WAYNE STATE
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Analyzing a new feature for State of Charge Estimation of Li-ion Batteries

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Outline

- Introduction
- Challenges for State Estimations
- Battery States and State of Charge
- Research Inspiration and Hypothesis
- Terminology for models
- Research Strategy
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- Results
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Introduction & Challenges

Coming Era of Li-ion Batteries

Li-ion Battery market valued at $ 32.9 Bn as of 2019 and growing at rate of 16%[1].

In Automotive: All OEMs moving towards electrification[2].

General Motors: 30 new global electric vehicles by 2025.

Ford: 40% of volume all-electric by 2030.

Toyota: 15 new Battery Electric Vehicles by 2025.

Practical Challenges with Li-ion Batteries

Degrades over time: Stores less and less charge as it gets old.

Internal resistance changes with temperature, usage conditions and age.

Complex, Non-linear system to model

Indirect measurement of States

Battery States and State of Charge(SOC)

Battery States

State of Charge(SOC): Available capacity expressed as a percentage of the nominal capacity.

State of Health(SOH): Used to quantitatively assess the level of battery aging in terms of capacity fade and internal resistance.

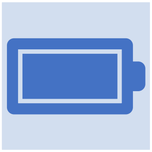
State of Energy(SOE): Available Energy expressed as a percentage of the nominal energy capacity. Used to reliably forecast driving range.

State of Power(SOP):Available power that a battery can supply to or absorb over a time horizon. Use case: Regenerative braking and friction brake split.

State of Temperature(SOT): Core, Average and Surface Temperature and/or temperature distribution often constitutes SOT. Relatively new state.

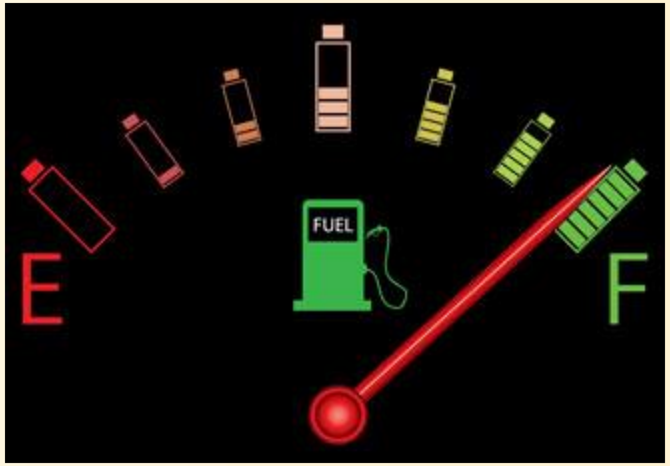
State of Safety(SOS): Probabilistic function to define the safe operating zone for battery. Function covers all battery dynamics: Terminal Voltage, Operating Temperature, Internal Impedance, External Deformation etc.

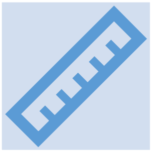
State of Charge – Importance and Estimation Techniques



State Of Charge = Fuel gage

Describes how much 'fuel' is left in the tank.





Estimation techniques:

- Direct Measurements
- Book-Keeping
- Model Based
- **Computer Intelligence**

Image Credits: [3]

Research Inspiration and Hypothesis

Research Inspiration

- Stanford, MIT and Toyota Research Institute’s jointly developed machine learning models to predict cycle life of batteries using early cycle life data[4].
  - Several features are evaluated and used in a regularized linear model. Example: Initial discharge capacity, Charge time, Cell can temperature
  - To capture, electrochemical evaluation, cycle to cycle evolution Q(V) are considered and proved to have a good predictive ability. Summary statistics were used as feature: Minimum, Mean, Variance

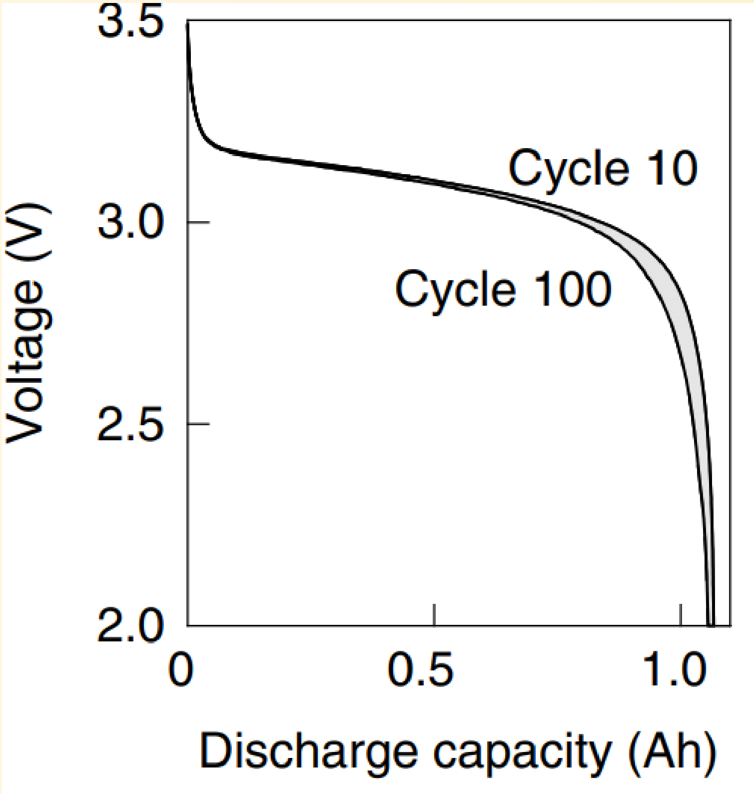


Chart credits:[4]

Bulb Image Credits: [5]

Hypothesis

- What if additional information about change in Voltage is supplied along with physical signals?
- Is it going to help with SOC prediction?

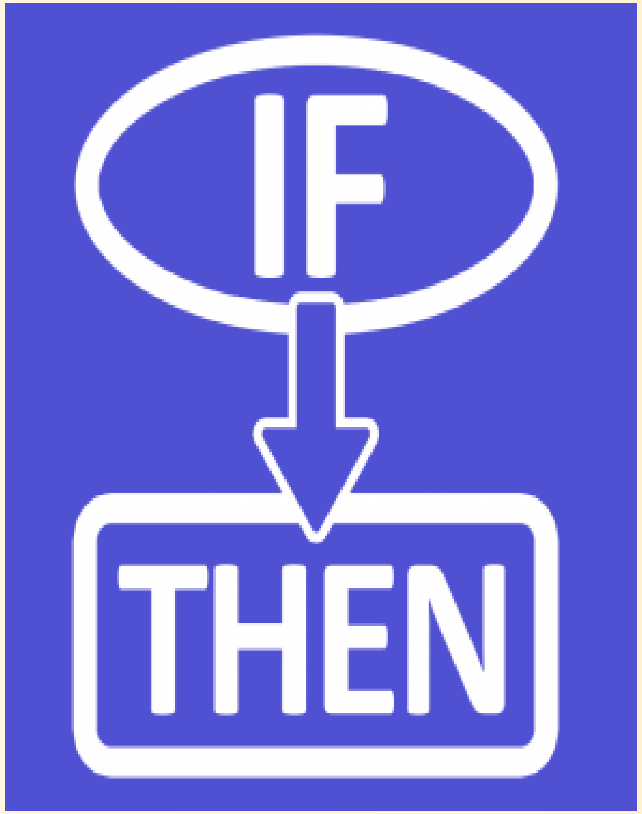


Image Credits: [6]

Terminology for Models

Dense Unit

1) Multiply inputs(a1,a2,..) with respective weights(w1,w2,..)
2) Add bias(b)
3) Apply non-linear activation function(g)
4) Output(a_{out})

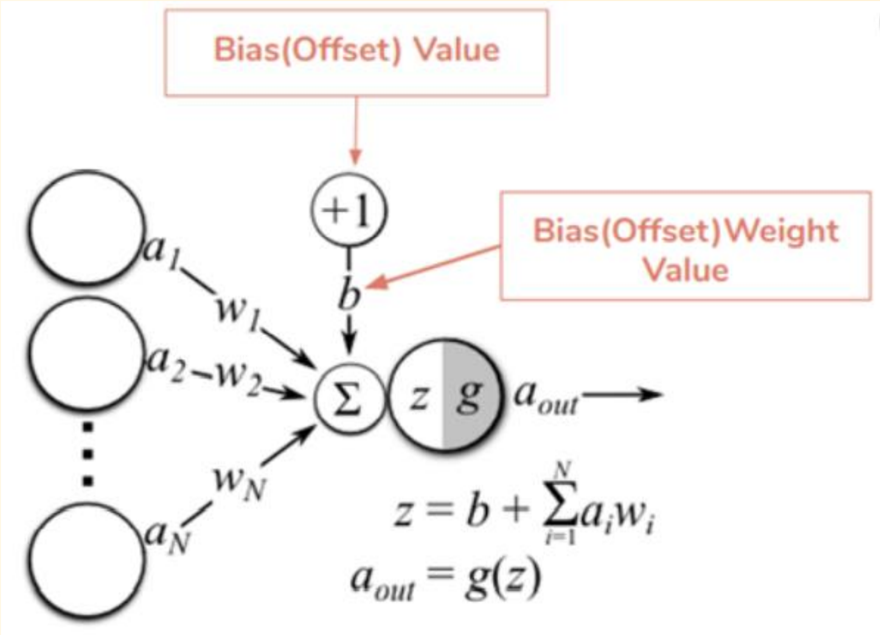
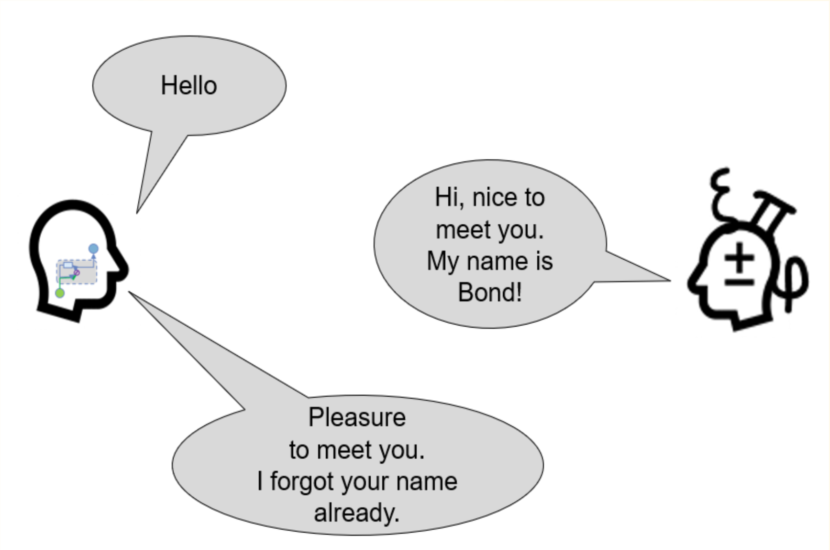


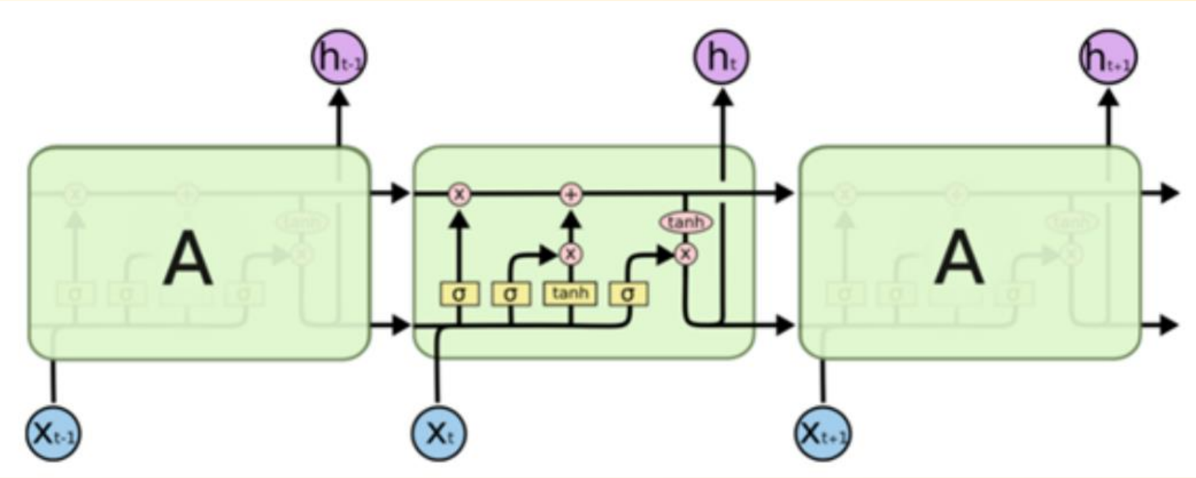
Image Credits: [7]

LSTM-RNN unit

Gradient vanishing can lead to difficulty in training long term.



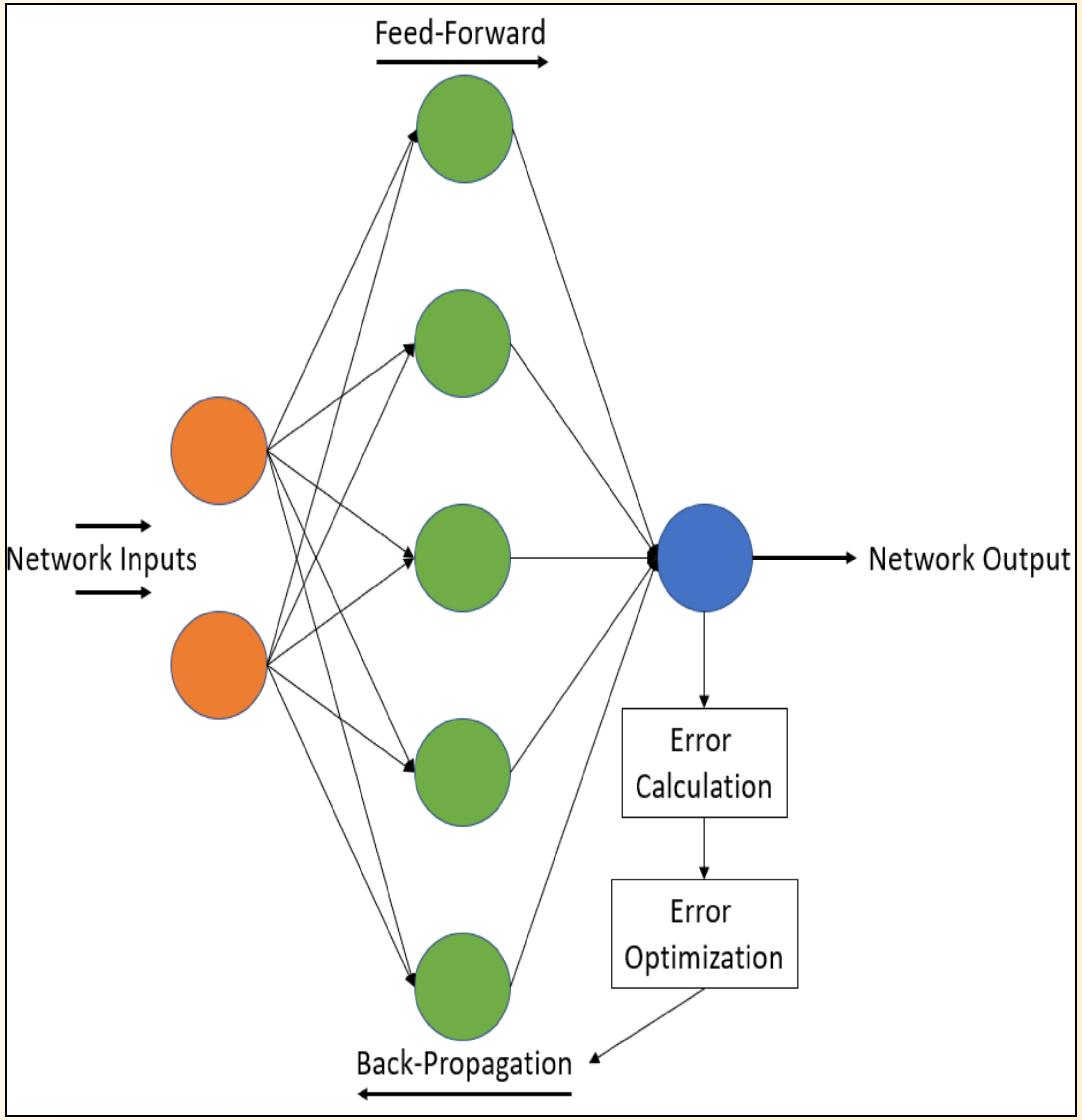
Uses various gates to retain a portion of information from past.



