted based on historical data. However, some data contributes more to constructing the trajectory because the historical data is noisy and can even possess outliers limited to the present measurement technology. It is thus reasonable and efficient to predict the degradation trajectory by extracting key information from the inputs [7]. The difficulty for RUL prediction of lithium-ion batteries lies in how to store and update the key information from the degradation data via effective learning of long-term dependencies. RUL prediction methods for batteries can be categorized into two main categories: model-based methods and data-driven methods.

[IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, VOL. 67, NO. 7, JULY 2018]

- **Index Terms – Lithium-ion battery, remaining useful life, deep learning, long short-term memory, Monte Carlo simulatio**

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ Abstract

- **Remaining useful life (RUL) prediction** of lithium-ion batteries can assess the battery reliability to determine **the advent of failure and mitigate battery risk.**
- **The existing RUL prediction** techniques for lithium-ion batteries are **inefficient** for learning **the long-term dependencies** among the capacity degradations.
- This paper investigates **deep-learning-enabled battery RUL prediction**.
- **The long short-term memory (LSTM) recurrent neural network (RNN)** is employed **to learn the long-term dependencies** among the degraded capacities of lithium-ion batteries.
- The LSTM RNN is adaptively optimized using the resilient mean square backpropagation method, and **a dropout technique** is used to address the **overfitting problem**.

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ Abstract

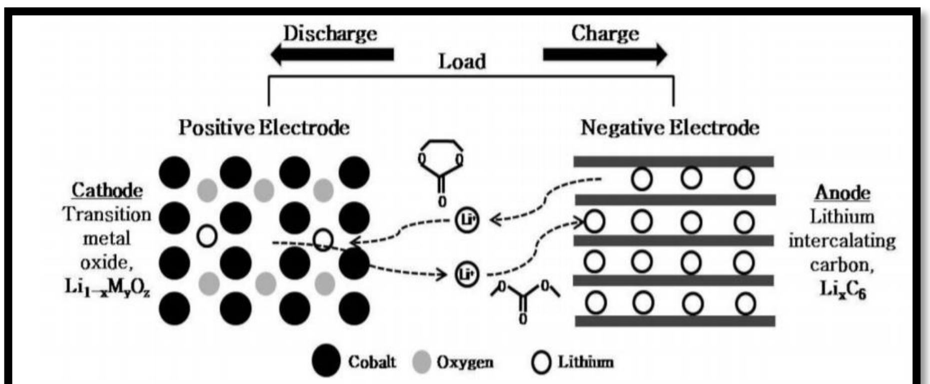
- The developed LSTM RNN is able to capture the underlying long-term dependencies among the degraded capacities and construct an explicitly capacity-oriented RUL predictor, whose long-term learning performance is contrasted to the support vector machine model, the particle filter model, and the simple RNN model.
- **Monte Carlo simulation** is combined **to generate a probabilistic RUL prediction**.
- Experimental data from multiple lithium-ion cells at two different temperatures is deployed for model construction, verification, and comparison.
- The developed method is able to predict the battery's RUL independent of offline training data, and when some offline data is available, the RUL can be predicted earlier than in the traditional methods.

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ Introduction

Four major components of secondary battery

- **양극재** : 양이온(e.g. Li, Ni), 소스로 배터리의 용량과 평균 전압을 결정
- **음극재** : 양극에서 나온 양이온을 저장했다가 방출하면서 회로를 통해 전류를 흐르게 함
- **분리막** : 양극과 음극의 접촉을 차단하는 역할
- **전해액** : 이온이 원활하게 이동하도록 돕는 매개체



<리튬 이온, 2차 전지 구조>

Cathode (+): 양극 Positive

$$LiCoO_2 \underset{discharge}{\overset{charge}{\rightleftarrows}} Li_{1-x}CoO_2 + xLi^+ + xe^-$$

Anode (-): 음극 Negative

$$C_n + xLi^+ + xe^- \underset{discharge}{\overset{charge}{\rightleftarrows}} C_nLi_x$$

Overall:

$$LiCoO_2 + C_n \underset{discharge}{\overset{charge}{\rightleftarrows}} C_nLi_x + Li_{1-x}CoO_2$$

<리튬 이온, 2차 전지 원리>

Use case

- consumer electronics, electric vehicles (EVs), airplanes, and spacecrafts, owing to their **high energy density**, **high galvanic potential**, and **long lifetime**

- **2차 전지 : secondary cell, storage battery, rechargeable battery**

☐ Introduction

- **Battery Failure is considered** to occur when the battery's capacity decreases **below 80% of its initial capacity**

- Battery failure could result in degraded capability, unavailable operation, downtime, and even catastrophic occurrence.

- Lithium-ion battery degradation can cover hundreds of cycles, and **the degradation evolution** among these **cycles is highly related**.

- The degradation characteristics data consists of a trajectory that can be predicted based on historical data.

- However, some data contributes more to constructing the trajectory because the historical data is noisy and can even possess outliers limited to the present measurement technology.

- It is thus reasonable and efficient to predict the degradation trajectory by extracting key information from the inputs.

