

# 인공지능 기법을 적용한 배터리 노화상태 실시간 예측 시뮬레이션

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# 문제 배경

Electric Vehicle, Energy Storage System 등  
여러 분야에 리튬 이온 배터리 사용

-> 효과적인 SOH 예측 알고리즘 필수

## SOH (State of Health) : 배터리 열화 상태

- 전기를 담을 수 있는 용량
- 배터리 충/방전 횟수(Cycle)가 증가할수록 대략적으로 SOH 감소
- 대체로 SOH가 60% ~ 70%로 감소할 때까지 사용

## 1. 수행개요



$Q_{nom}$  : 초기 배터리 방전 전하량 (배터리 생산 시 제공) -> 2Ah

$Q_m$  :  $m$ 번째 Cycle에서의 배터리 방전 전하량

### SOH 계산 방법

$$SOH = \frac{Q_m}{Q_{nom}}$$

-> NASA PCoE Datasets을 활용하여 계산



# 데이터 실험 조건에 따른 3가지 분류

- 데이터 그룹 A: 상온 충/방전 데이터 (B05, B07, B18)
- 데이터 그룹 B: 상온 고출력 충/방전 데이터 (B33, B34)
- 데이터 그룹 C: 저온 충/방전 데이터 (B46, B47, B48)

## 목표

- 선형회귀와 LSTM을 이용한 SOH 예측 시뮬레이션 구현

- 1) 데이터의 50%를 이용한 학습
- 2) 데이터의 70%를 이용한 학습

- 예측 시각화
- RMSE, MAE를 이용한 결과분석

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i|$$

## 2. 수행과정



### SOH 계산

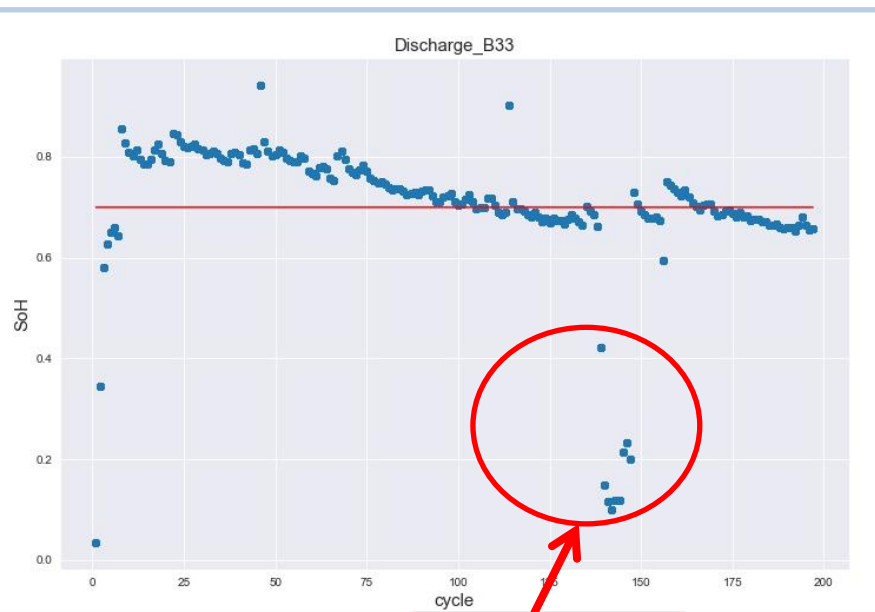
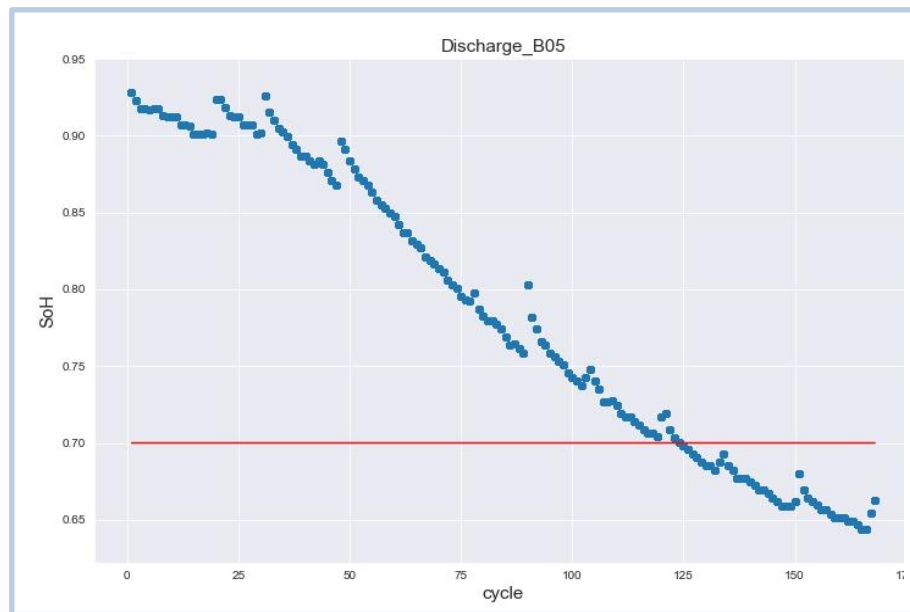
fx =G2/\$J\$2					
F	G	H	I	J	K
time	capacity	cycle	SOH	Qnom	
0	1.856487	1	=G2/\$J\$2	2	
16.781	1.856487	1			
35.703	1.856487	1			
53.781	1.856487	1			
71.922	1.856487	1			
90.094	1.856487	1			
108.281	1.856487	1			