LSTM Image Credits: [8]

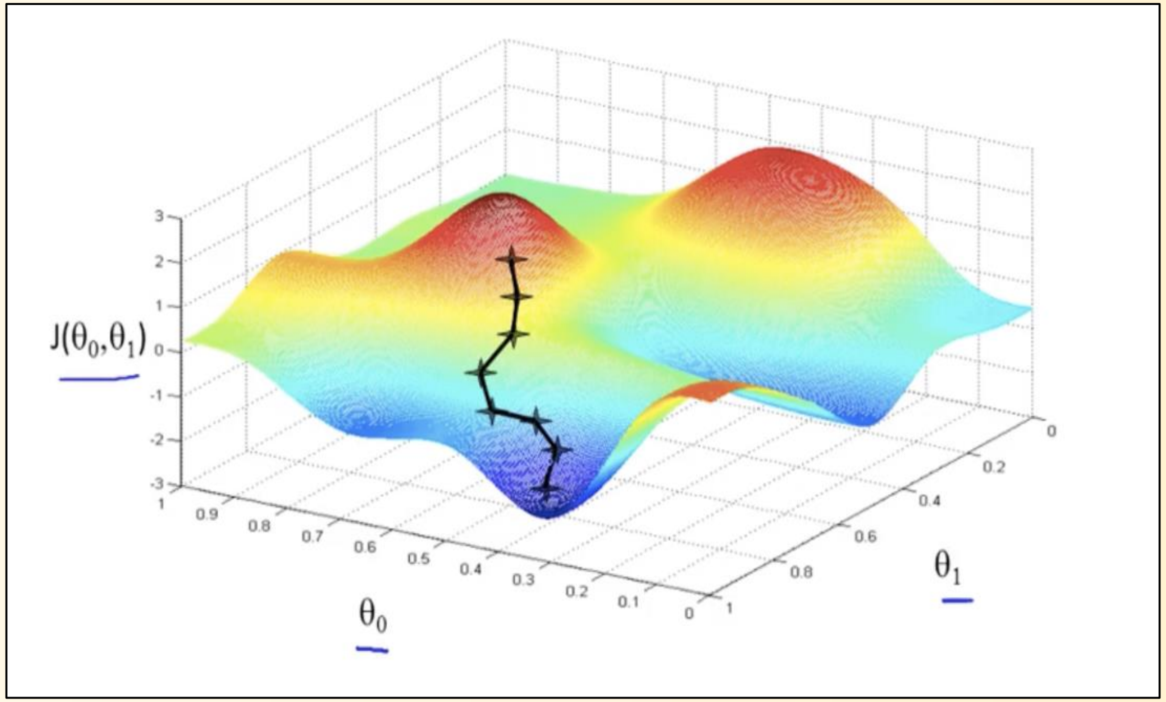
Forward and Backward Propagation

- Feed-Forward Propagation: Inputs gets multiplied by weights and biases to produce final Network output.
- Back-Propagation: Weights and biases are changed to reduce the error.



Adam Optimizer

- Mechanism to optimize error by adjusting weights and biases.
- Combination of 2 algorithms: RMSProp and Stochastic Gradient Descent.
- General purpose algorithm, adjusts the learning rate automatically.



θ_0, θ_1 = Model parameters
$J(\theta_0, \theta_1)$ = Cost function

Image Credits: [9]

L1L2 regularizer

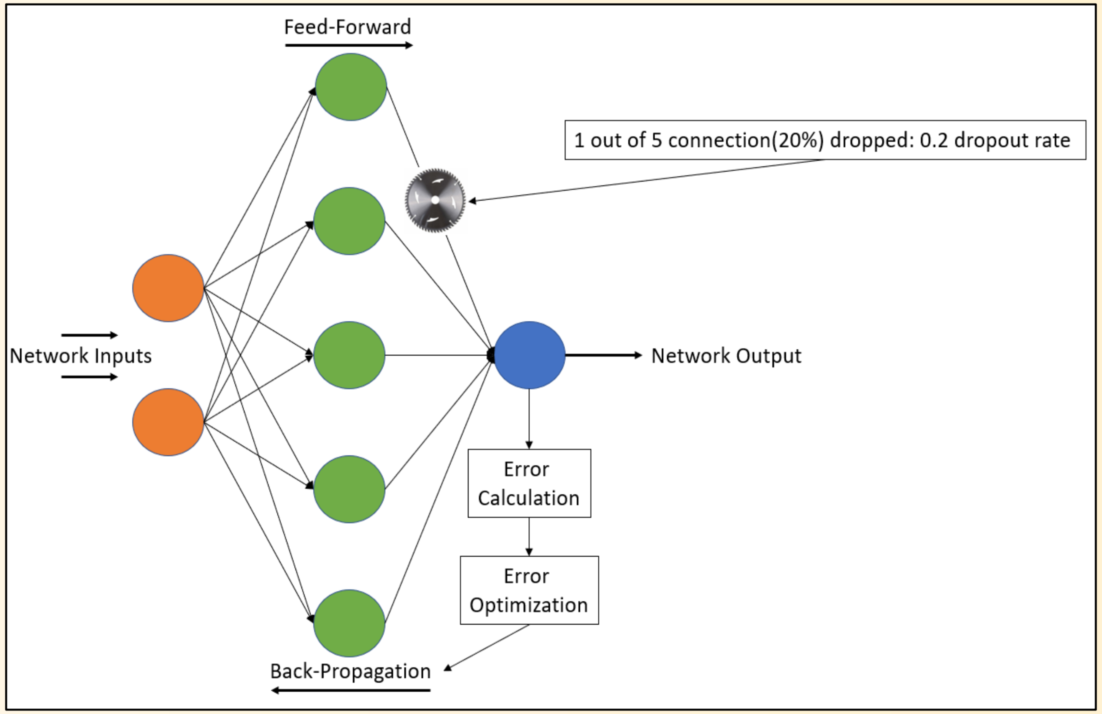
- Cost function is updated with L1 and L2 regularizer

Cost = Error(y,ỹ)+$\sum_{1}^{N} |w| + \sum_{1}^{N} |w^2|$

- Updated cost function penalizes higher magnitude weights.
- Useful to prevent over-fitting.

Dropout Layer

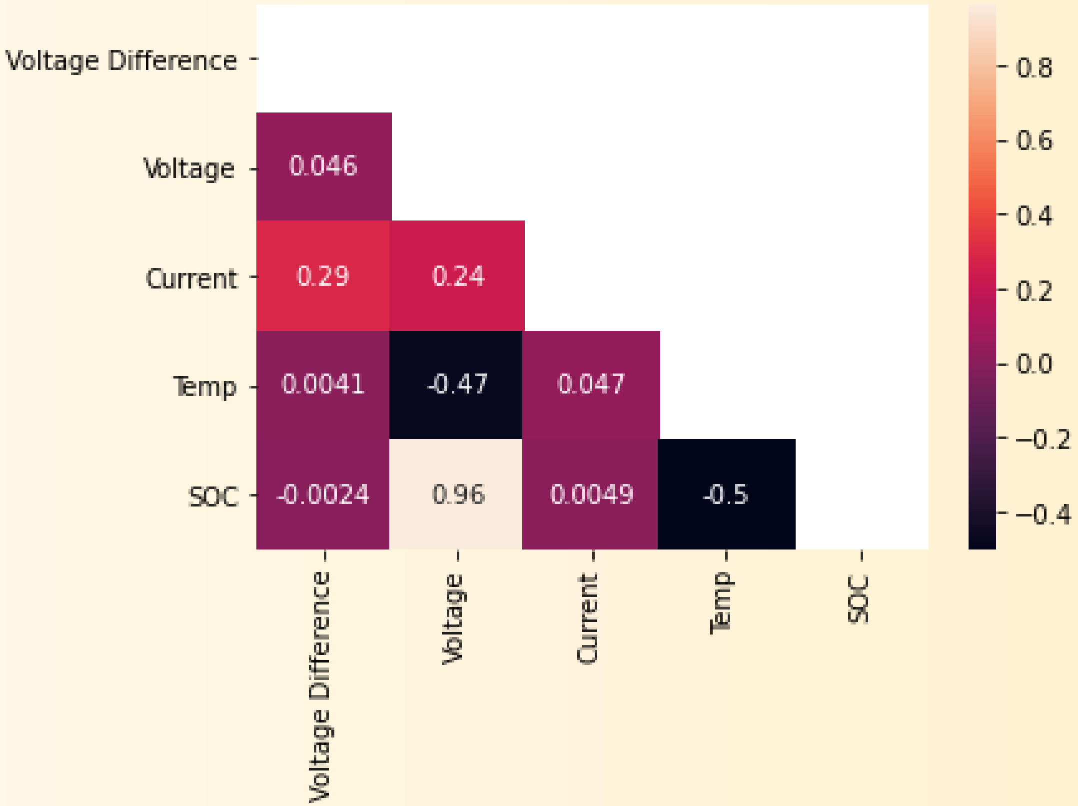
- Prevents overfitting by dropping out inputs to a layer in a probabilistic manner.
- Dropout rate of 0.2 indicates that 20% of total connections are dropped out.
- Different connections are dropped out each time, which prevents model from relying on certain inputs heavily.



Research Strategy

Understanding new feature and its impact on SOC

- Voltage difference = V_t - V_{t-1}
- Statistical correlation between Voltage difference is quantified by Spearman Correlation Coefficient(σ).
- σ = -0.0024 indicates a poor predictive ability of this feature when used for linear regression models(y=mx+c).



Problem Formulation

Compare 3 feature and 4 feature models using neural networks.

Expose both types of models to same treatment: Test data, Train data, Architecture and Hyper-parameters.

Workflow

Data Preparation

Experimental Data

Data cleaning

Data Conversion

Training

Base Model

Hyper-parameter Search

L1L2

Dropout rate

Combination: L1L2 and Dropout rate

Training

Base Model updated with L1L2

Base Model updated with Dropout layer

Base Model updated with L1L2 and Dropout layer

Performance Comparison and Conclusion

Data Preparation

Experimental Setup

- Data collected from Panasonic 18650 cell, NCA chemistry.
- Ambient temperature maintained using Thermal chamber.
- Energy profile for battery cycler is derived by scaling energy consumption at cell level.
- Train drive-cycles: LA92, UDDS, NN, Cycle 1, Cycle 2, Cycle 3, Cycle 4.
- Test drive-cycles: US06, HWFET

- Fig a: Physical Setup
- Fig b: Test procedure
- Fig c: Schematics of test bench and DAQ
- Experimental Data Courtesy: Dr. Ephrem Chemali's

PhD Thesis at McMaster University

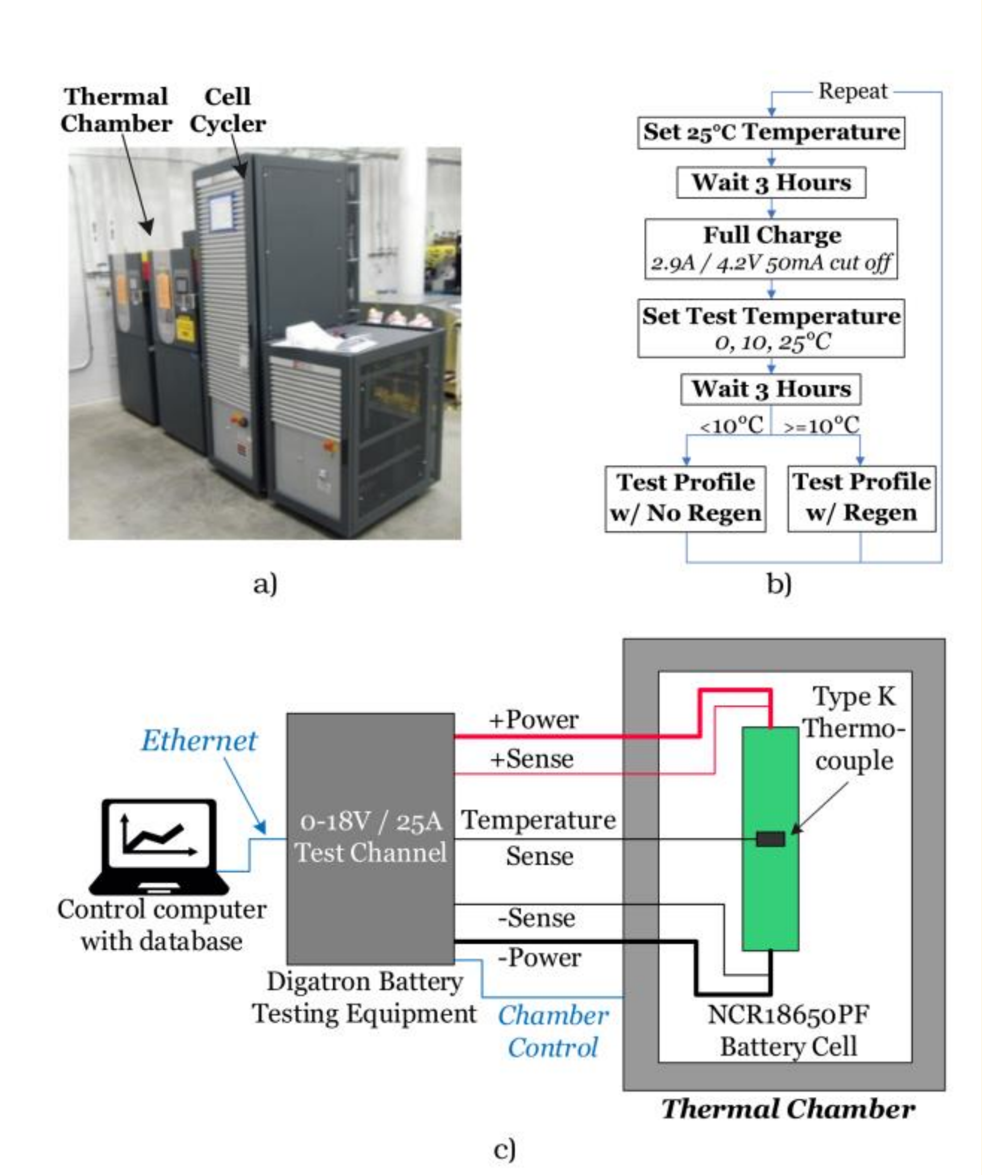


Image Credits: [10]

Data Treatment

Data Trimming

- Original data is recorded at 10 Hz. Only 1 out of 10 reading is considered to keep the dataset manageable.