- **PHM** (Prognostics and health management)

☐ Introduction

✓ **model-based methods :** to capture the long-term dependencies of battery degradations

- PF (Particle Filter) algorithm
- DST (Dempster-Shafer theory)
- Ensemble model
- AIC (Akaike information criterion)
- PF framework
- IMMPF (Interacting multiple model particle filter)

drawbacks

1. **No accurate aging model**
2. **PF is limited by the particle degeneracy problem**

✓ **data-driven methods :** data-driven methods do not need an explicit mathematical model to describe the degradation evolution of batteries and are only dependent on historical degradation data

- SVM (support vector machine)
- RVM (relevance vector machine)
- kernel techniques
- NN, RNN, LSTM

- **PEVs – Plug-in electric vehicles (PEV)**

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ Introduction

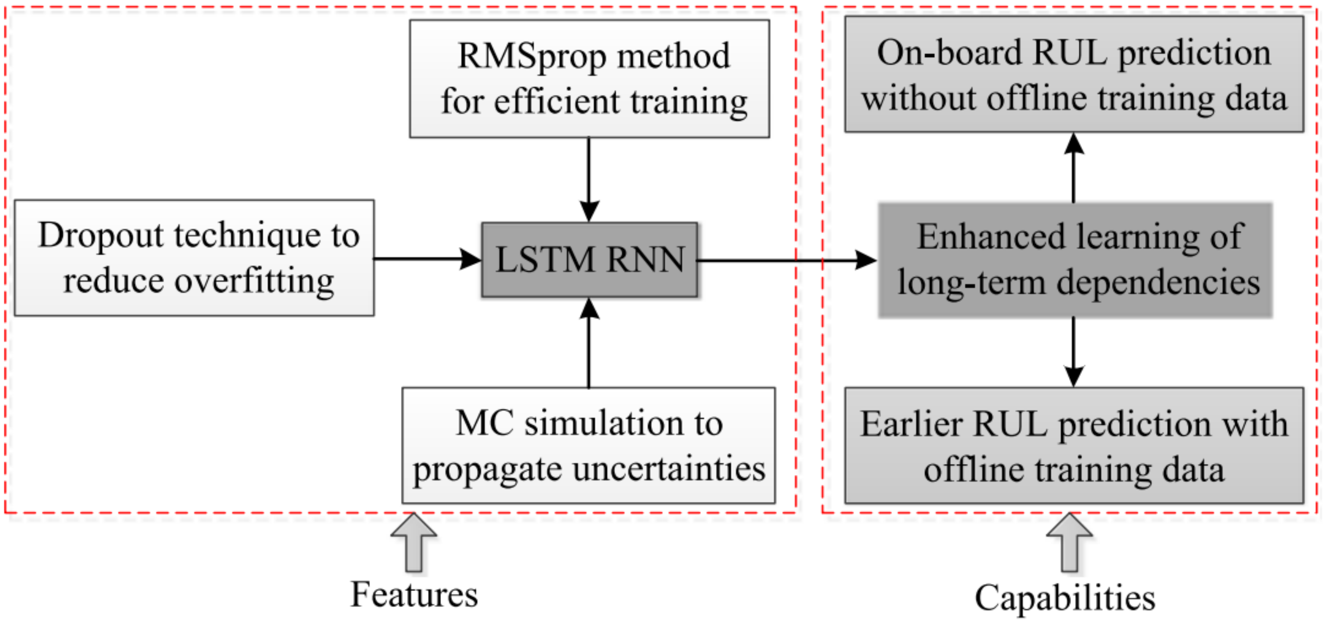


Fig. 1. Features and capabilities of the constructed LSTM RNN.

- **RMSprop :** the resilient mean square back-propagation
- **online-data :** the data collected in real applications
- **offline-data :** the data collected in the experiments

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ Battery testing and degradation data

"온도" 및 "C-rate"가 Cycle/Capacity에 미치는 영향

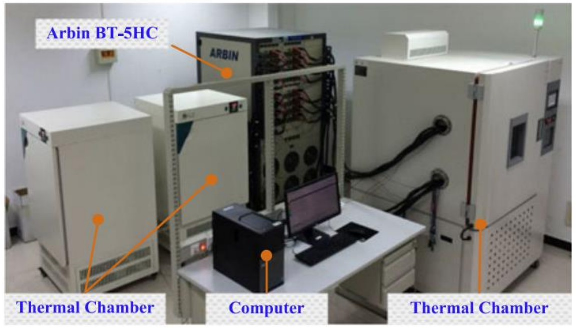


Fig. 2. Battery test equipment.

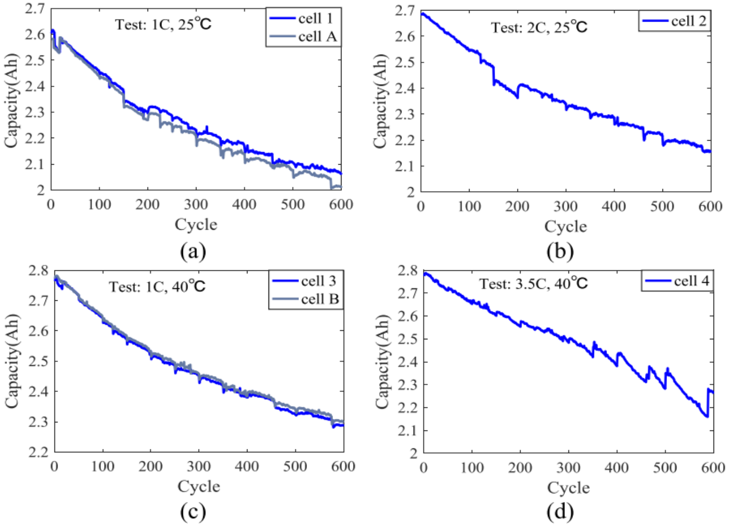


Fig. 3. Capacity degradation trajectories of batteries under different temperatures and currents.