fx =G2/\$J\$2					
	G	H	I	J	K
	capacity	cycle	SOH	Qnom	
0	1.856487	1	0.928244	2	
781	1.856487	1	0.928244		
703	1.856487	1	0.928244		
781	1.856487	1	0.928244		
922	1.856487	1	0.928244		
094	1.856487	1	0.928244		
281	1.856487	1	0.928244		

## 2. 수행과정



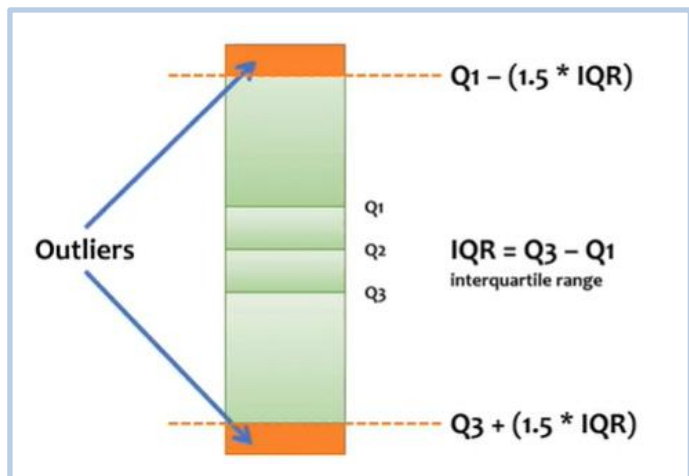
### SOH 시각화



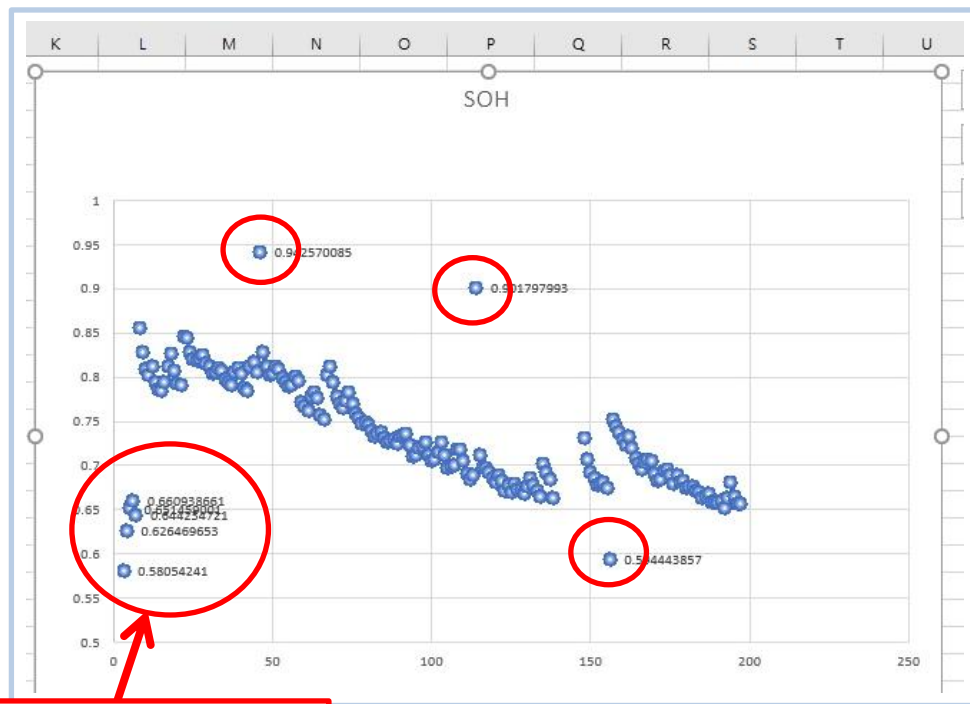
## 2. 수행과정



# 사분위수를 이용한 이상치 제거



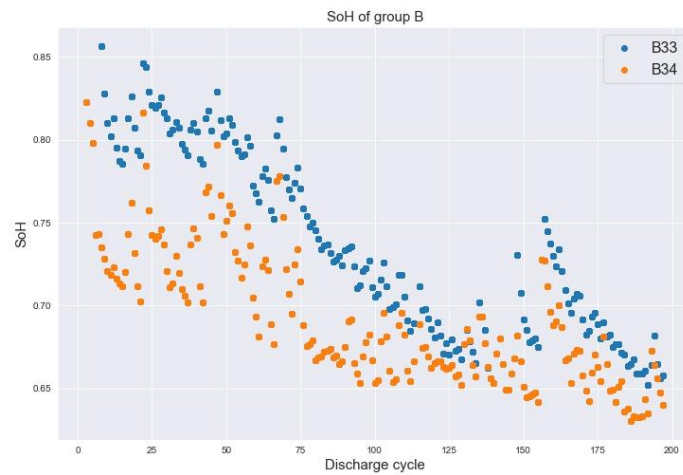