Addition of Voltage difference column

- Insert the data column for Voltage difference feature

Series to Supervised Transformation

- Columns for past 400 timesteps are calculated and added.

Data Scaling

- Features are scaled from 0 to 1 or -1 to 1 depending on feature.

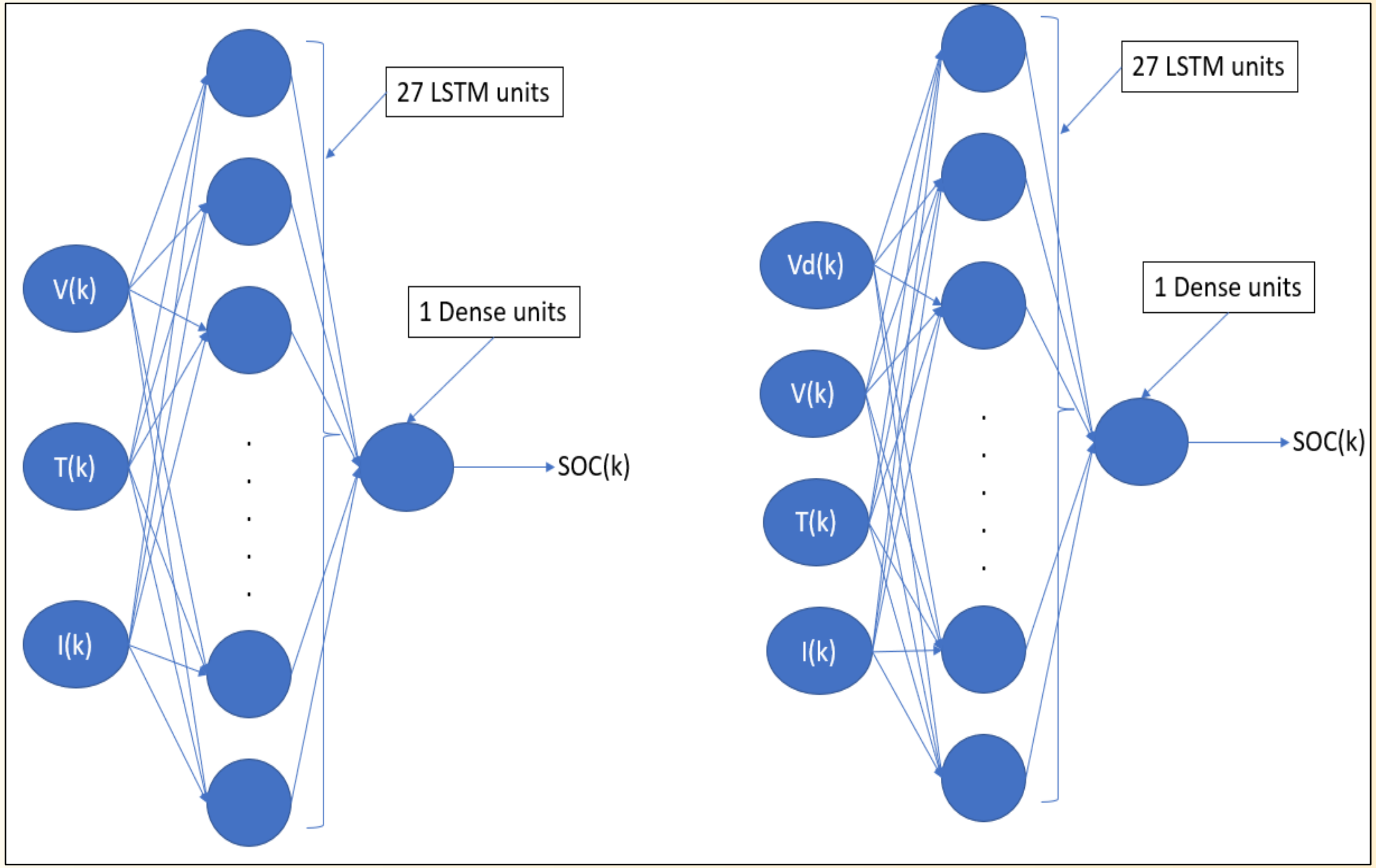
Shape Conversion

- 2D data is converted to the 3D matrix of shape [samples, timesteps, features].

Model Variants and Results

Base Model

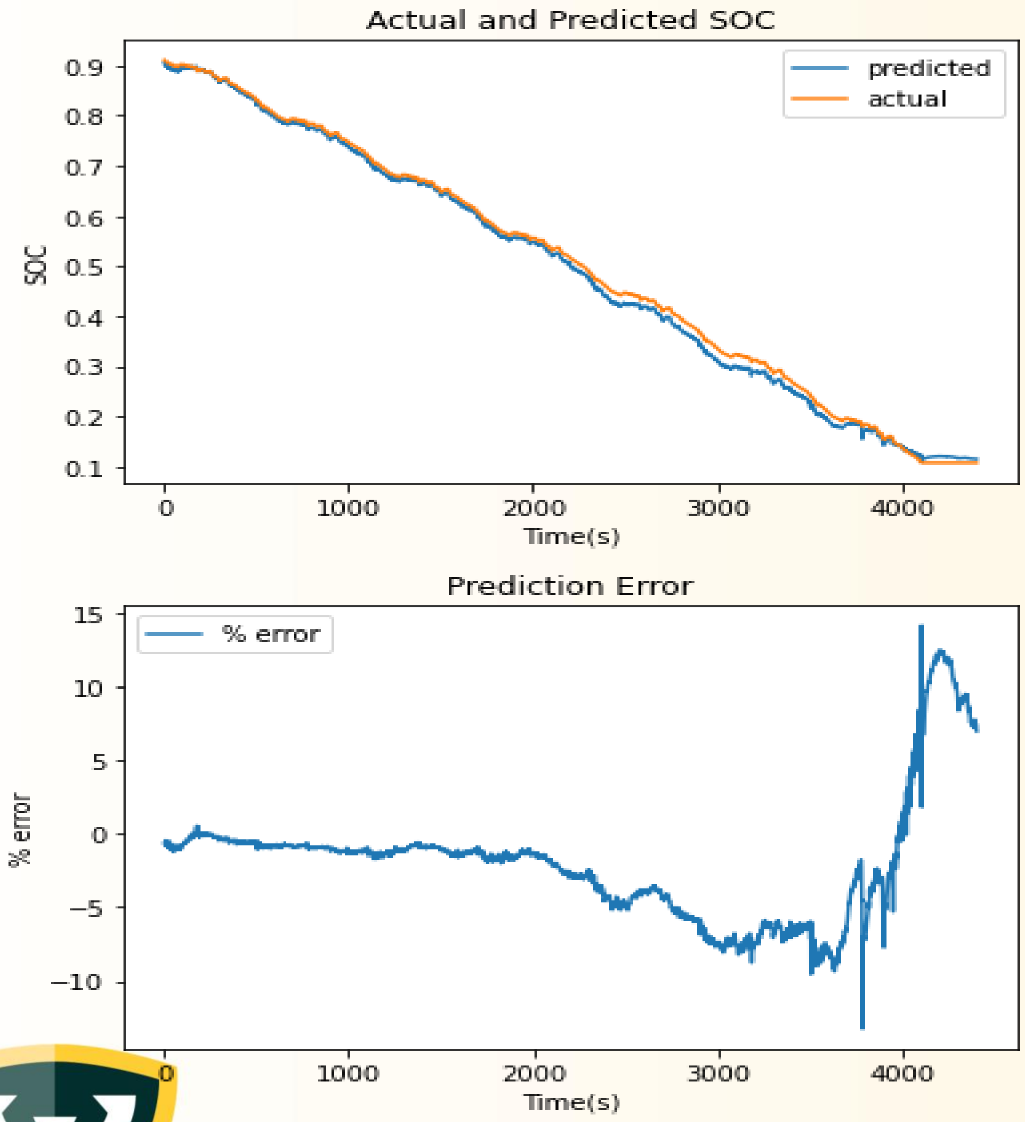
- ADAM optimizer
- ReLU activation for Dense unit.
- 500 epochs.

