End Term Presentation of BTP project

Real Time Battery Monitoring System Using Machine Learning

Presented by

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Introduction

BMS Systems

- To track the **use of energy** inside a battery and to prevent the risk of damage.
- Sensing, Protection and Estimation
- Measuring the data, capturing and estimating the State of Charge and other metrics.
- Application in portable electronic devices

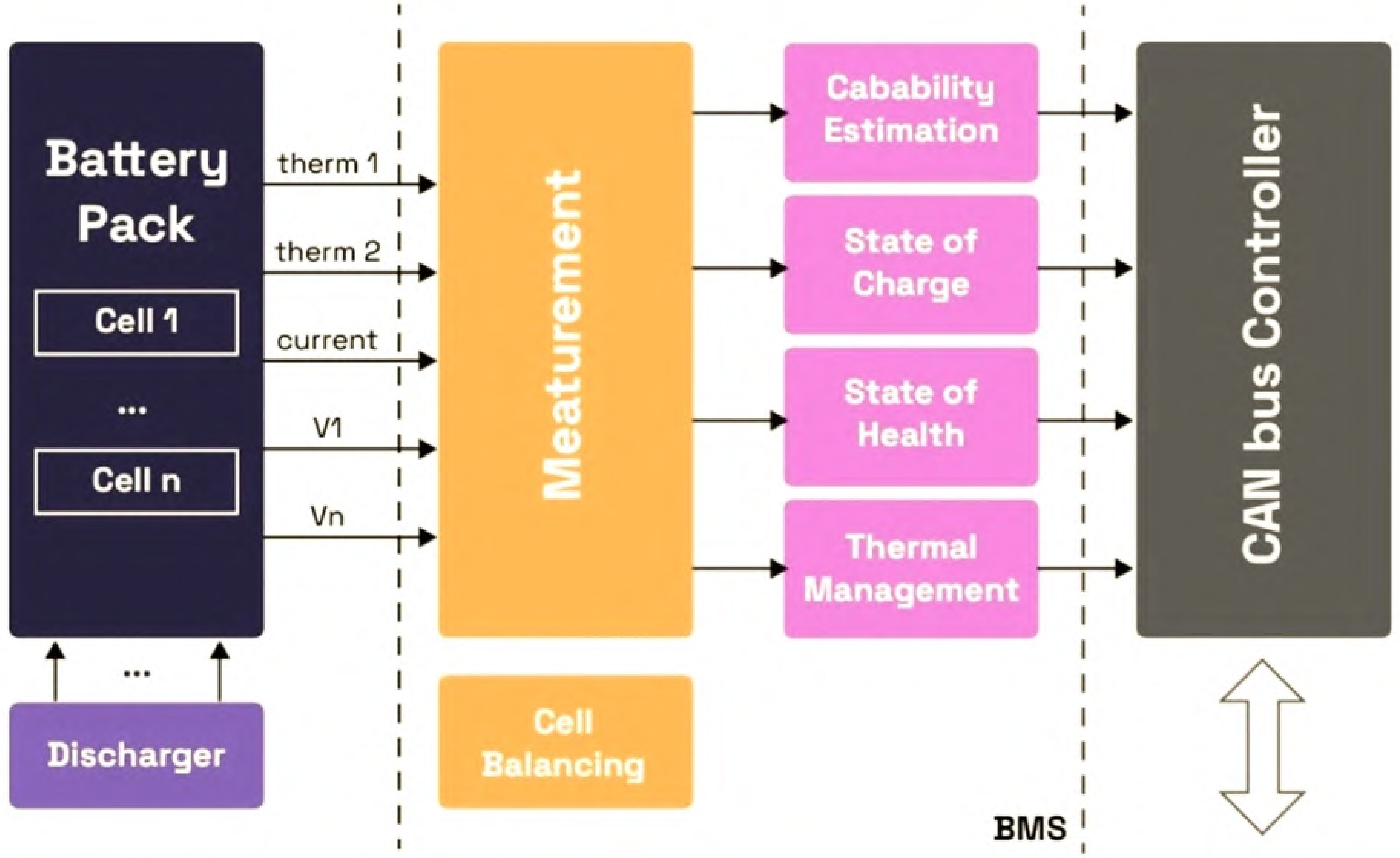


Fig 1 - BMS Working

Literature Review

Sr.No	Paper Title	Authors
1.	XGBoost: A Scalable Tree Boosting System (2016) *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794	Chen, T. Guestrin, C.
2.	Prediction of soil water infiltration using multiple linear regression and random forest in a dry flood plain, eastern Iran. *CATENA*, *194*, 104715.(2020)	Pahlavan-Rad M. R. Dahmardeh K. Hadizadeh M., Keykha G. Mohammadnia N. Gangali M.Keikha M. Davatgar N.Brungard
3.	A tutorial on support vector regression. Statistics and Computing, 14(3), 199–222.(2004).	*Smola, A. J. Schölkopf, B.*
4	Overview of machine learning approach for Lithium Ion Battery Remaining Useful Lifetime Prediction. Electronics	Si Siyu Jin Xin Siyu Xinroug Huang Shunli Wang Remus Tedorescu Daniel Ioan Stroe

Table 1

Literature Review

Sr.No	Paper Title	Authors