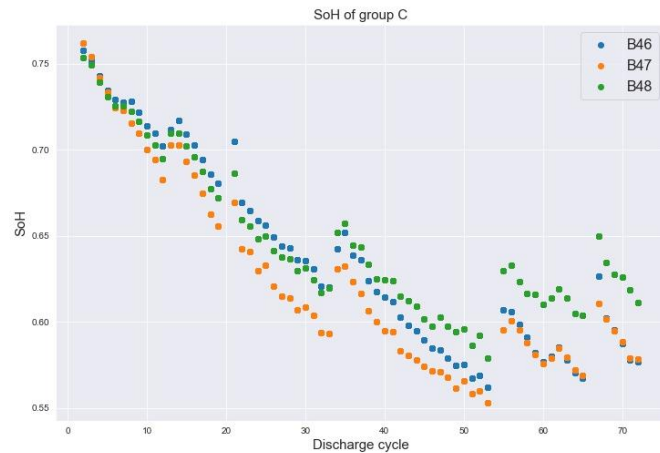
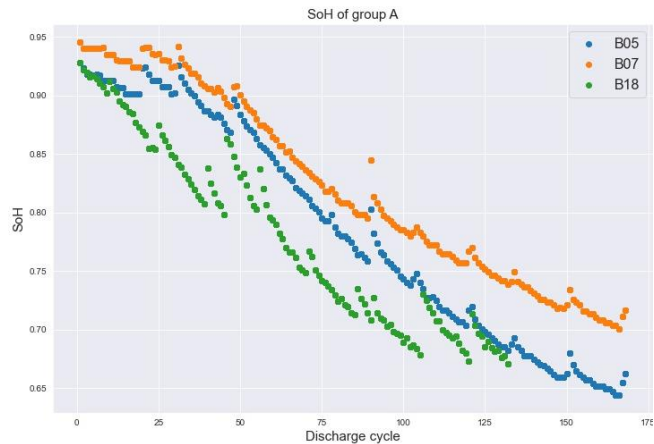
=IF(OR(I2<\$M\$6,I2>\$M\$7),"outlier","")					
I	J	K	L	M	
SOH	find outliers				
1	0.034213	outlier			
1	0.034213	outlier	Q1	0.682305	
1	0.034213	outlier	Q3	0.796535	
1	0.034213	outlier	IQR	0.114231	
1	0.034213	outlier	L Bound	0.510959	
1	0.034213	outlier	U Bound	0.967881	
1	0.034213	outlier			