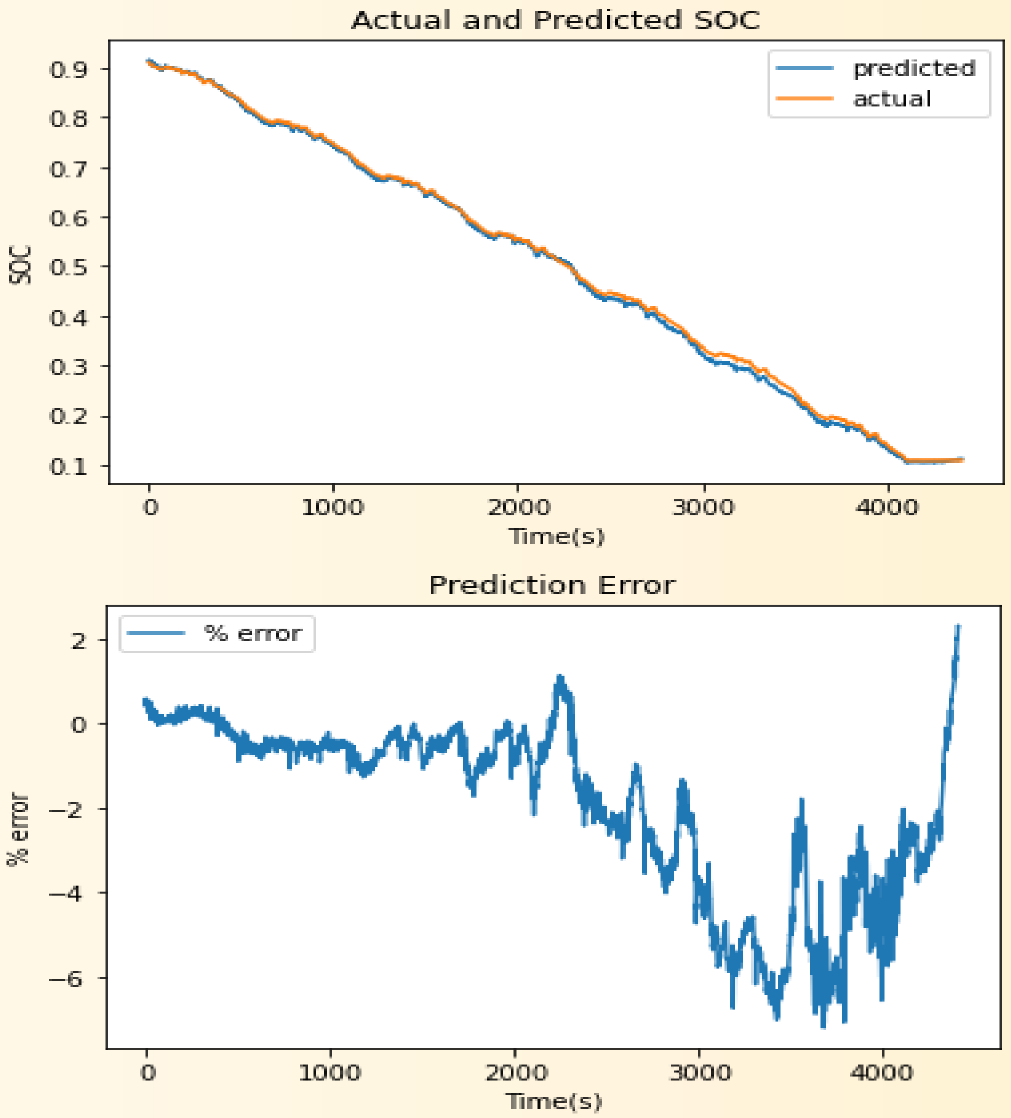


Base Model – 3 feature

Base Model – 4 feature

25°C Ambient results

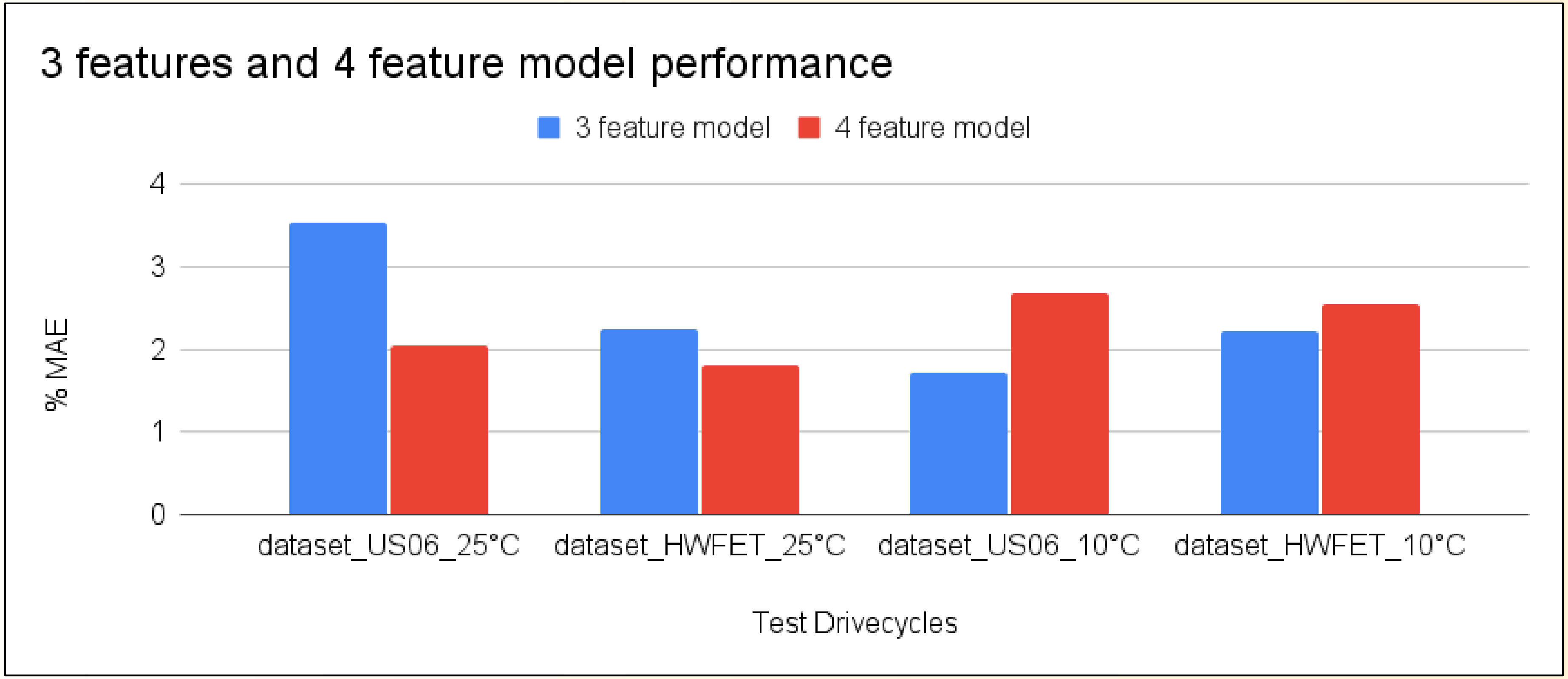




Base Model Performance Summary

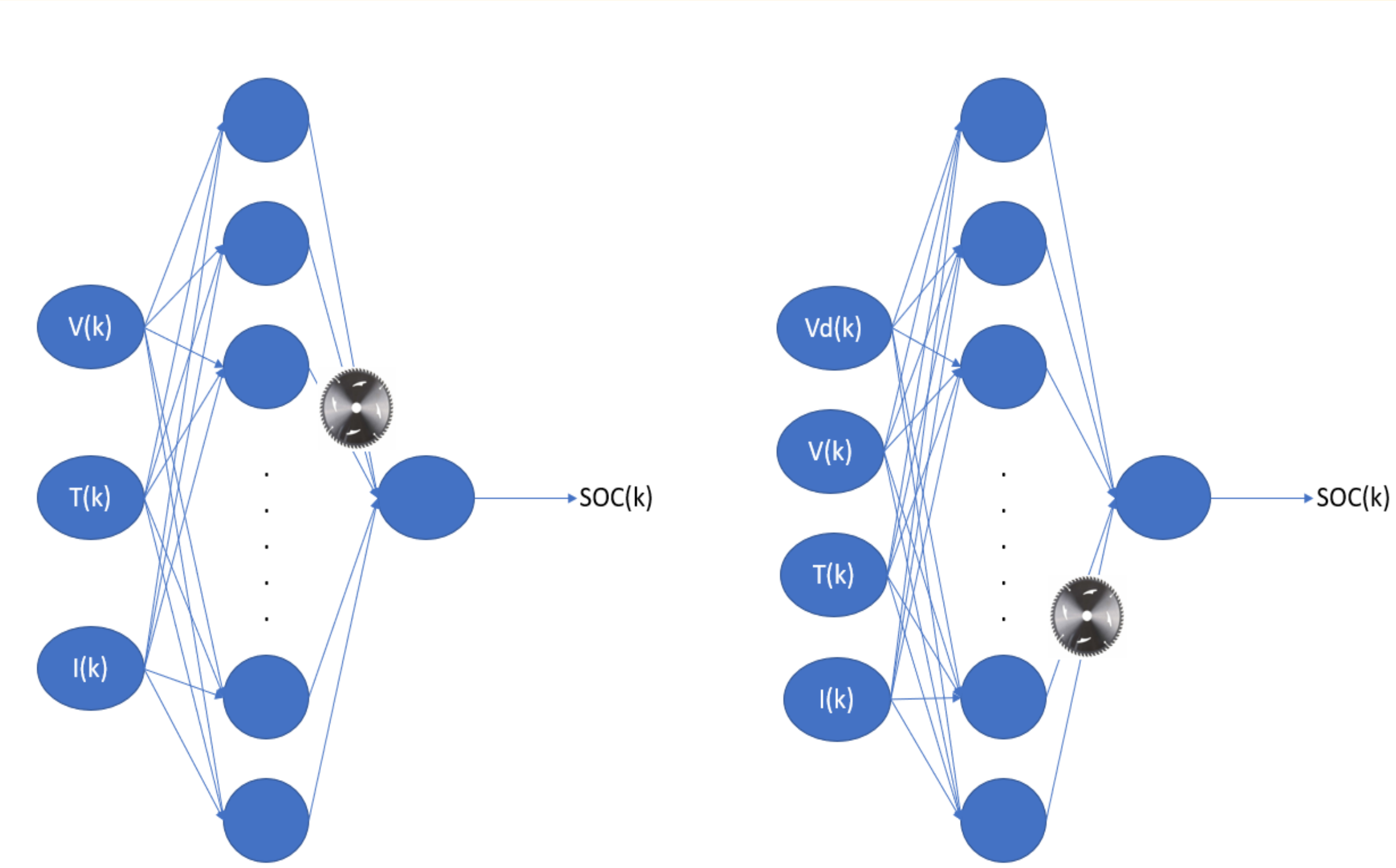
<u>Takeaway</u>

- 4 feature model performed poor for 10°C ambient conditions.
- It might indicate model's over reliance on temperature feature.



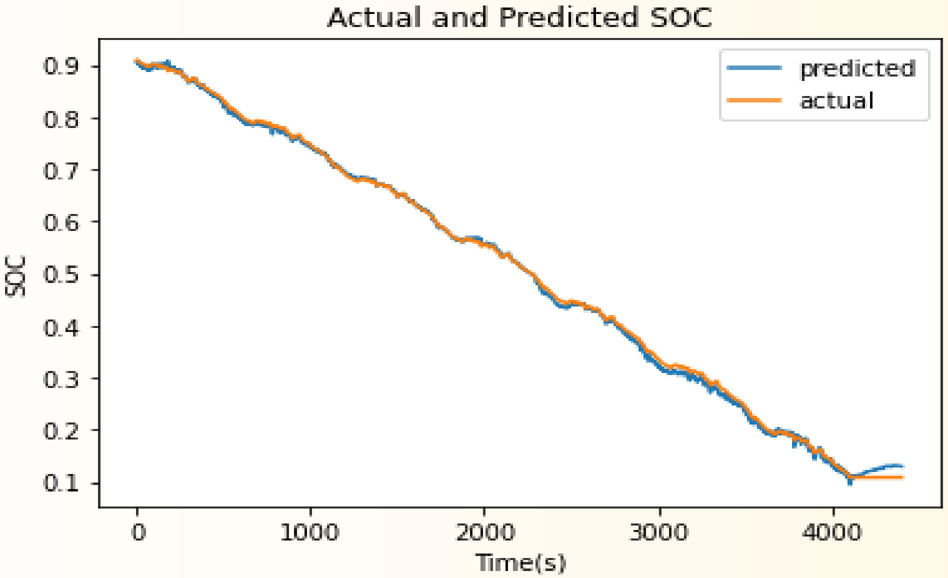
Base Model with dropout layer

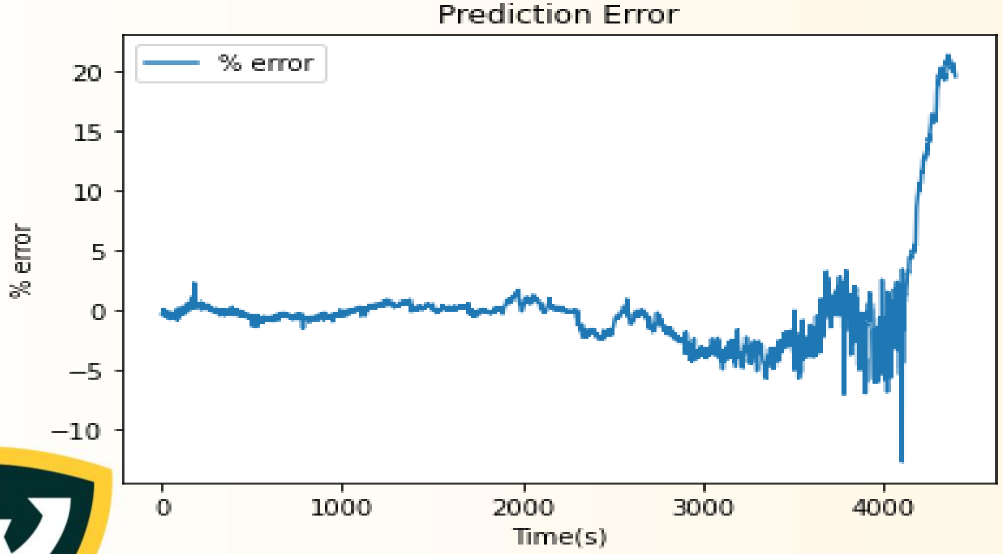
- Base model updated with dropout layer between LSTM and Dense layer.
- Gridsearch space: 11 configurations/model
- Dropout rate:
  - 3 feature: 0.1
  - 4 feature: 0.1



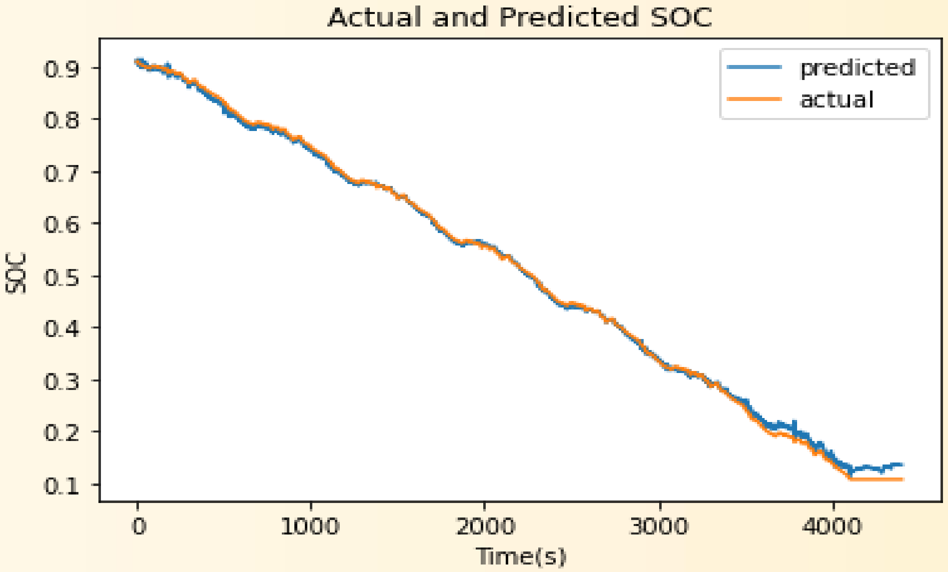
25°C Ambient results

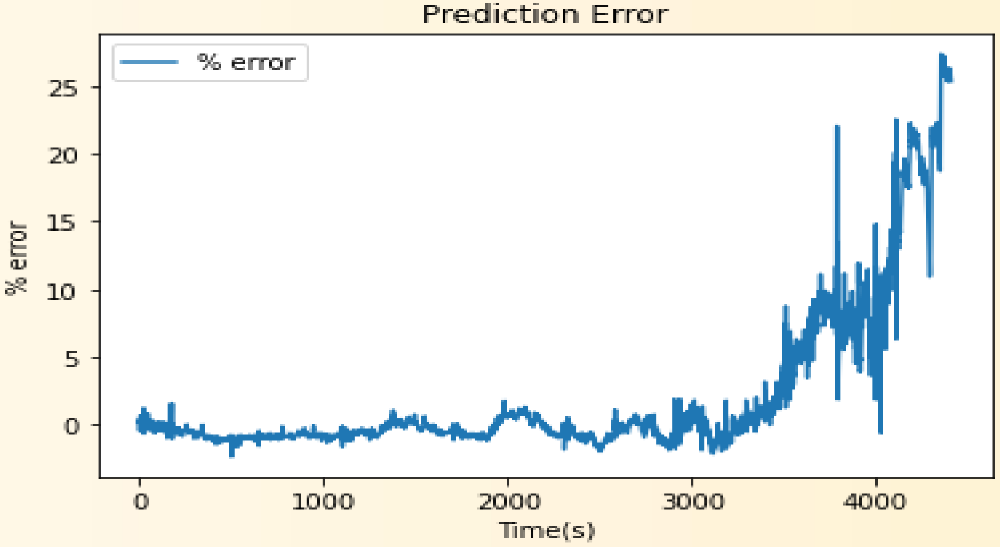
Base Model with dropout layer – 3 feature