5.	Stock price prediction using support vector regression on daily and up to the minute prices. *The Journal of Finance and Data Science*, *4*(3), 183–201.(2018).	Henrique, B. M. Sobreiro, V. A. Kimura, H.
6.	Decision tree methods: applications for classification and prediction. Shanghai Archives of Psychiatry	Ying LU Yan-yan Song
7.	Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *J Big Data* 53 (2021)	*Alzubaidi, L.* *Zhang, J.* *Humaidi, A.J. et al.*
8.	Predicting the current and future state of the battery using data driven machine learning Natural Machine Intelligence	Man-Fai Ng Jin Zhao Qingyu Yan Gareth Conduit Zhi Wei Seh

Table 2

Literature Review

Sr.No	Paper Title	Authors
9.	A Guide to Lithium Polymer Batteries for Drones Article – Tyro Robotics	Lauren Nagel
10.	Battery Management System : Hardware Concepts – An Overview Applied Sciences MDPI (Page 2-14)	Markus Lelie Thomas Braun Marcus Knips Hannes Nordmann Florian Ringbeck Hendrick Zappen Dirk Uwe Sauer
11.	Design a Battery Monitoring System for Lead-Acid Battery International Journal of Creative Research Thoughts (IJCRT) (Page 302-310)	*Niraj Agarwal* *Phulchand Saraswati* *Ashish Malik* *Yogesh Bateshwar*
12.	Machine Learning Approaches in Battery Management Systems: State of the Art: Remaining useful life and fault detection IEEE Explore (Page 63-64)	Ardeshiri, R. R., Balagopal, B., Al-Sabah, A., Ma, C., Chow, M.-Y