TABLE I
CELL SPECIFICATIONS OF THE NCR18650PF BATTERY

Nominal Capacity	2.7 Ah
Material	Li(NiCoAl)O_2/Carbon
Maximum continuous discharge current	10 A
Allowed voltage range	2.5–4.2 V
Temperature range	
Charge	10–45 °C
Discharge	−20–60 °C
Storage	−20–50 °C

TABLE II
CAPACITY RETENTION AT 600 CYCLES

Capacity	Cell 1	Cell 2	Cell 3	Cell 4	Cell A	Cell B
Initial capacity (Ah)	2.62	2.69	2.78	2.79	2.58	2.78
Capacity retention	79%	81%	83%	77%	78%	82%

- **C-rate :** if 1 C → 1h (discharging/charging)

- **online-data** : the data collected in **real applications**
- **offline-data** : the data collected in **the experiments**

☐ LSTM-RNN-Oriented RUL Prediction

- **There are three concerns.**

1. **Traditional training algorithms** based on <u>batch gradient descent</u> or <u>stochastic gradient descent</u> for deep-learning networks can be significantly **slow to converge** to the correct network weights, which are thus **not applicable for the purpose of online failure prediction** of lithiumion batteries.

    ▶ network parameter optimization using the **RMSprop method**

2. **Overfitting** is a serious problem in deep neural networks like **the LSTM RNN**.

    ▶ a **dropout technique** to prevent the neural network from overfitting

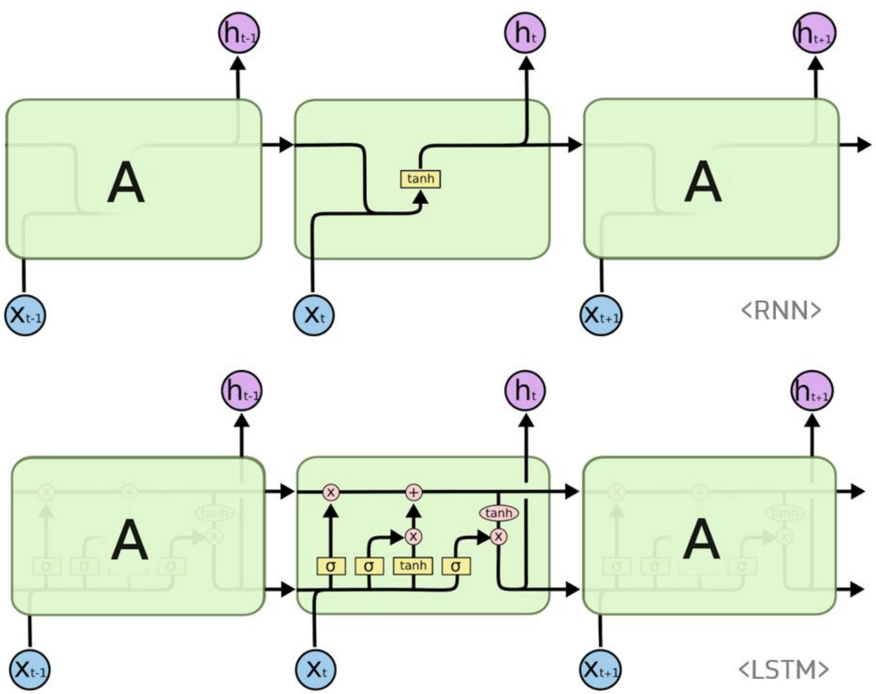
3. The maintenance of lithium-ion batteries is based on an RUL probability distribution function (PDF), while **LSTM RNN** is **unable to obtain uncertainties** of the RUL predictions.

    ▶ **MC simulation** to generate prediction uncertainties

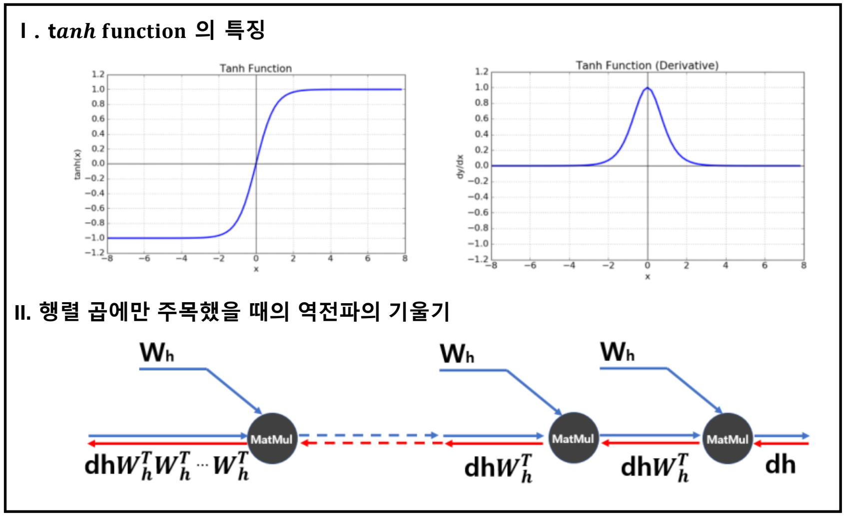
Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ LSTM-RNN-Oriented RUL Prediction