임의로 제거



## 2. 수행과정





## 선형회귀

$$\hat{y}_i = a_1 x_i + a_0$$

Linear Least Squares

$$E \equiv E_2(a_0, a_1) = \sum_{i=1}^m [y_i - (a_1 x_i + a_0)]^2$$

$$a_0 = \frac{\sum_{i=1}^m x_i^2 \sum_{i=1}^m y_i - \sum_{i=1}^m x_i y_i \sum_{i=1}^m x_i}{m \sum_{i=1}^m x_i^2 - \left( \sum_{i=1}^m x_i \right)^2},$$

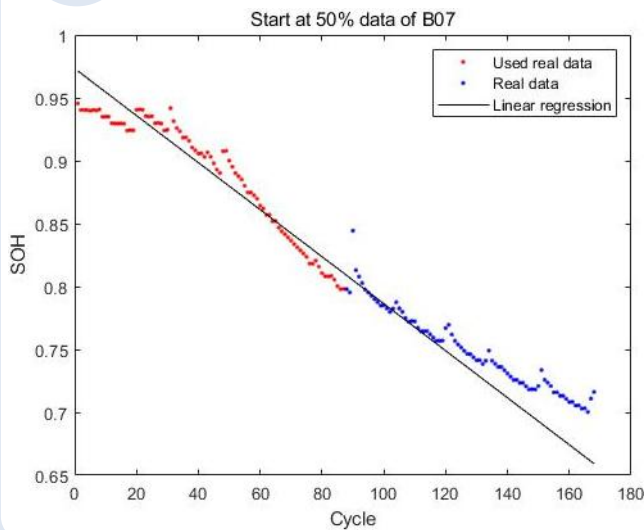
$$a_1 = \frac{m \sum_{i=1}^m x_i y_i - \sum_{i=1}^m x_i \sum_{i=1}^m y_i}{m \sum_{i=1}^m x_i^2 - \left( \sum_{i=1}^m x_i \right)^2}.$$