Base Model with dropout layer – 4 feature

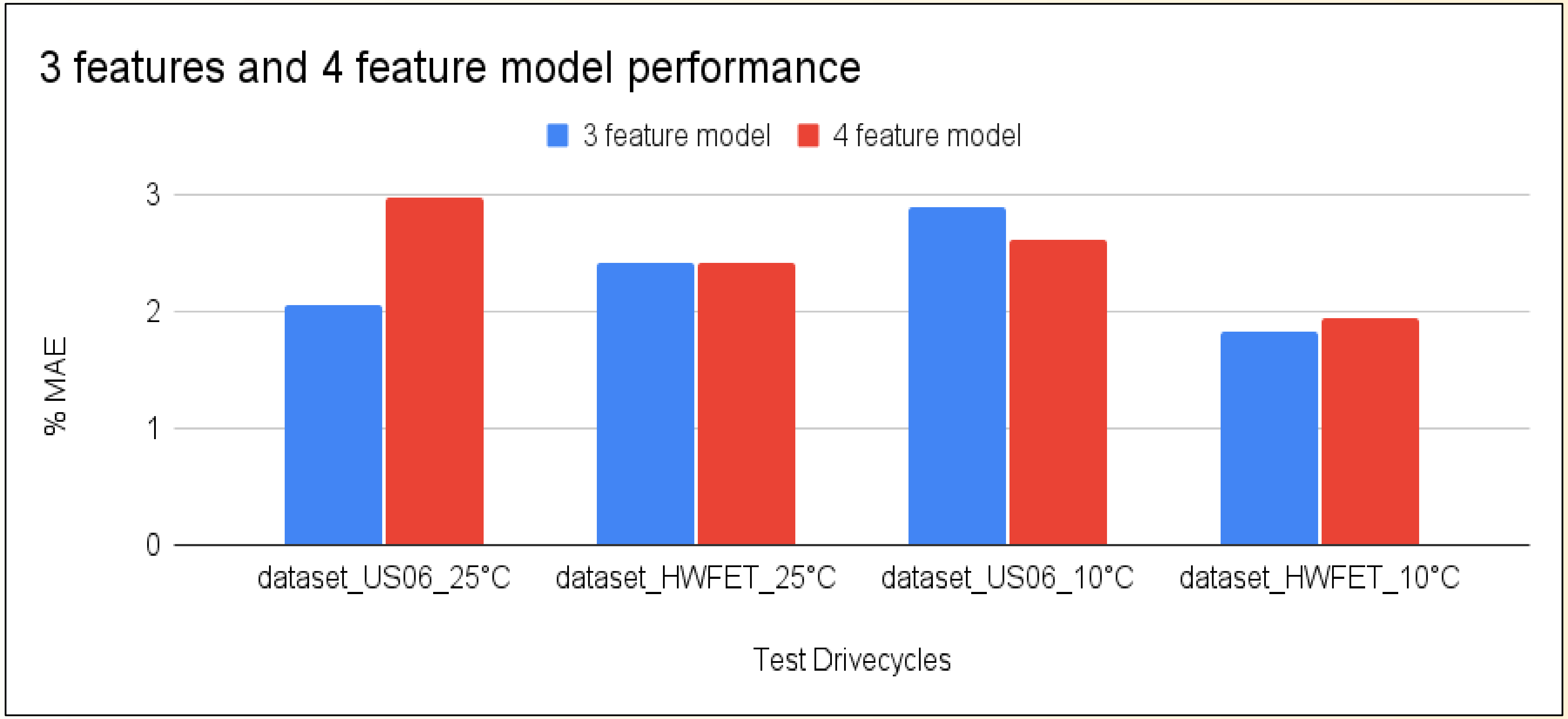




Base Model with dropout layer Performance Summary

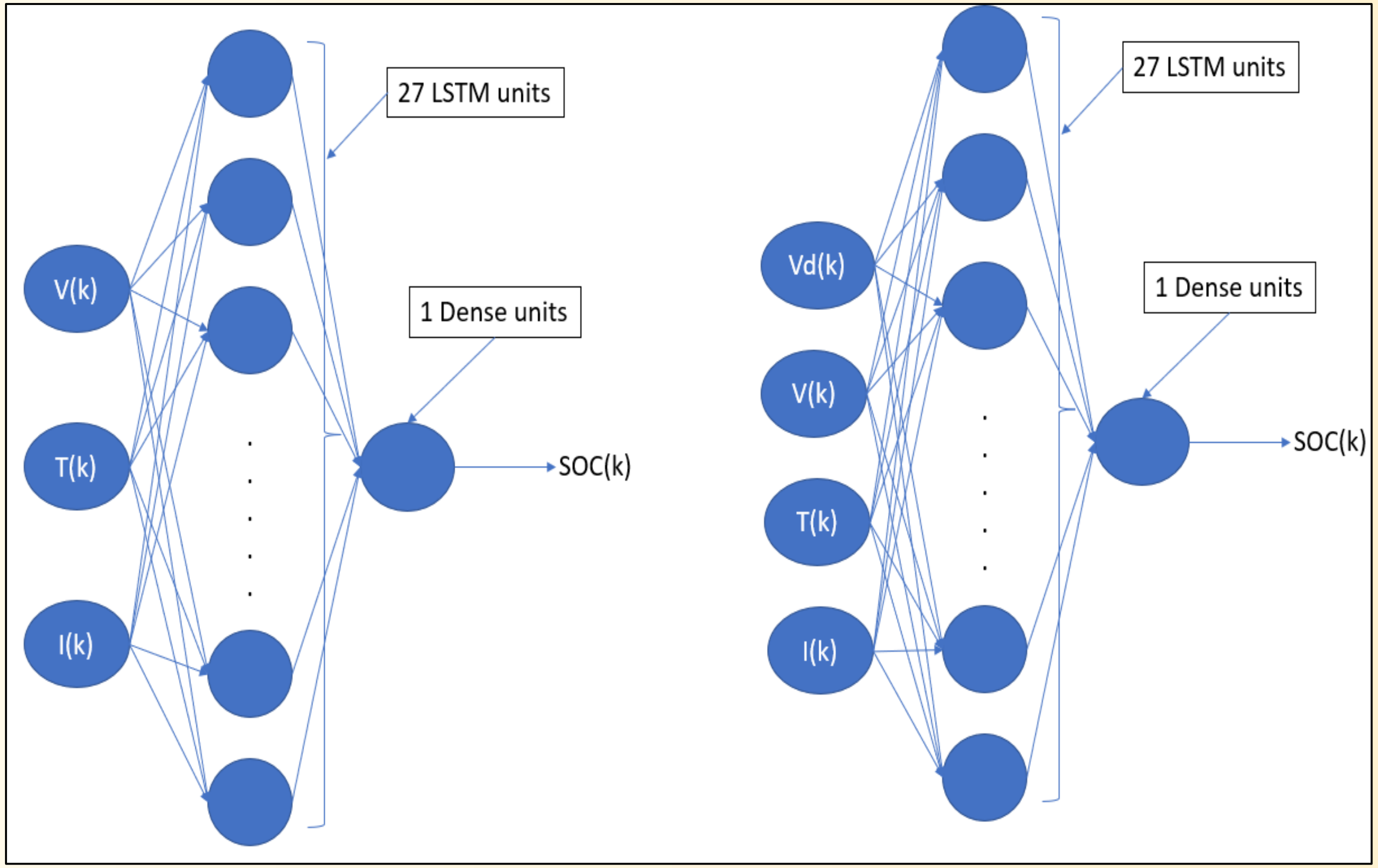
Takeaway

- Dropout layer removed over reliance on temperature feature.
- 4 feature model performed marginally better for 1 out of 4 drive cycles.



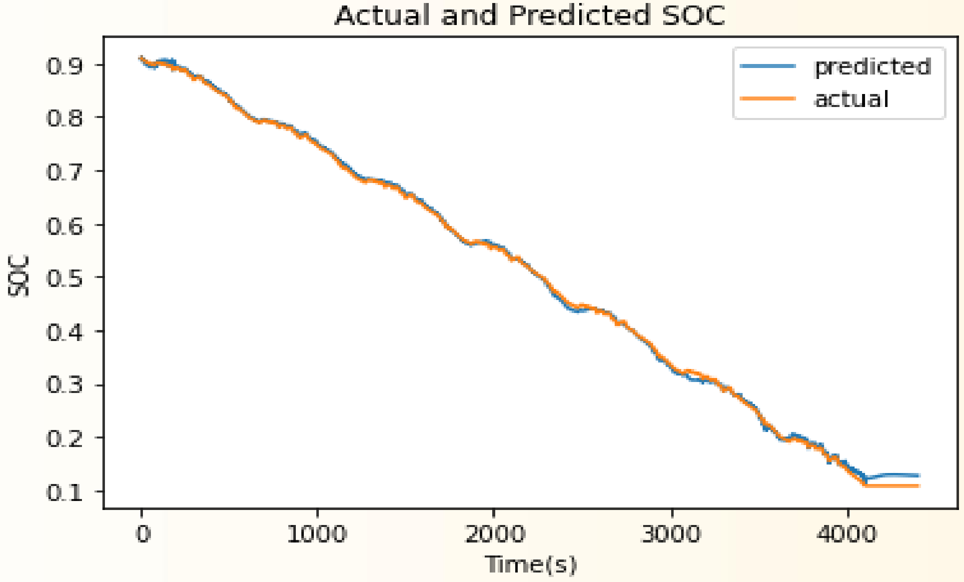
Base Model with L1L2 regularizer

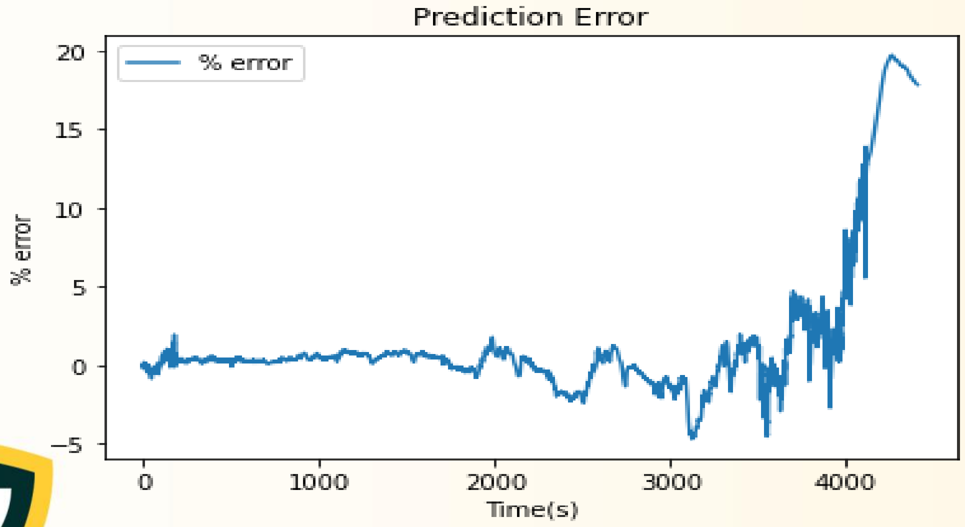
- Base model cost function updated to include L1L2 regularizer.
- Gridsearch space:25 configurations/model.
- L1L2 regularizer values:
  - 3 feature: L1=0.0,L2=0.01
  - 4 feature: L1=0.0,L2=0.1



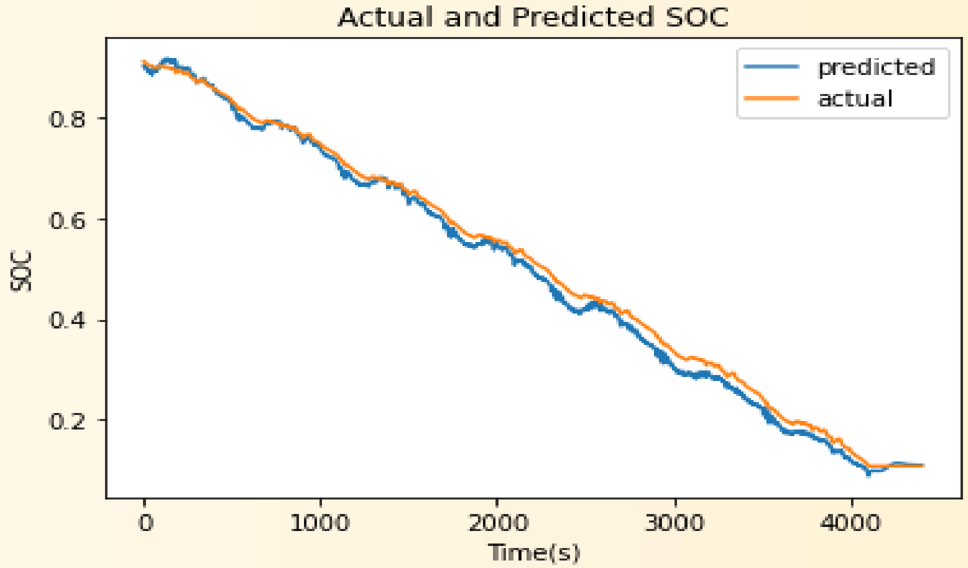
25°C Ambient results

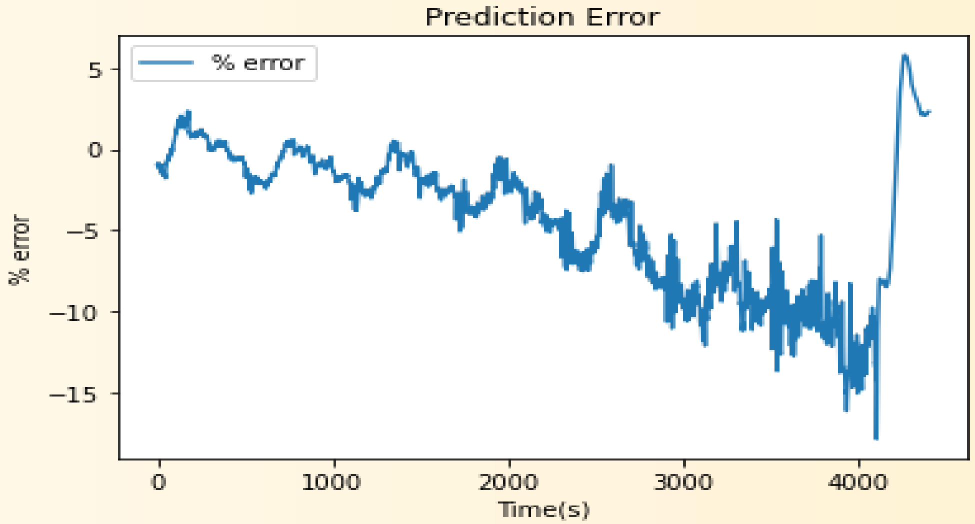
Base Model with L1L2 regularizer – 3 feature