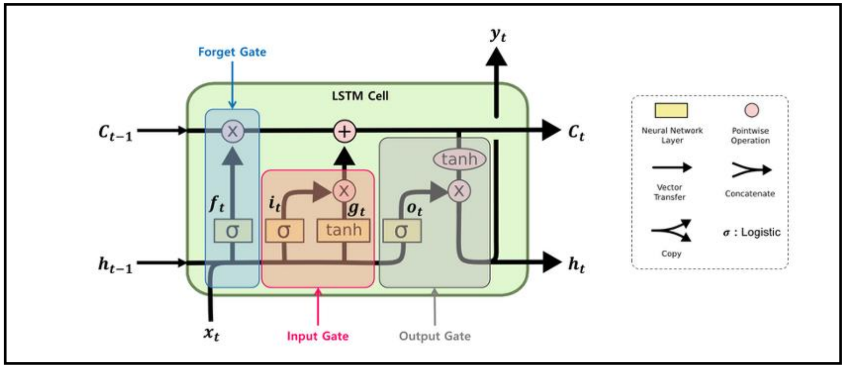
A. LSTM RNN Architecture



RNN : vanishing gradient problem



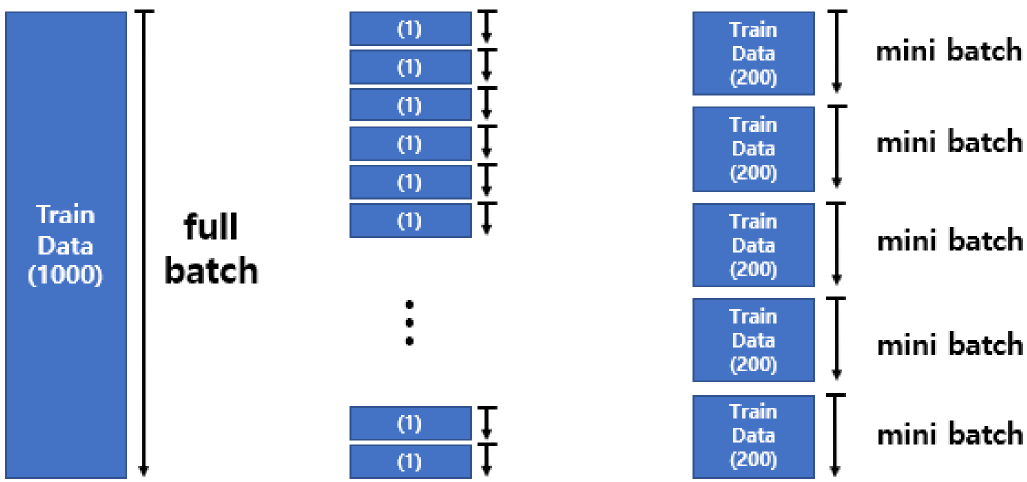
LSTM Structure



- https://colah.github.io/posts/2015-08-Understanding-LSTMs/

☐ LSTM-RNN-Oriented RUL Prediction

B. LSTM RNN Training I



batch	SGD (Stochastic)	Mini batch SGD
slow	variance	local minimum

$$\boxed{\theta_{t+1} = \theta_t - \eta \nabla_\theta J(\theta; x^{(i)}, y^{(i)})}$$

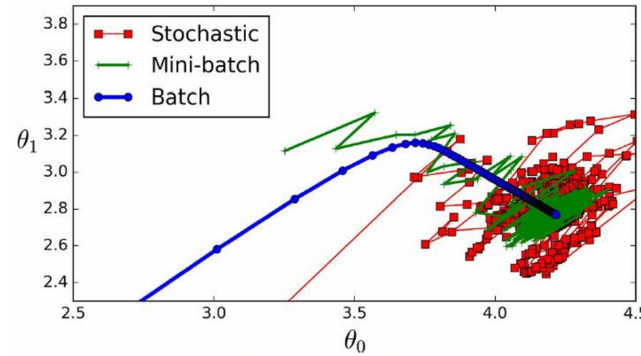
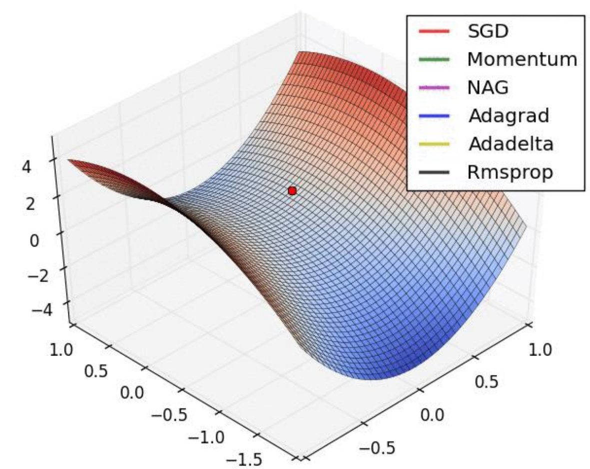