## 2. 수행과정

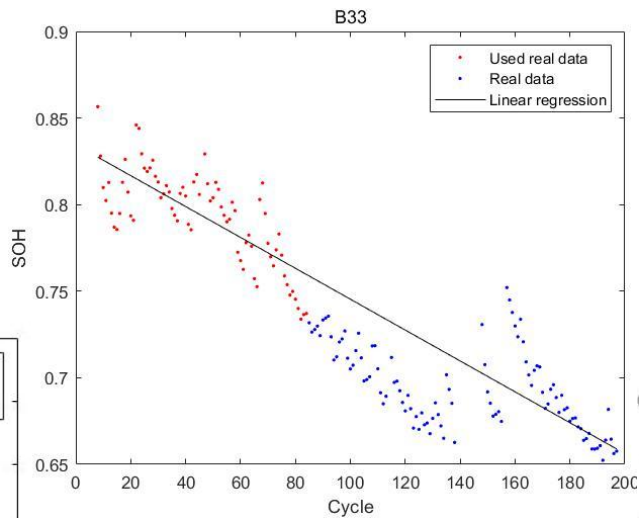


### 데이터의 50%를 이용한 결과

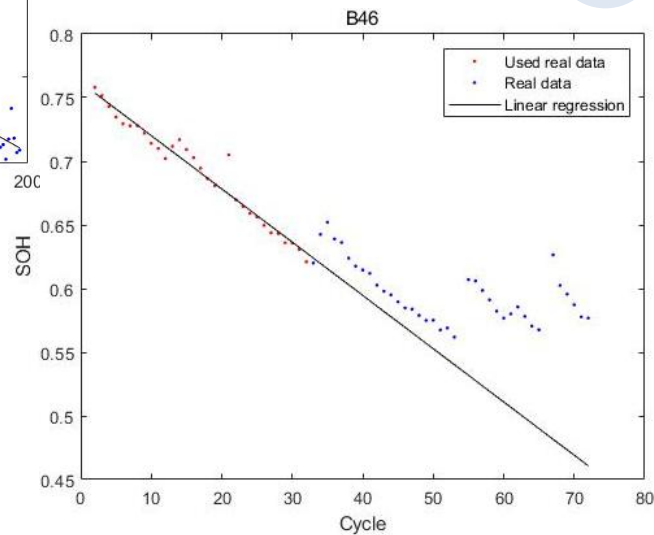
A



B



C

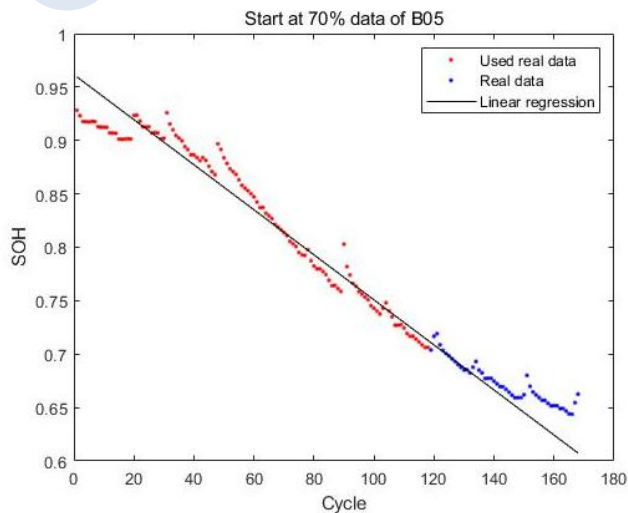


## 2. 수행과정

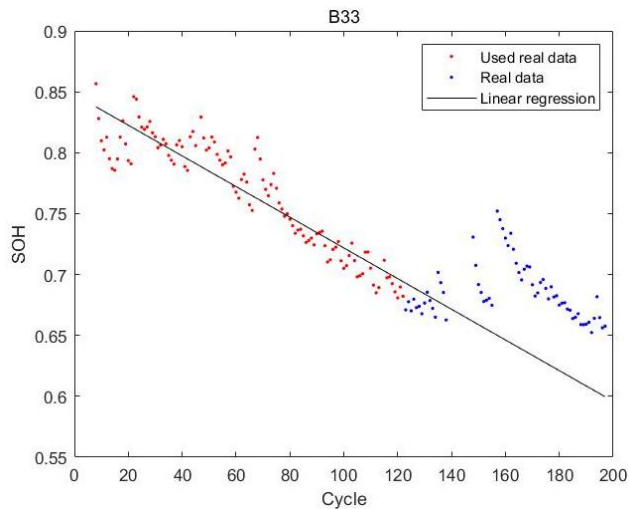


### 데이터의 70%를 이용한 결과

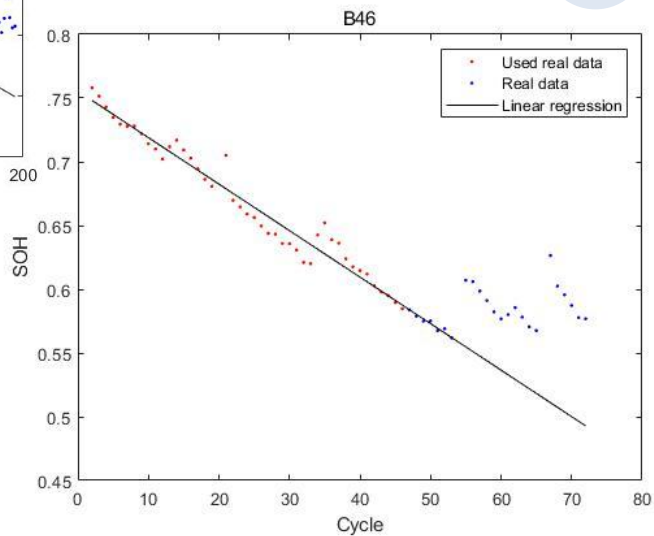
A



B



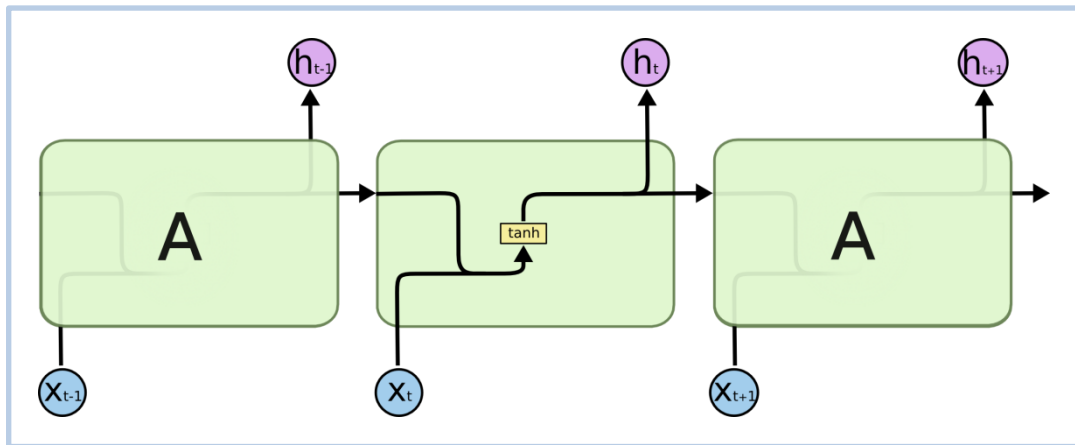
C



## 2. 수행과정



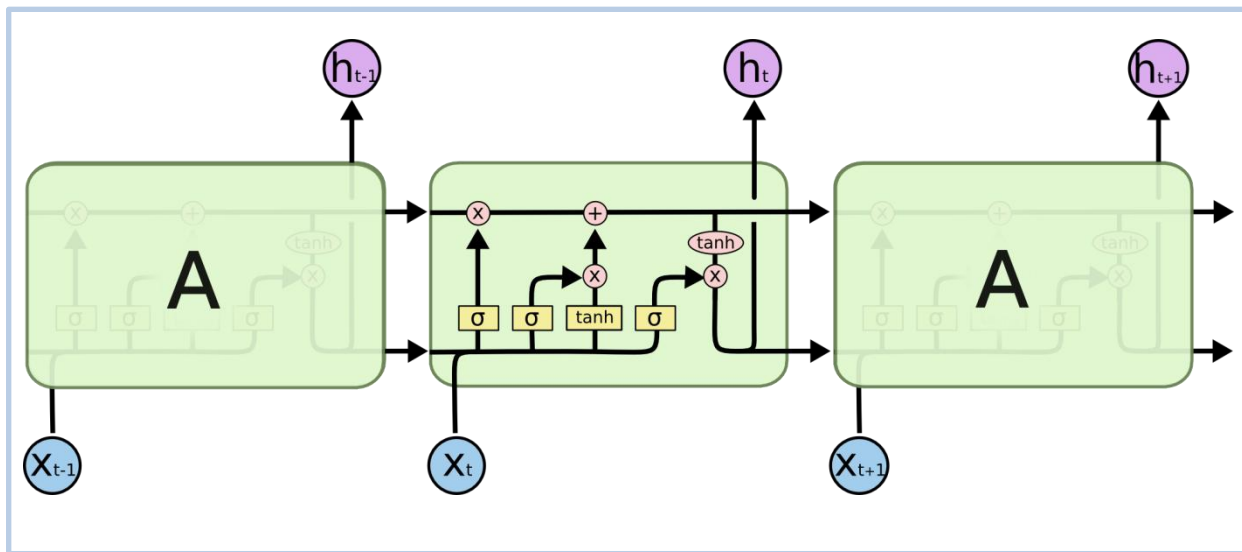
# RNN



$$\begin{aligned} h_t &= f_w(h_{t-1}, x_t) \\ &= \tanh(w_{hh}h_{t-1} + w_{xh}x_t) \\ y_t &= w_{hy}h_t \end{aligned}$$

$x_t$  : 현재 입력,  $h_{t-1}$  : 과거 기억,  $h_t$  : 현재 기억

# LSTM



$$\begin{aligned}
 f_t &= \sigma(W_{xh_f}x_t + W_{hh_f}h_{t-1} + b_{h_f}) \\
 i_t &= \sigma(W_{xh_i}x_t + W_{hh_i}h_{t-1} + b_{h_i}) \\
 o_t &= \sigma(W_{xh_o}x_t + W_{hh_o}h_{t-1} + b_{h_o}) \\
 \hat{c}_t &= \tanh(W_{xh_{\hat{c}}}x_t + W_{hh_{\hat{c}}}h_{t-1} + b_{h_{\hat{c}}}) \\
 c_t &= f_t \odot c_{t-1} + i_t \odot \hat{c}_t \\
 h_t &= o_t \odot \tanh(c_t)
 \end{aligned}$$