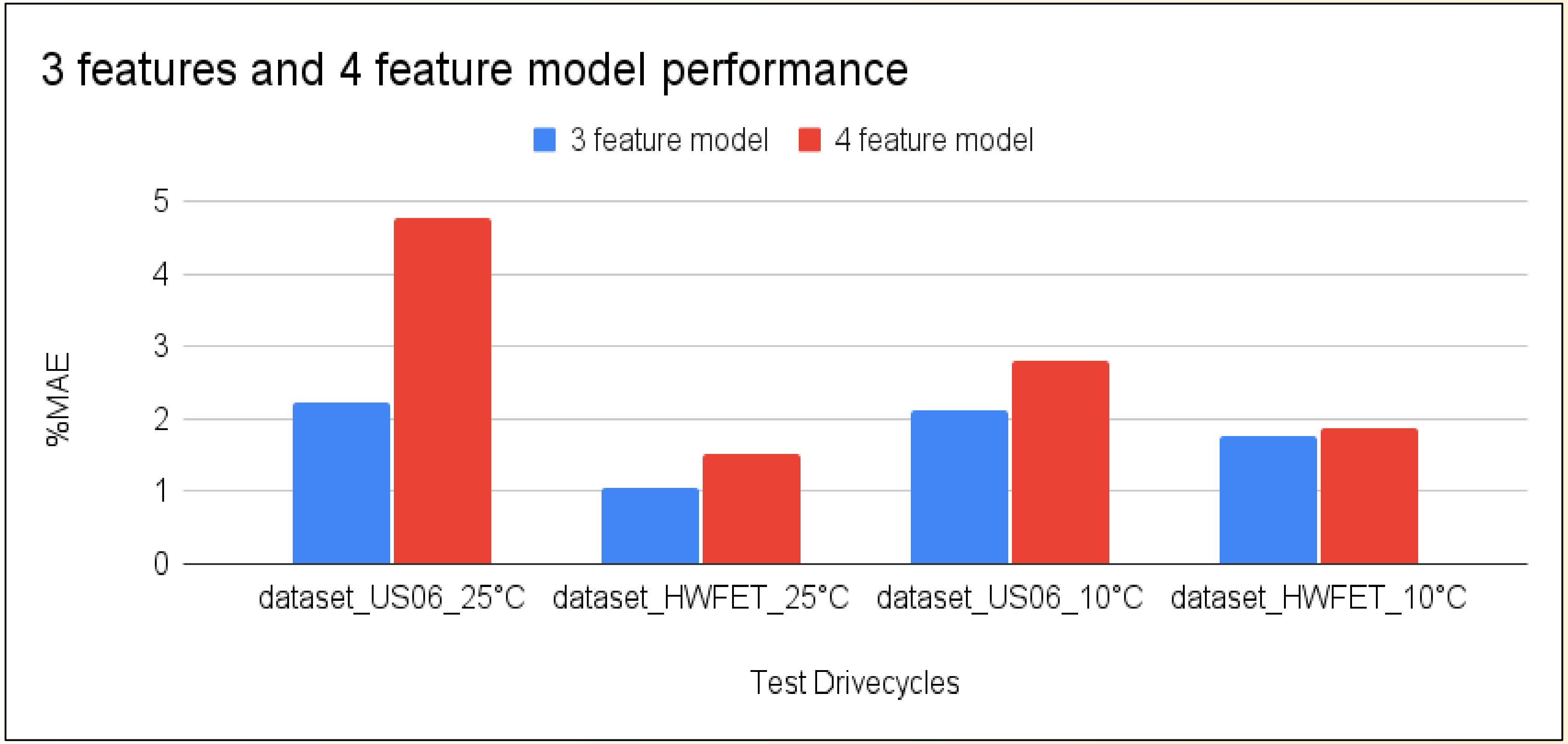


Base Model with L1L2 regularizer – 4 feature





Base Model with L1L2 regularizer Performance Summary

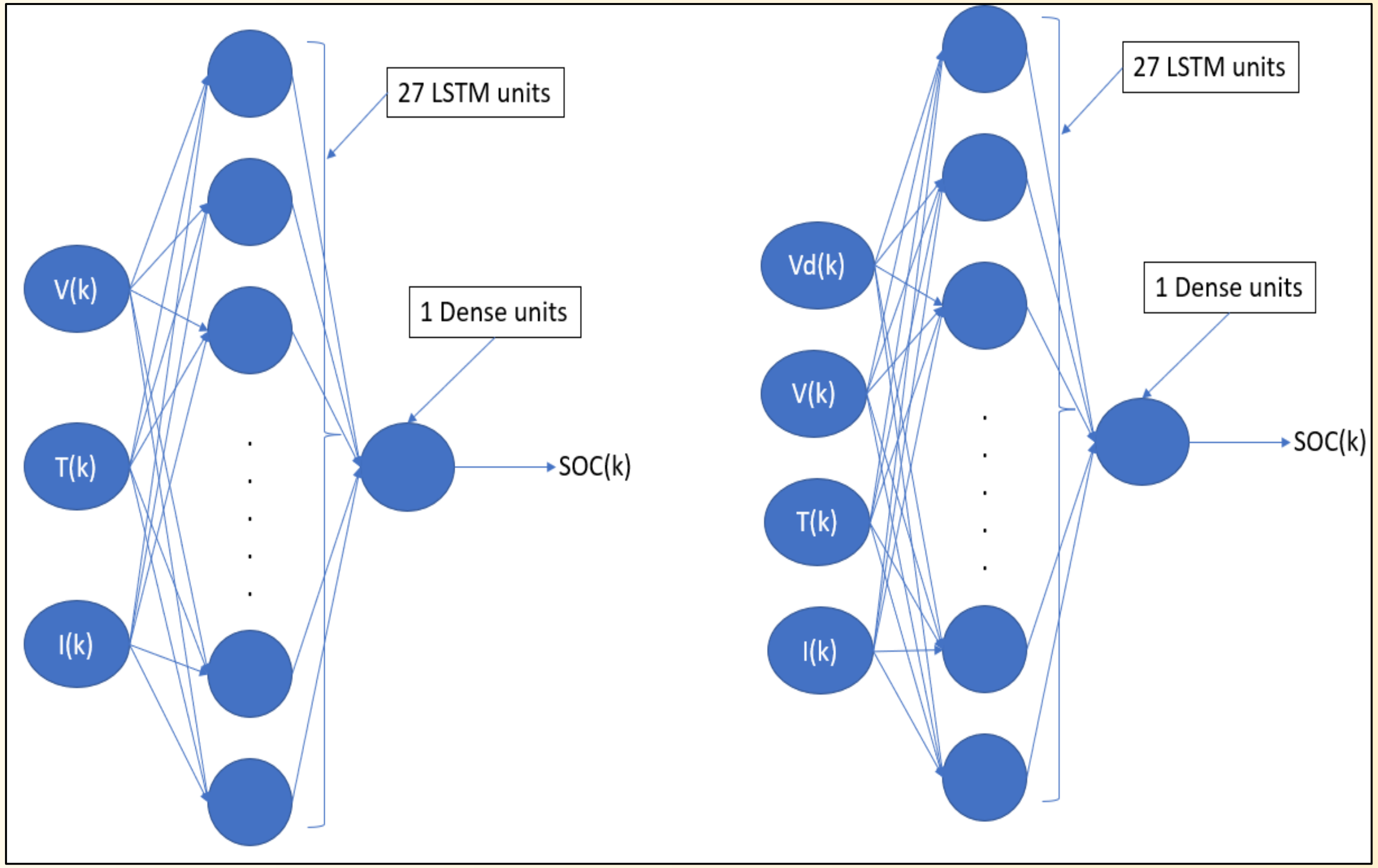


<u>Takeaway</u>

- 4 feature model performed poor for all drive cycles.

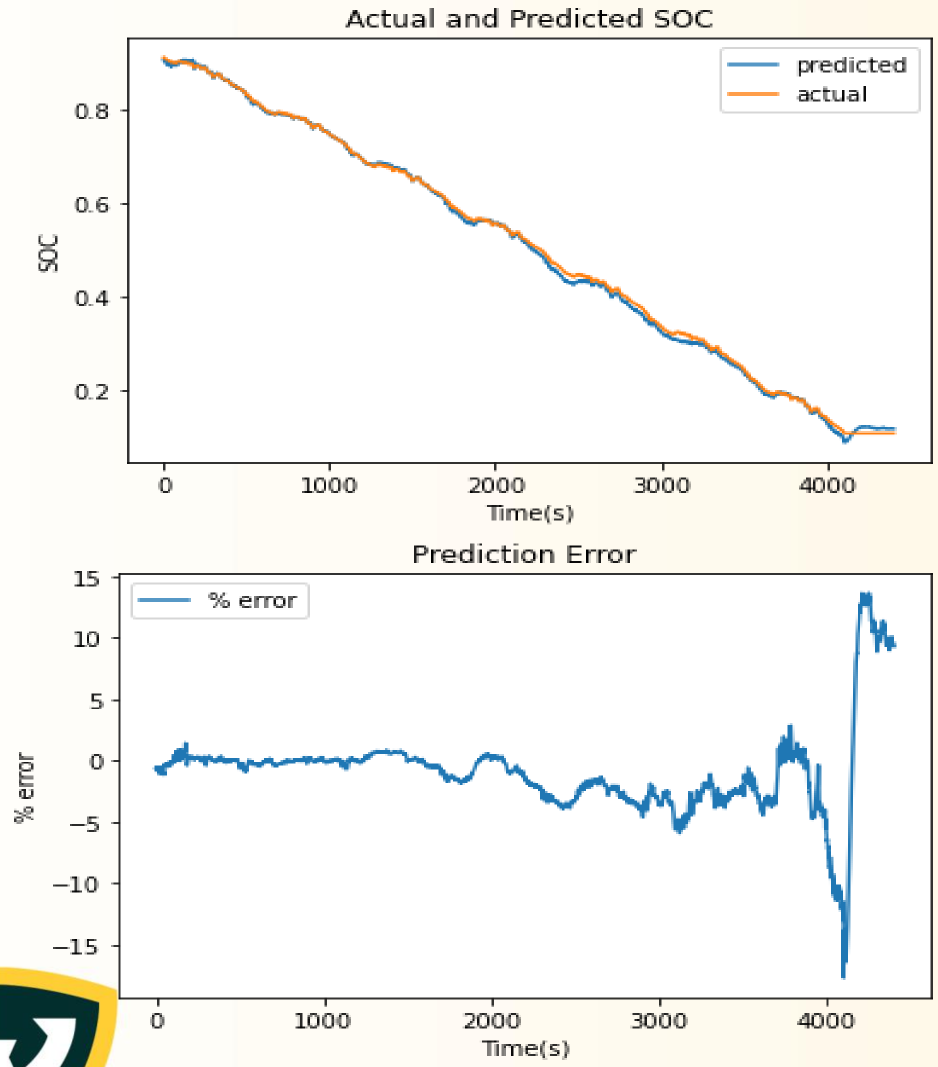
Base Model with Dropout layer and L1L2 regularizer

- Base model updated with dropout layer and cost function updated to include L1L2 regularizer.
- Gridsearch size: 275 configurations/model.
- Dropout rate:
  - 3 features: 0.0
  - 4 features: 0.0
- L1L2 regularizer values:
  - 3 feature: L1=0.0,L2=0.001
  - 4 feature: L1=0.0,L2=0.01

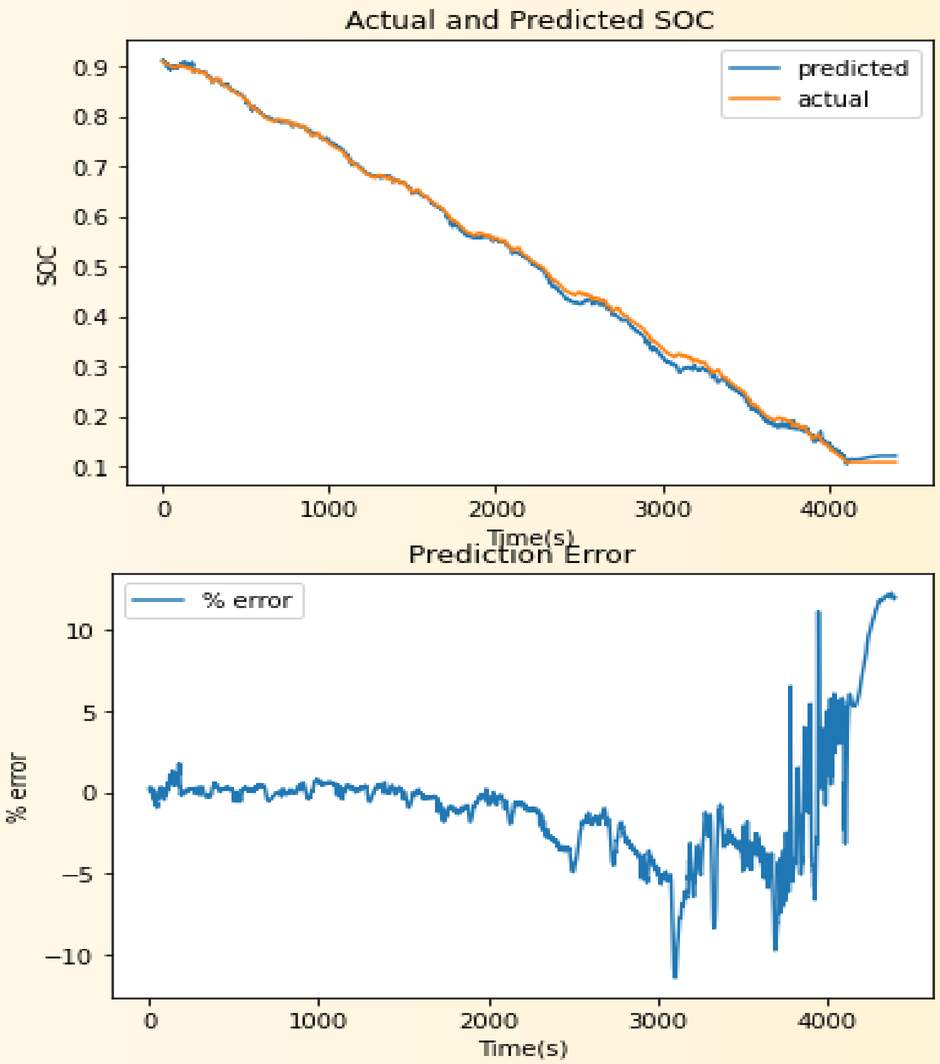


25°C Ambient results

Base Model with Dropout layer and L1L2 regularizer – 3 feature



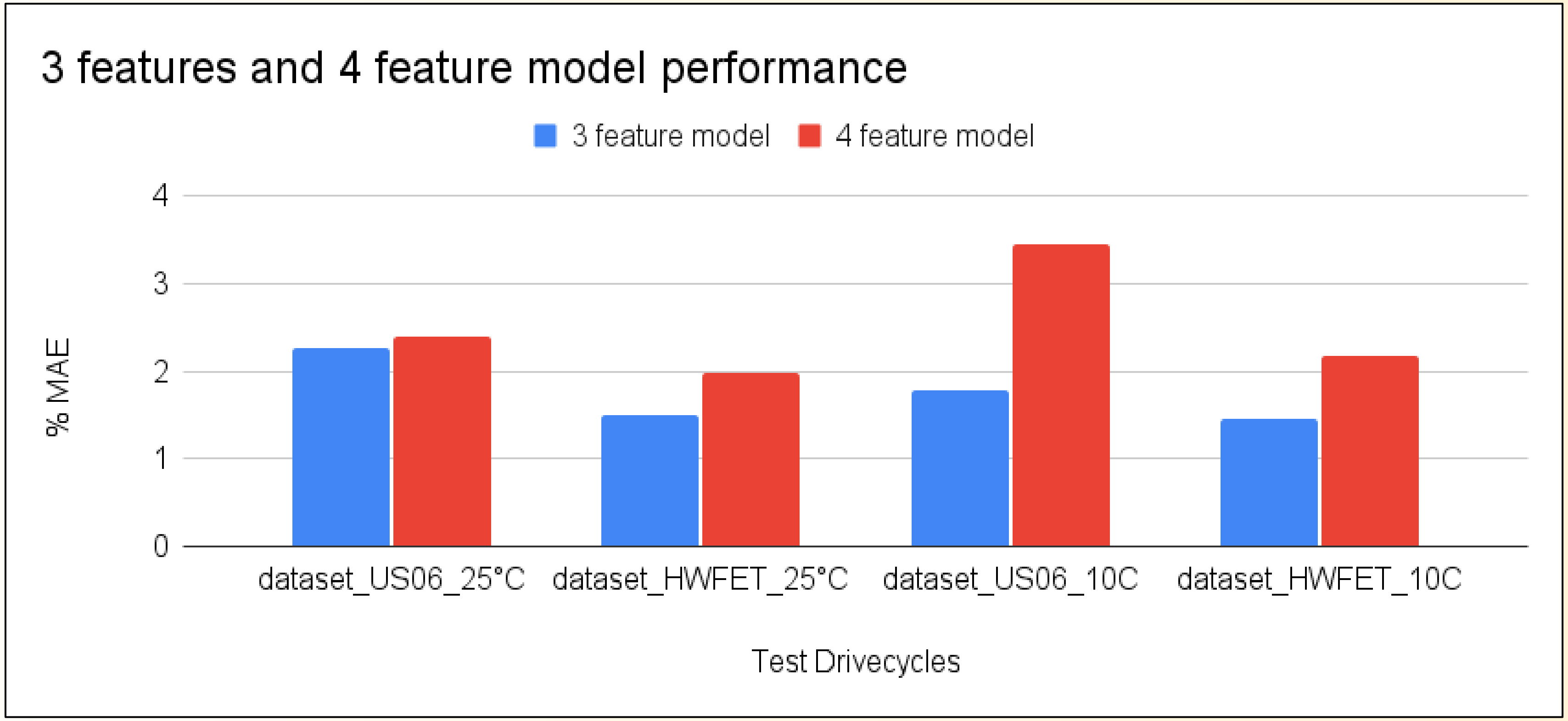
Base Model with Dropout layer and L1L2 regularizer – 4 feature



Base Model with Dropout layer and L1L2 regularizer Performance Summary

<u>Takeaway</u>

- 4 feature model performed poor for all drive cycles.



Conclusions and Future Work

Conclusions

Model Variant	4 feature model performance relative to 3 feature model performance
Base Model	Better for 25°C ambient condition
Base Model with Dropout layer	Marginally better for 1 out of 4 drive cycles
Base Model with L1L2 regularizer	Poor for all drive cycles
Base Model with Dropout layer and L1L2 regularizer	Poor for all drive cycles

- 2-layer LTSM-RNN networks can predict SOC with in excellent manner with relatively less training.
- Under given circumstances: Voltage difference as a feature did not provide any additional useful information to LSTM-RNN models which can aid in SOC prediction.

Future work

- Use more diverse experimental data – varying ambient temperature, sub 0°C temperatures etc.
- Change the time horizon in Voltage difference feature.
- Use Deep Feed Forward Neural Networks instead of LSRM-RNN.
- Test hypothesis using synthetic data : experimental data + noise

Contributions

- Established a frame-work for experimental data processing
- Architected LSTM-RNN models for SOC Prediction using 3 and 4 features
- Statistical analysis of “Voltage difference” feature
- Benchmarked 3 feature and 4 feature models objectively.