Figure 4-11. Gradient Descent paths in parameter space



- [Unit Tests for Stochastic Optimization]

☐ LSTM-RNN-Oriented RUL Prediction

B. LSTM RNN Training II

Rprop

For all weights and biases{

$$
\begin{aligned}
&\textbf{if } \left(\frac{\partial E}{\partial w_{ij}}(t-1) * \frac{\partial E}{\partial w_{ij}}(t) > 0\right) \textbf{ then } \{\\
&\quad \Delta_{ij}(t) = \textbf{minimum } (\Delta_{ij}(t-1) * \eta^{+}, \Delta_{max})\\
&\quad \Delta w_{ij}(t) = - \textbf{ sign } \left(\frac{\partial E}{\partial w_{ij}}(t)\right) * \Delta_{ij}(t)\\
&\quad w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t)\\
&\}\\
&\textbf{else if } \left(\frac{\partial E}{\partial w_{ij}}(t-1) * \frac{\partial E}{\partial w_{ij}}(t) < 0\right) \textbf{ then } \{\\
&\quad \Delta_{ij}(t) = \textbf{maximum } (\Delta_{ij}(t-1) * \eta^{-}, \Delta_{min})\\
&\quad w_{ij}(t+1) = w_{ij}(t) - \Delta w_{ij}(t-1)\\
&\quad \frac{\partial E}{\partial w_{ij}}(t) = 0\\
&\}\\
&\textbf{else if } \left(\frac{\partial E}{\partial w_{ij}}(t-1) * \frac{\partial E}{\partial w_{ij}}(t) = 0\right) \textbf{ then } \{\\
&\quad \Delta w_{ij}(t) = - \textbf{ sign } \left(\frac{\partial E}{\partial w_{ij}}(t)\right) * \Delta_{ij}(t)\\
&\quad w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t)\\
&\}
\end{aligned}
$$

}

- For **batch learning** → **slow convergence**

RMSprop

$$g_t = \nabla_\theta J\left(\theta_t; x^{(i:i+n)}; y^{(i:i+n)}\right) \quad (7)$$

$$E\left[g^2\right]_t = \gamma E\left[g^2\right]_{t-1} + (1-\gamma)\, g_t^2 \quad (8)$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E[g^2]_t + \varepsilon}} g_t \quad (9)$$

$\gamma : 0.9$
$\eta : 0.001$

- For **Mini-batch learning**

- **Rprop :** The resilient back-propagation (Rprop) algorithm
- **RMSprop :** Root Mean Squared Prop

☐ LSTM-RNN-Oriented RUL Prediction

C. Dropout to Prevent LSTM RNN From Overfitting

L1 Regularization

$$E(w) = \frac{1}{2}\sum_{n=1}^{N}\{y(x_n, w) - t_n\}^2 + \lambda\|w\|$$

Lasso

L2 Regularization

$$E(w) = \frac{1}{2}\sum_{n=1}^{N}\{y(x_n, w) - t_n\}^2 + \frac{\lambda}{2}\|w\|^2$$

Ridge

Dropout

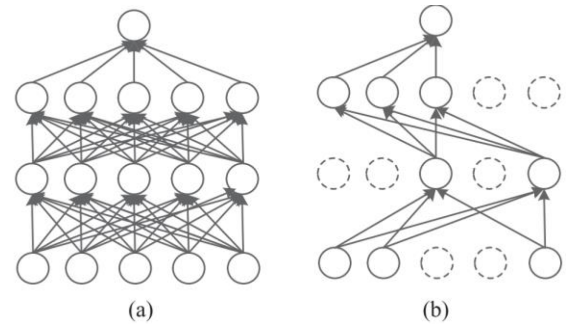


Fig. 5. Dropout neural network model: (a) standard neural network with 2 hidden layers; (b) neural network after applying dropout.

$p : 0.5 \rightarrow 0.2$

- The network thus becomes **less sensitive** to the specific weights of neurons.
  → **better generalization.**

☐ LSTM-RNN-Oriented RUL Prediction

D. Monte Carlo Simulation

- LSTM RNN is **unable to provide prediction confidence.**
- The predicted value and its confidence are both vital parameters to evaluate the performance of a predictor.
- **The Monte Carlo simulation** allows us to see all the possible outcomes of our decisions and assess risk impact, in consequence allowing **better decision making under uncertainty**.

Estimating PI using circle and square :

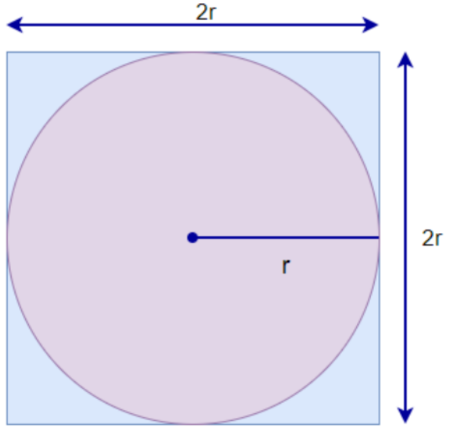


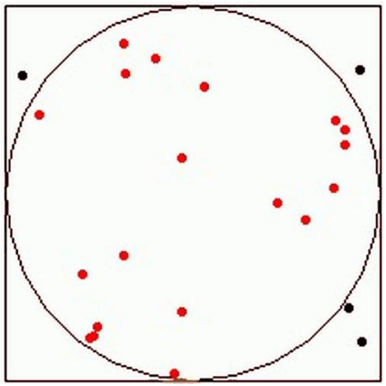
Figure 9: Simple area of a circle and of a square.

$$\frac{\textit{Area of square}}{\textit{Area of circle}} = \frac{(2r)^2}{\pi r^2}$$

$$\frac{\textit{Area of square}}{\textit{Area of circle}} = \frac{4}{\pi}$$

Figure 10: Calculation of the area of a circle and square respectively.