Table 3

Problem Statement

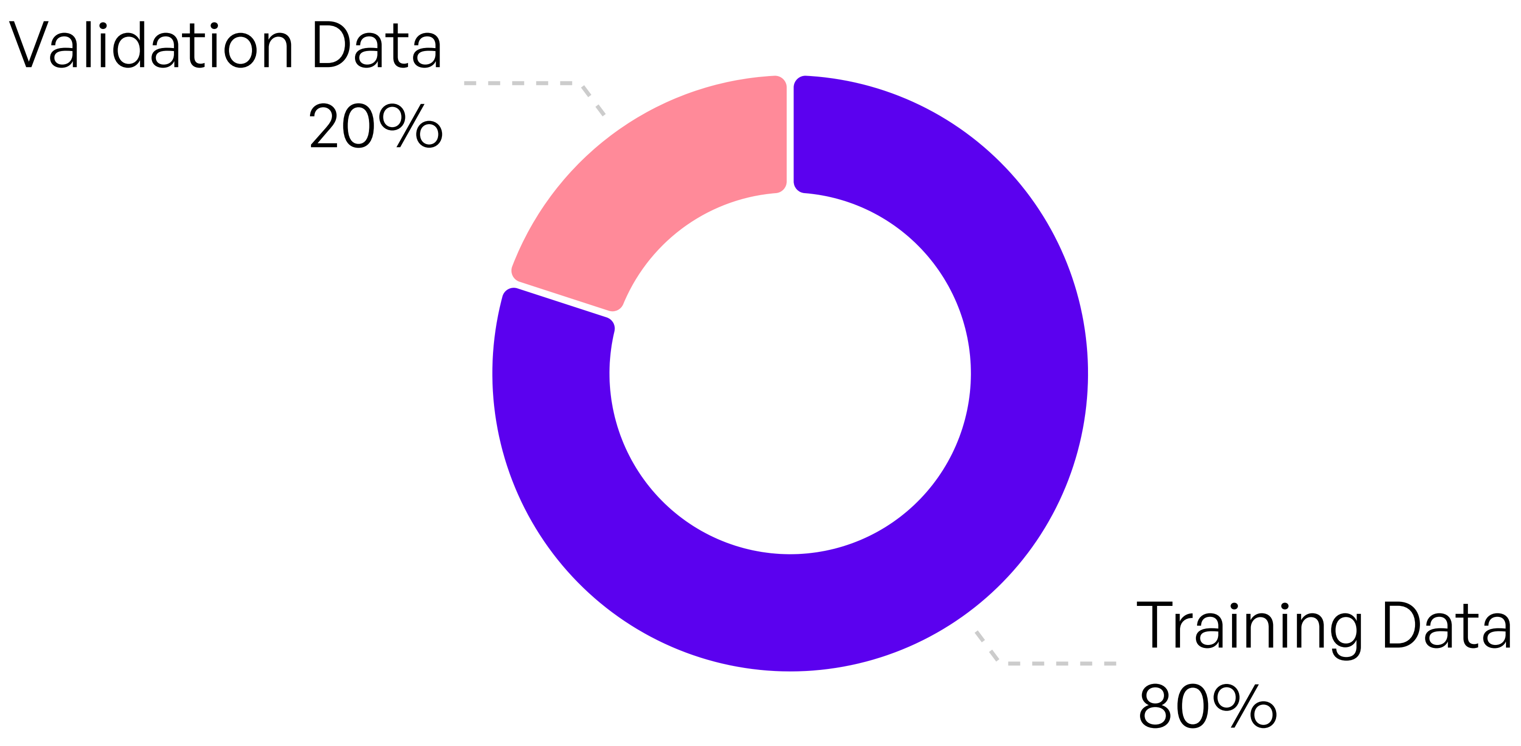
- Current methods rely on ***complex circuitory*** and techniques to measure and calculate charge and health of the battery.
- Most techniques ***neglect*** the temperature of the battery.
- ***Hysteresis*** reduces the accuracy in the methods like Coulimb Counting, Voltage Acquisition.
- ***Battery aging*** is not taken into account.