Image Credits: [11]

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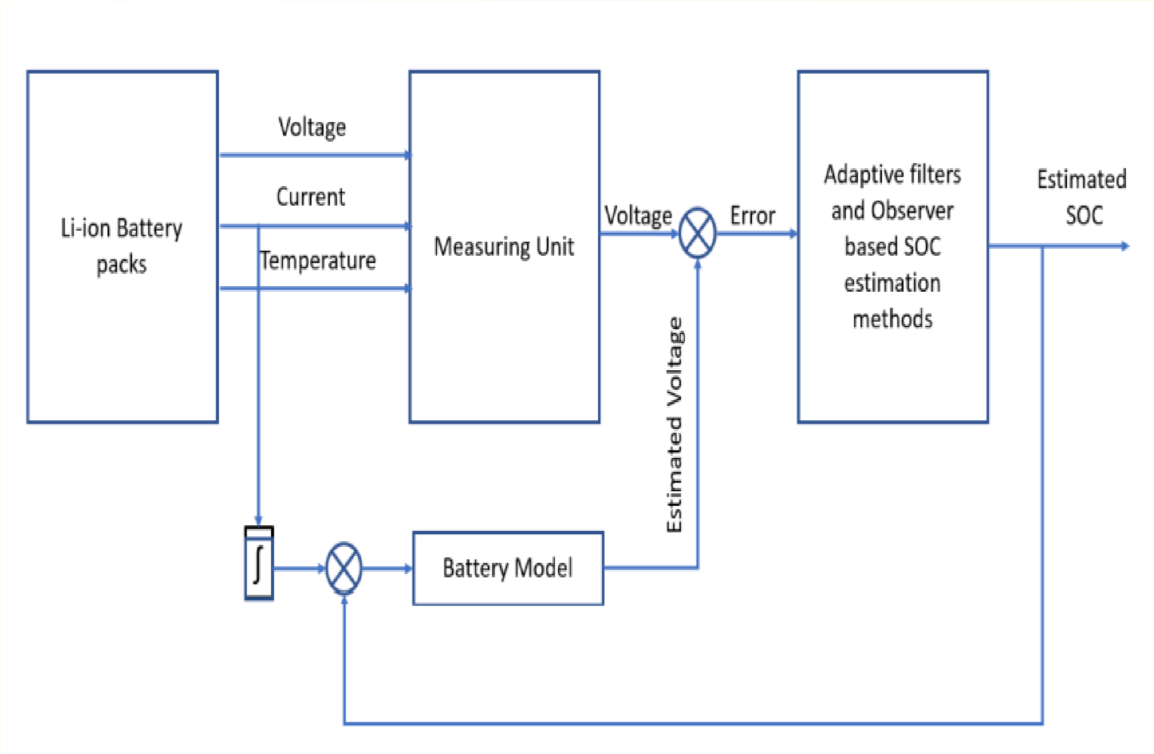
Backup

Model Based Methods

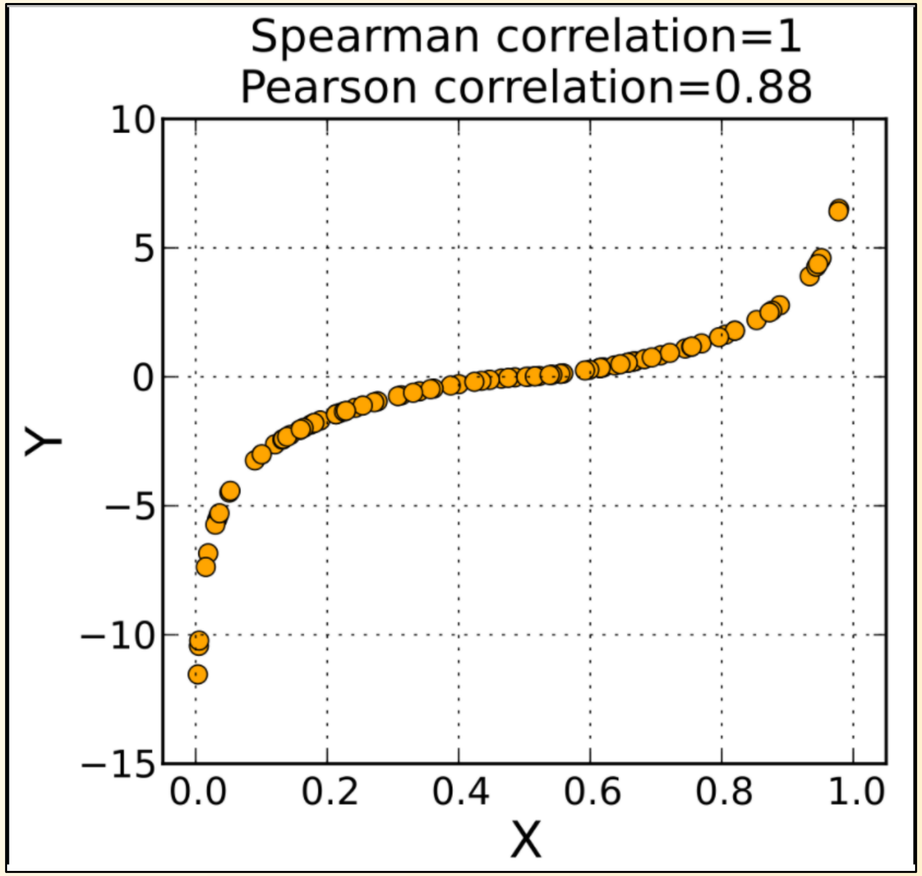
- Voltage, Current, and Temperature are used to model the battery.
- Error for Voltage is calculated.
- This error when fed to an Observer, will predict the SOC Value. SOC value is fed back to the Battery model to make a closed loop.
- Observers: Luenberger, Adaptive, Sliding Mode, Kalman Filter.



Spearman Coefficient

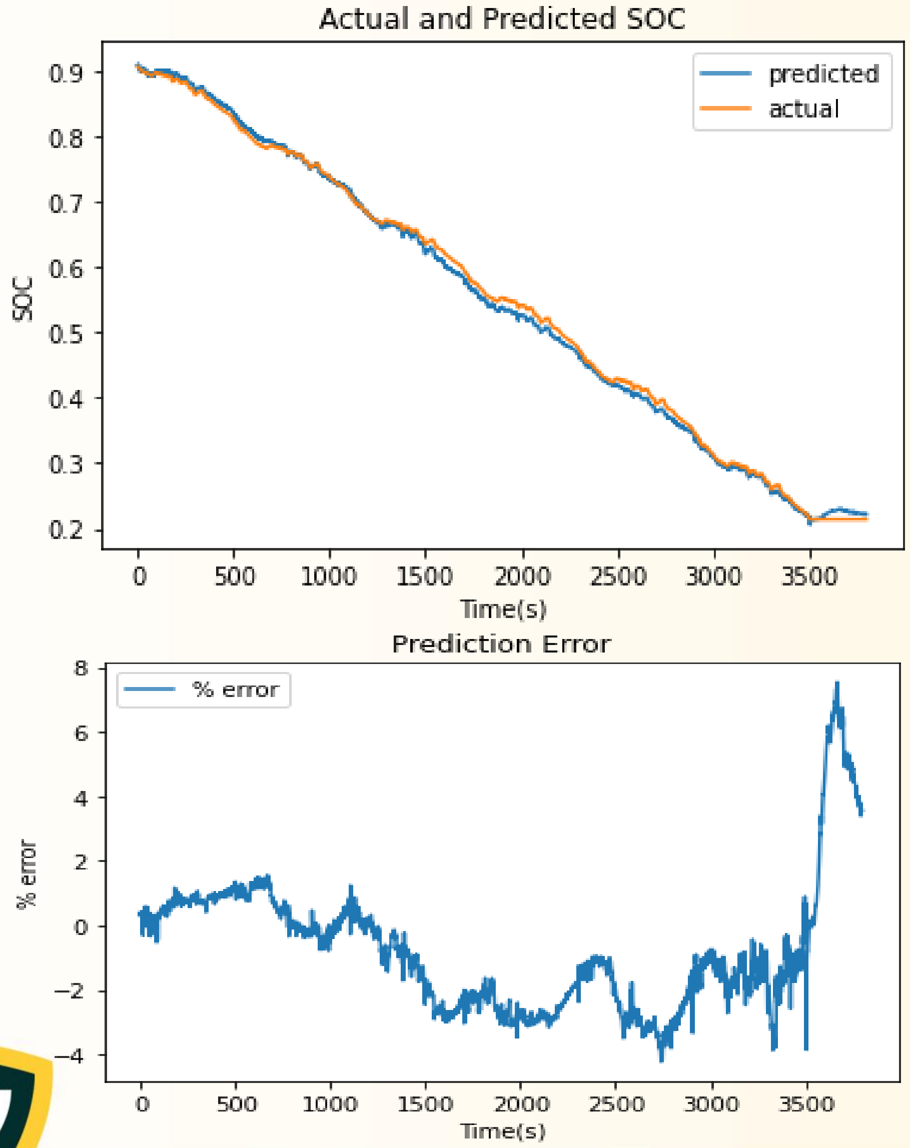
- Used to summarize the strength between two data samples.
- Coefficient value: -1 to 1.
- Useful for non-gaussian distributions.

Spearman's correlation coefficient = covariance(rank(X), rank(Y)) / (stdv(rank(X)) * stdv(rank(Y)))