Simulation :



$$\pi \approx 4 \times \frac{N_{red}}{N_{red} + N_{black}}$$

- Monte Carlo Simulation An In-depth Tutorial with Python

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ Results and discussion

A. Dropout to Prevent LSTM RNN From Overfitting

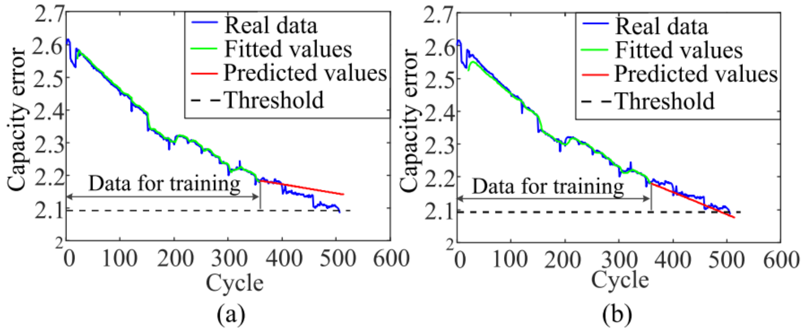


Fig. 6. LSTM RNN-based RUL prediction results for cell 1: (a) prediction results with no methods to prevent overfitting; (b) prediction results with dropout.

TABLE III
RUL PREDICTION RESULTS FOR CELL 1

Overfitting Prevention Method	Capacity Fitting Error (Ah)	Capacity Prediction Error (Ah)	RUL Prediction Error (Cycle)
No method	5.7×10^{-3}	2.4×10^{-2}	NAN
Dropout	6.6×10^{-3}	1.2×10^{-2}	16
L1 regularization	5.7×10^{-3}	8.2×10^{-2}	93
L2 regularization	1.4×10^{-2}	1.2×10^{-2}	–170

Capacity prediction error
- the mean absolute error between **real capacity** and **fitting** or **prediction capacity**

RUL prediction error
- the error between the **real failure cycle** and the **predicted failure cycle**.

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ Results and discussion

B. RUL Prediction Without Offline Training Data (cell 1)

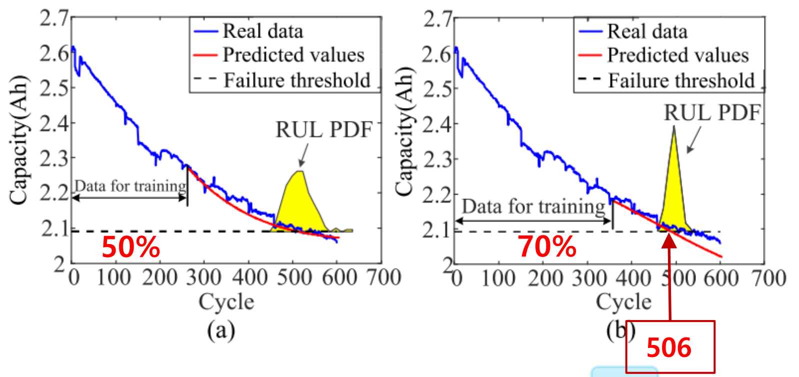


Fig. 7. LSTM RNN-based prediction results of RUL for cell 1: (a) prediction results at 253 cycles; (b) prediction results at 354 cycles.

Test: 1C, 25°C

TABLE IV
RUL PREDICTION RESULTS FOR CELL 1

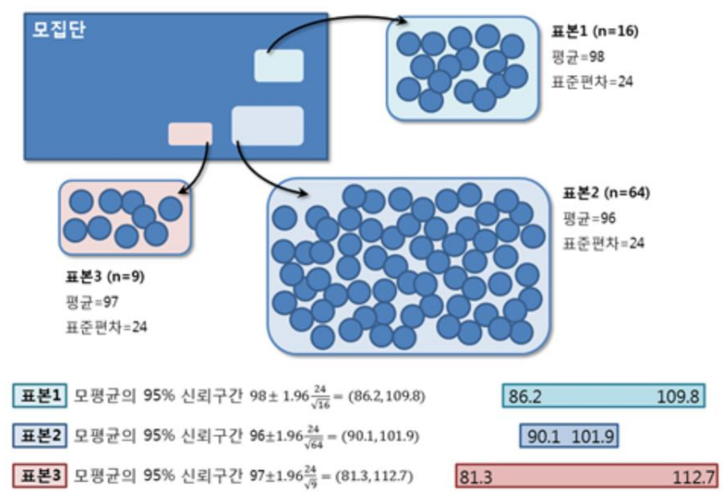
Method	Starting Cycle	Error	STD	95% Confidence Bound	Training Time (s)
LSTM RNN	253	–3	28	[470, 564]	20.74
	354	15	11	[473, 511]	23.04
SVM	253	–21	9	[511, 546]	0.003
	354	30	9	[458, 496]	0.008
SimRNN	253	135	7	[358, 388]	44.15
	354	78	19	[395, 470]	55.25