1. **Forget Gate** : 과거 정보를 잊기 위한 게이트
2. **Input Gate** : 현재 정보를 기억하기 위한 게이트
3. **Output Gate**

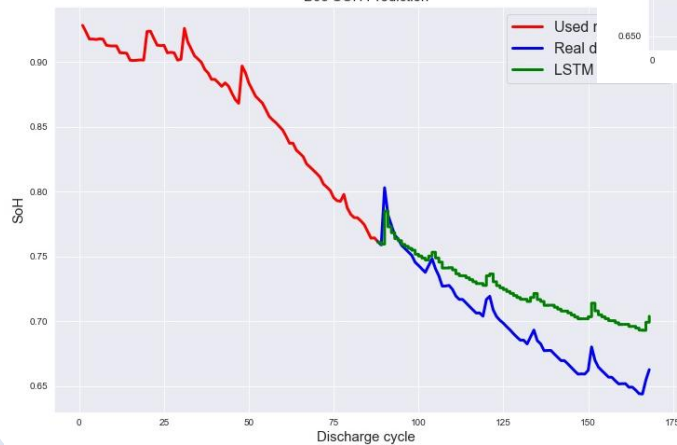
## 2. 수행과정



### 데이터의 50%를 이용한 결과

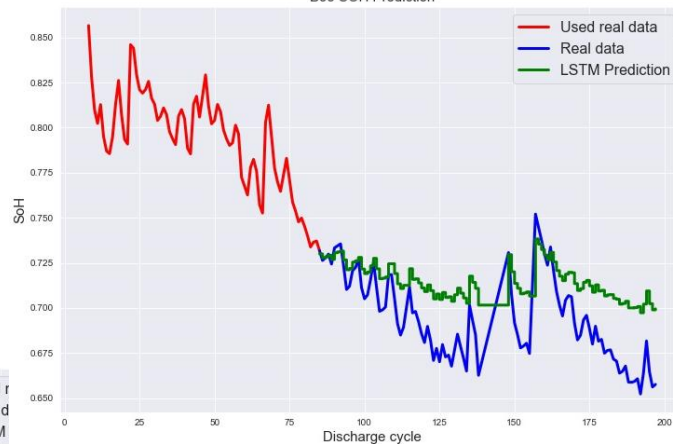
A

B05 SOH Prediction



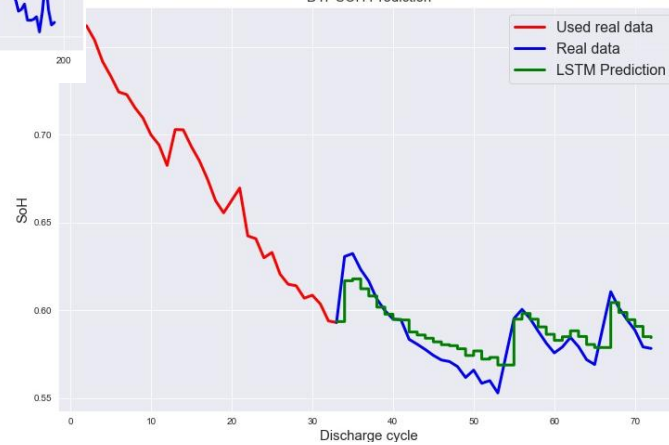
B

B33 SOH Prediction



C

B47 SOH Prediction

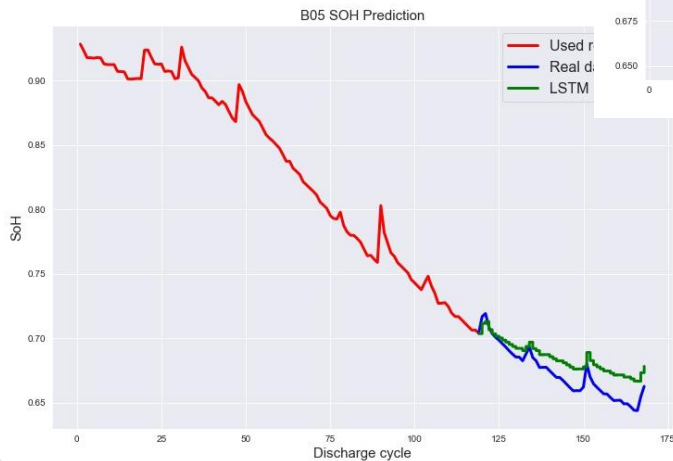


## 2. 수행과정

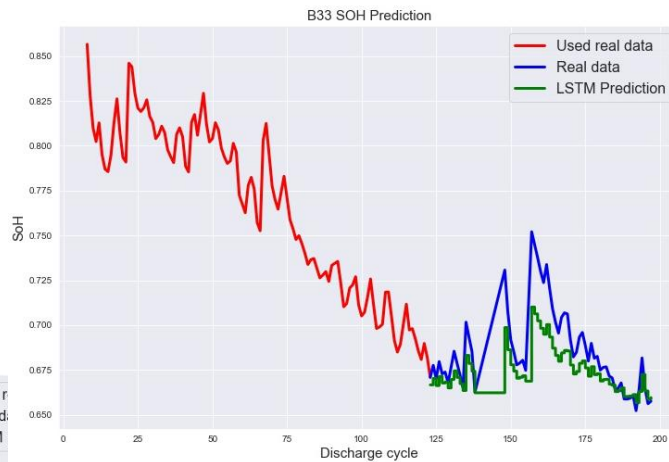


### 데이터의 70%를 이용한 결과

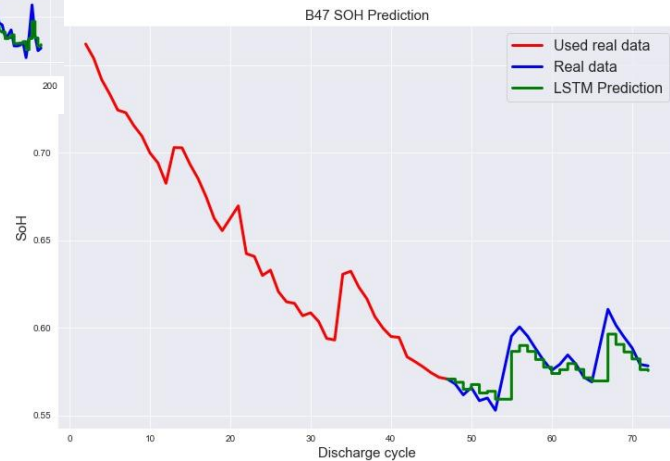
A



B



C





### 3. 결과분석



#### RMSE

선형회귀

LSTM

A						B				C					
B05		B07		B18		B33		B34		B46		B47		B48	
50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%
0.1599	0.1431	0.1190	0.1315	0.1389	0.1231	0.0303	0.0351	0.0255	0.0273	0.0654	0.0385	0.1129	0.0543	0.0973	0.0470
0.030	0.014	0.026	0.015	0.056	0.009	0.024	0.016	0.008	0.011	0.018	0.007	0.008	0.006	0.009	0.009

#### MAE

선형회귀

LSTM

A						B				C					
B05		B07		B18		B33		B34		B46		B47		B48	
50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%	50%	70%
0.1595	0.0934	0.0777	0.1307	0.1380	0.0803	0.0258	0.0202	0.0196	0.0154	0.0524	0.0207	0.0979	0.0314	0.0839	0.0266
0.026	0.012	0.023	0.013	0.053	0.007	0.020	0.012	0.006	0.008	0.016	0.005	0.007	0.005	0.008	0.007

## Dataset

**[1]** NASA PCoE Datasets: Experiments on Li-ion Batteries,  
<https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/>

## Reference

**[1]** 인공지능 기법을 적용한 배터리 노화 상태 (SOC, SOH) 실시간 예측 시뮬레이션, <https://icim.nims.re.kr/platform/question/24>.

**[2]** Pseudo code for LSTM computation  
<https://gist.github.com/manurastogi/d7656b8ece172c9e614e06dbbdbc9e10f>