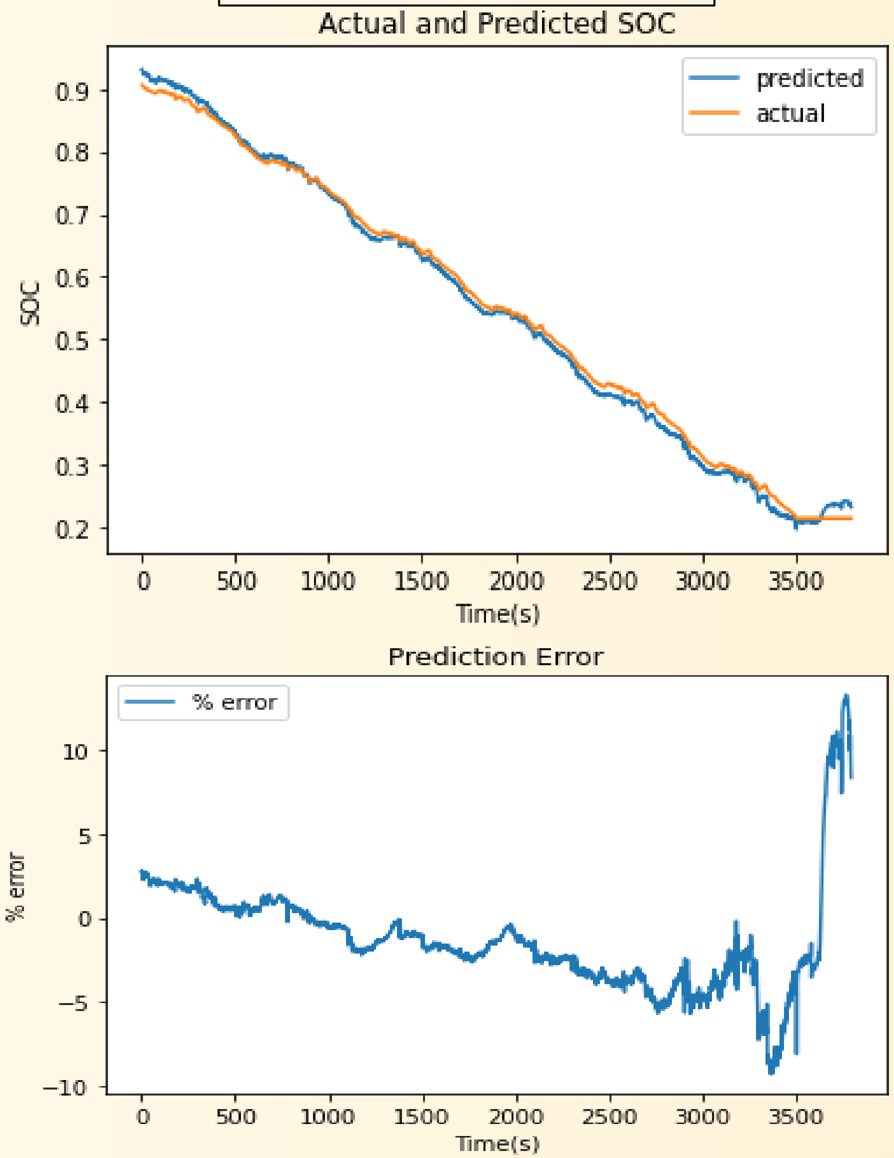


10°C Ambient results

Base Model – 3 feature

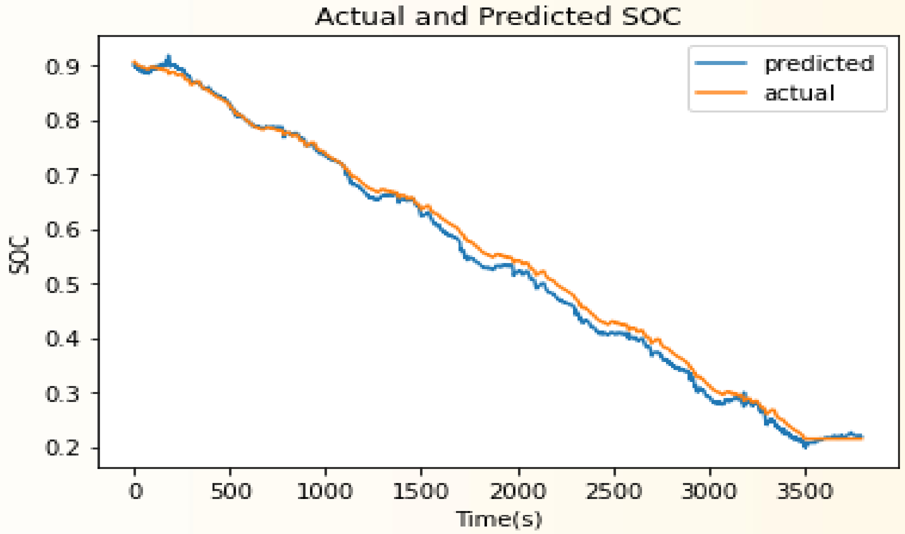


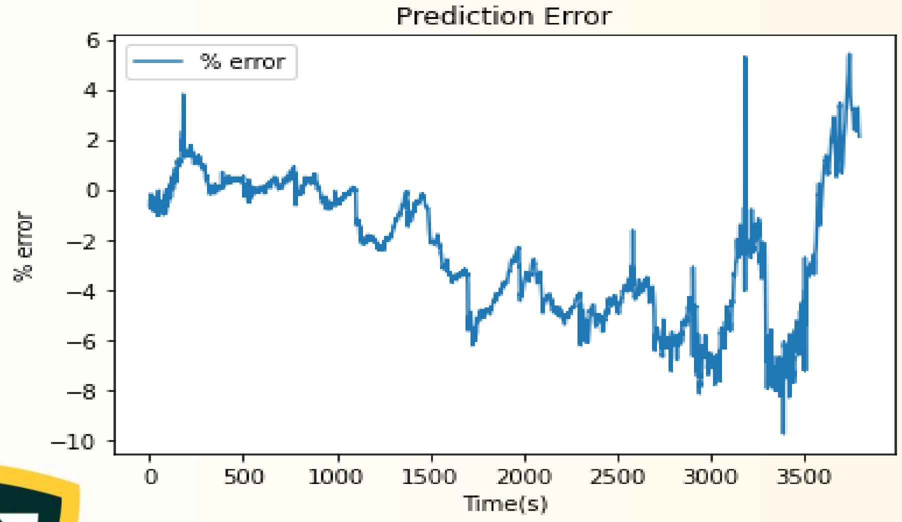
Base Model – 4 feature



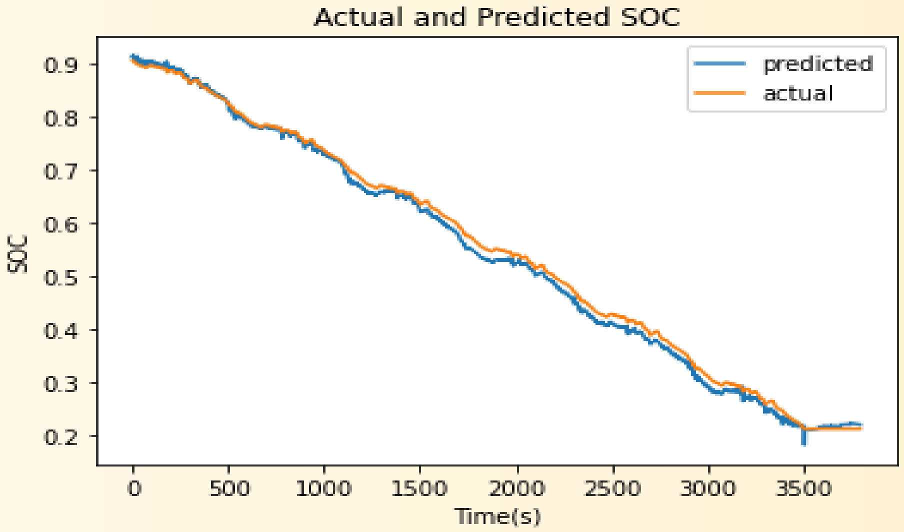
10°C Ambient results

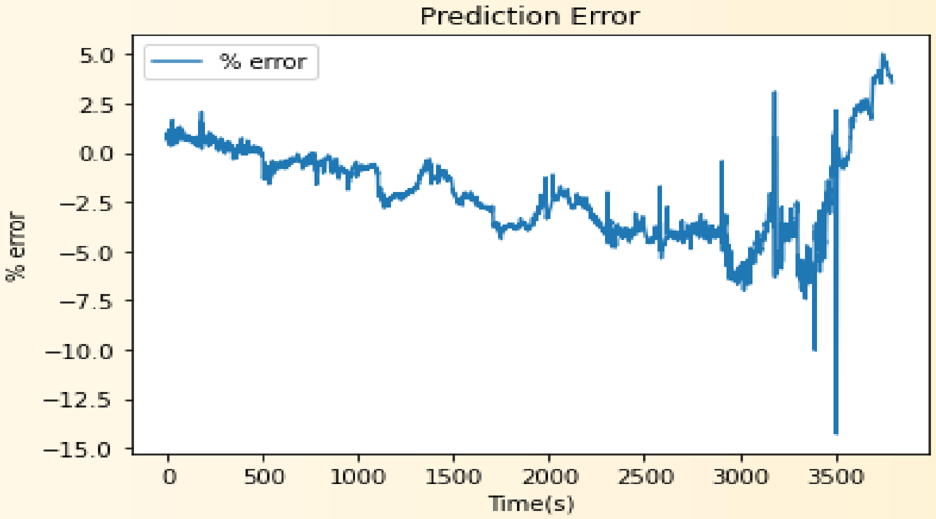
Base Model with Dropout layer – 3 feature





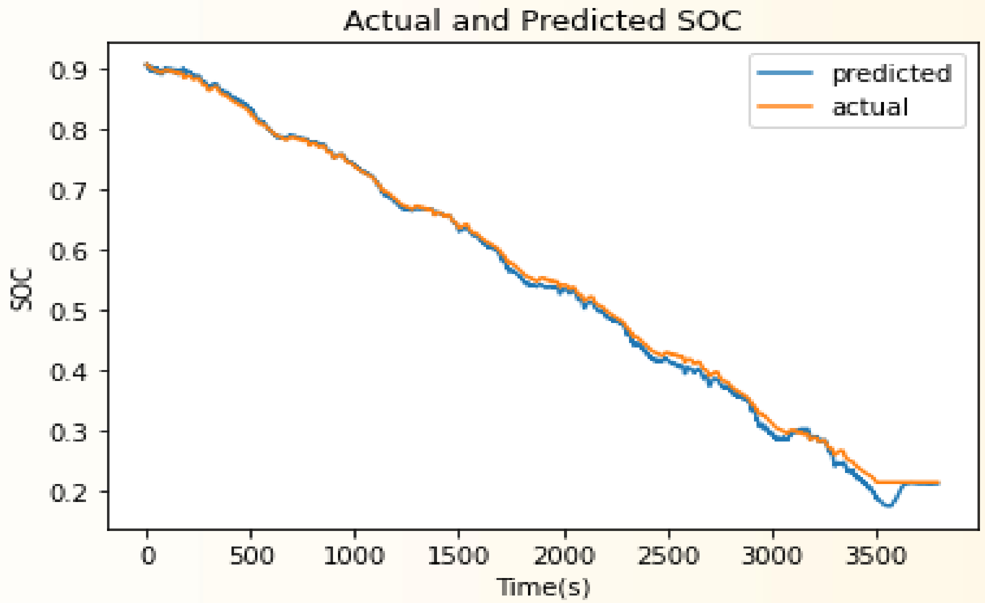
Base Model with Dropout layer – 4 feature

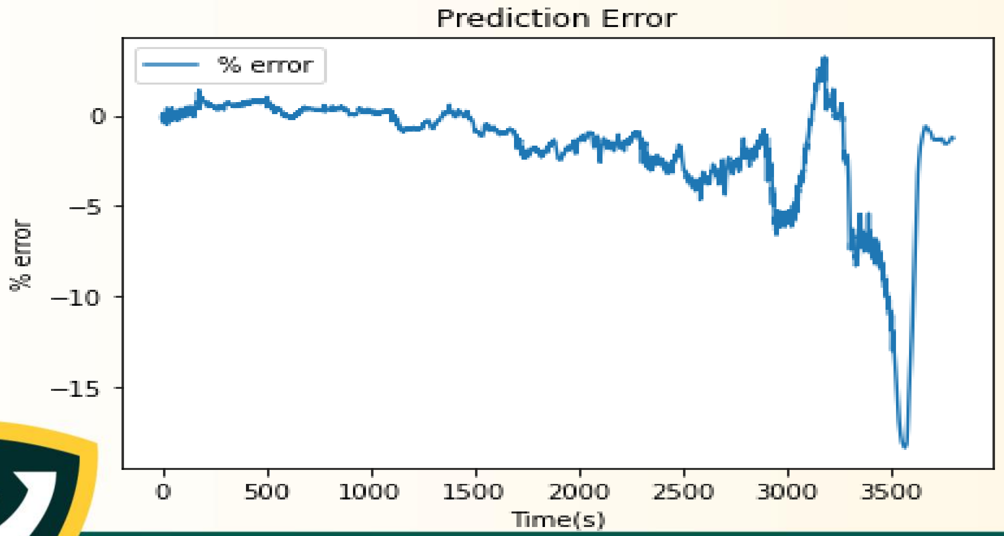




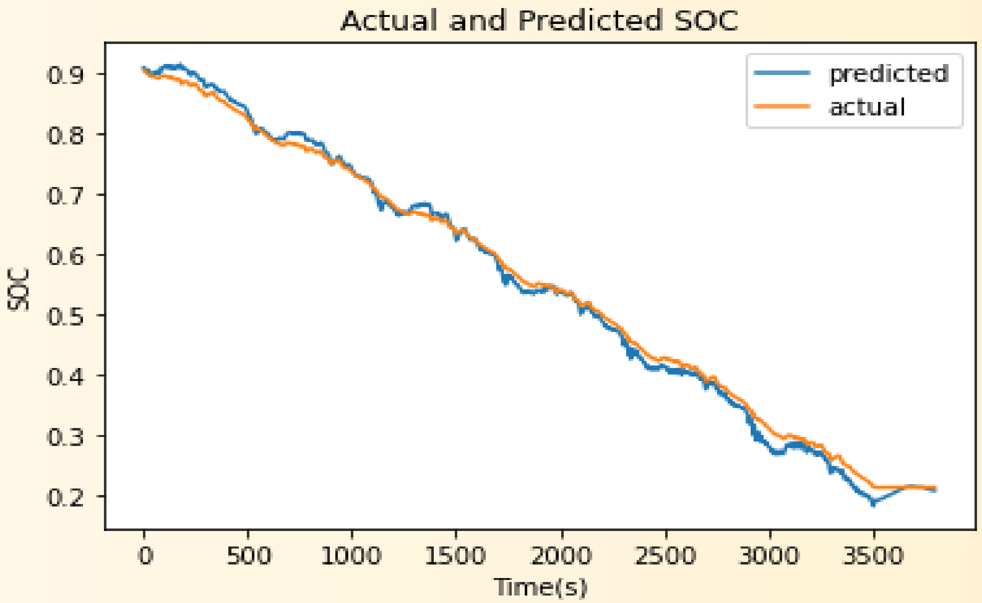
10°C Ambient results

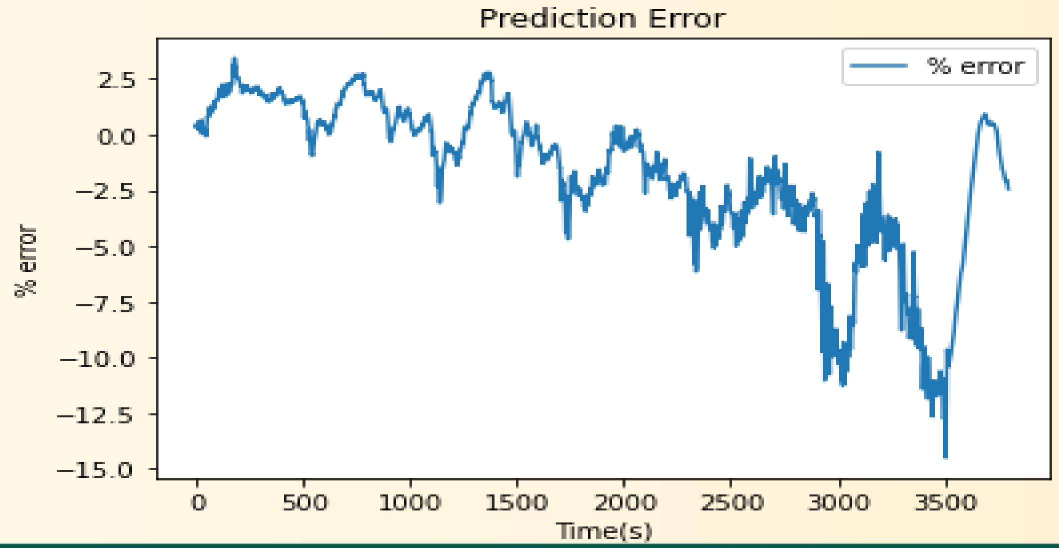
Base Model with L1L2 regularizer – 3 feature





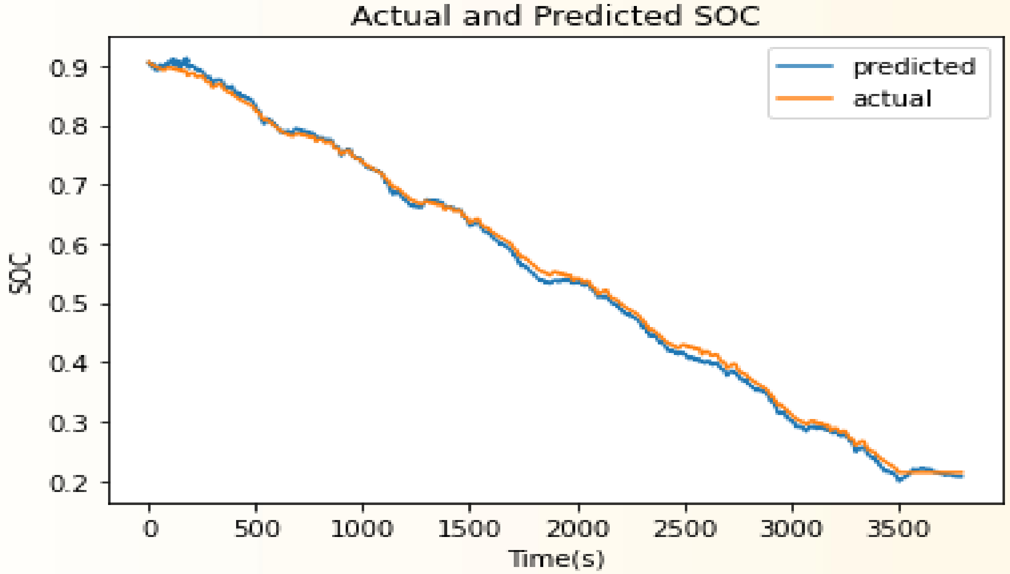
Base Model with L1L2 regularizer – 4 feature

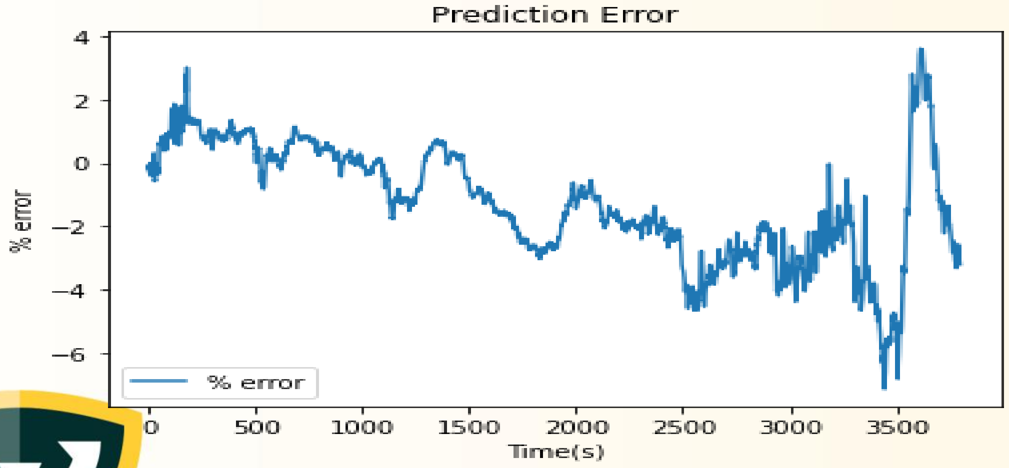




10°C Ambient results

Base Model with Dropout layer and L1L2 regularizer – 3 feature





Base Model with Dropout layer and L1L2 regularizer – 4 feature