Error

$$\textcolor{blue}{failuer\ real\ value} - \textcolor{red}{predicted\ failuer}$$

95% confidence interval

$$\left[\bar{x} - 1.96\frac{S_x}{\sqrt{n}}, \quad \bar{x} + 1.96\frac{S_x}{\sqrt{n}}\right]$$



- **C-rate :** if 1 C → 1h (discharging/charging)
- S_x : standard deviation
- 95% confidence interval

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Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

□ Results and discussion

B. RUL Prediction Without Offline Training Data (cell 2, 3)

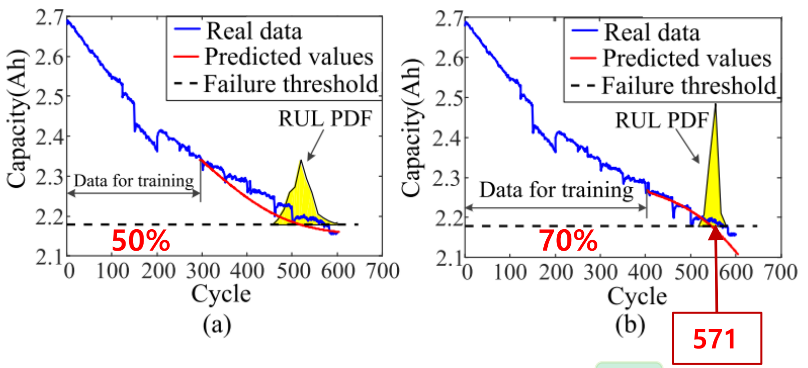

Fig. 8. LSTM RNN-based prediction results of RUL for cell 2: (a) prediction results at 285 cycles; (b) prediction results at 399 cycles.

Test: 2C, 25℃

TABLE V
RUL PREDICTION RESULTS FOR CELL 2

Method	Starting Cycle	Error	STD	95% Confidence Bound	Training Time (s)
LSTM RNN	285	48	24	[487, 585]	20.49
	399	26	7	[532, 561]	28.50
SVM	285	–34	9	[589, 623]	0.005
	399	42	8	[517, 546]	0.009
SimRNN	285	195	6	[368, 392]	41.73
	399	95	18	[442, 514]	56.86

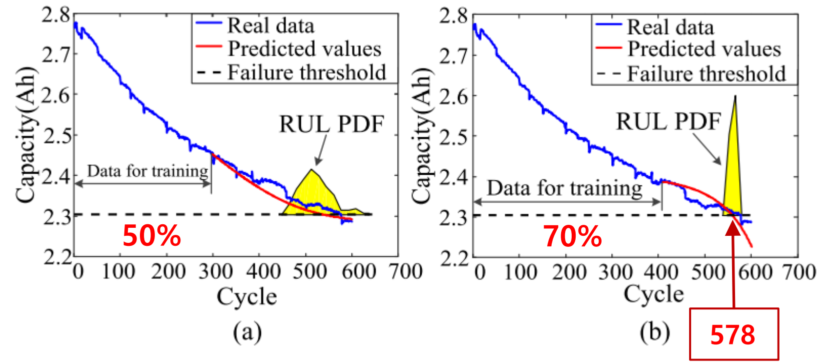

Fig. 9. LSTM RNN-based prediction results of RUL for cell 3: (a) prediction results at 289 cycles; (b) prediction results at 404 cycles.

Test: 1C, 40℃

TABLE VI
RUL PREDICTION RESULTS FOR CELL 3

Method	Starting Cycle	Error	STD	95% Confidence Bound	Training Time (s)
LSTM RNN	289	35	32	[499, 628]	21.53
	404	19	5	[550, 570]	28.98
SVM	289	40	8	[522, 554]	0.002
	404	23	11	[533, 577]	0.002
SimRNN	289	181	15	[370, 433]	39.27
	404	72	22	[465, 558]	55.36

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ Results and discussion

B. RUL Prediction Without Offline Training Data (cell 4)

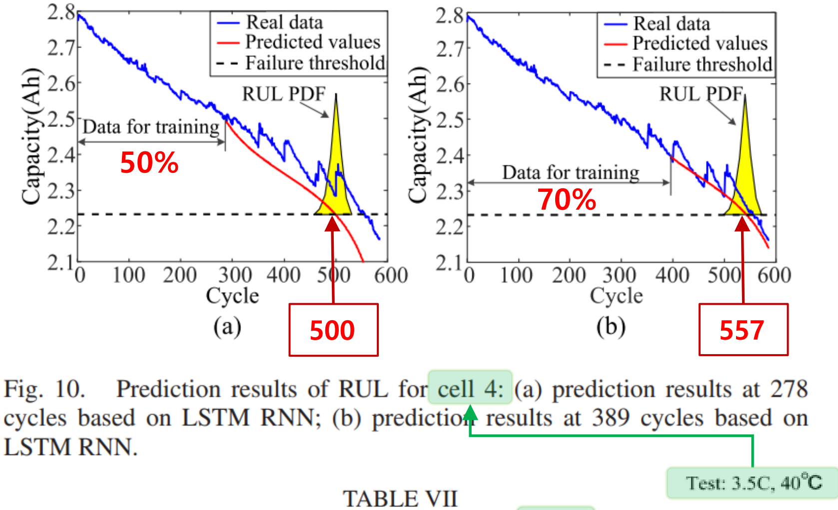

Fig. 10. Prediction results of RUL for cell 4: (a) prediction results at 278 cycles based on LSTM RNN; (b) prediction results at 389 cycles based on LSTM RNN.

TABLE VII
RUL PREDICTION RESULTS FOR CELL 4

Method	Starting Cycle	Error	STD	95% Confidence Bound	Training Time (s)
LSTM RNN	278	58	5	[490, 509]	22.67
	389	14	5	[534, 553]	28.55
SVM	278	−47	16	[575, 638]	0.008
	389	15	9	[526, 562]	0.013
SimRNN	278	–	–	–	–
	389	88	11	[448, 491]	63.32

Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries

☐ Results and discussion

C. RUL Prediction With Some Offline Training Data

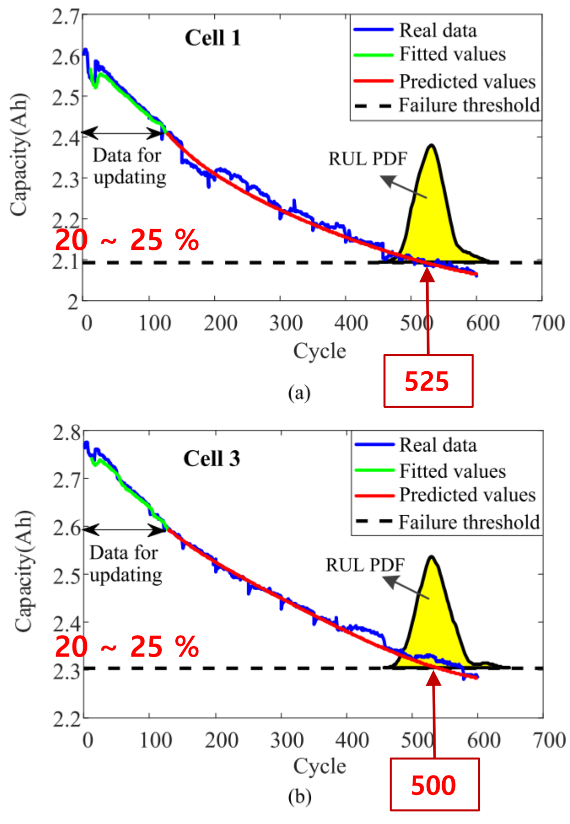

Fig. 11. LSTM RNN-based RUL prediction results based on some offline training data of: (a) cell 1; (b) cell 3.

the offline data should be collected under **similar working conditions** to those of **online cells**

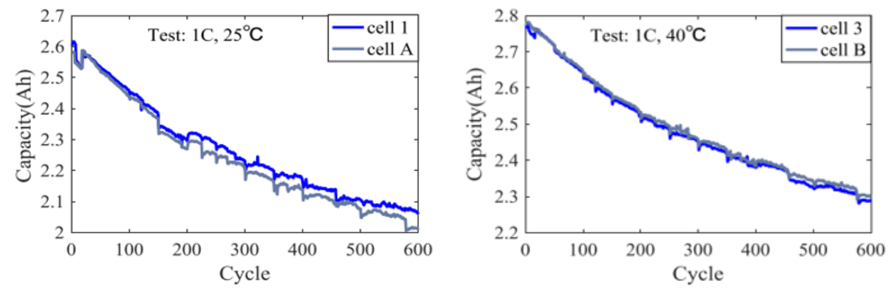

TABLE VIII
RUL PREDICTION RESULTS BASED ON OFFLINE DATA FOR CELL 1 AND CELL 3

Label	Method	Error	STD	95% Confidence Bound	Training Time (s)
Cell 1	LSTM RNN	–19	24	[477, 573]	3.23
	PF	52	25	[402, 506]	0.58
	SimRNN	110	16	[364, 428]	9.62
Cell 3	LSTM RNN	40	22	[494, 582]	4.49
	PF	58	27	[474, 566]	0.61
	SimRNN	93	14	[457, 513]	10.11

☐ Conclusions

- The challenge of RUL prediction for lithium-ion batteries lies in how to accurately learn the long-term dependencies over hundreds of cycles based on limited degradation data.

- **LSTM** (long-term dependencies) **+ RMSprop** (optimizer) **+ dropout** (overfitting) **+ Monte Carlo simulation (**uncertainties)

- The constructed LSTM RNN can be used to predict the battery RUL **independent of offline training data**.

Decentralized Plug-in Electric Vehicle Charging Selection Algorithm in Power Systems

☐ Reference

- Unit Tests for Stochastic Optimization
- Understanding RMSprop — faster neural network learning
- 95% confidence interval
- Monte Carlo Simulation An In-depth Tutorial with Python

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