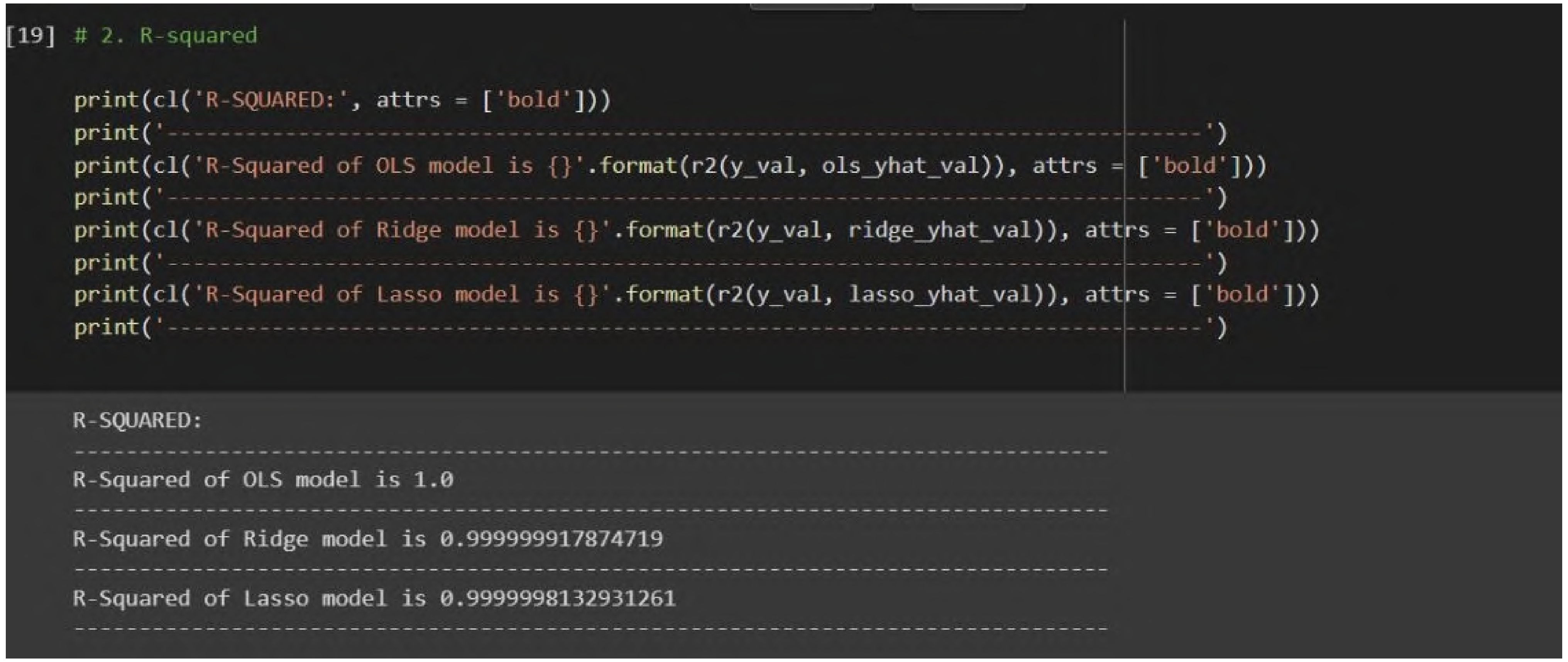
Objective

- Using ***data-driven approach*** for more efficient and accurate prediction
- Battery ***temperature*** to be considered.
- ***Making the BMS Module*** using sensor and microcontrollers.
- ***Comprehensive analysis*** of different regression algorithms to find the suitable one.
- ***Real-time implementation*** on self made hardware circuit.

Progress (7th Sem)

- Understood the working of a BMS System.
- Choose necessary sensors and hardware required for **data acquisition**.
- Decided the **training ratios.**
- Performed the initial algorithm analysis with **Ordinal Least Square Regression, Lasso Regression and Ridge Rigression**.
- Evaluation using **R-Squared Metric.**
- Pretty **Similar** Results





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[19] # 2. R-squared

     print(cl('R-SQUARED:', attrs = ['bold']))
     print('----------------------------------------------------------------------------------------')
     print(cl('R-Squared of OLS model is {}'.format(r2(y_val, ols_yhat_val)), attrs = ['bold']))
     print('----------------------------------------------------------------------------------------')
     print(cl('R-Squared of Ridge model is {}'.format(r2(y_val, ridge_yhat_val)), attrs = ['bold']))
     print('----------------------------------------------------------------------------------------')
     print(cl('R-Squared of Lasso model is {}'.format(r2(y_val, lasso_yhat_val)), attrs = ['bold']))
     print('----------------------------------------------------------------------------------------')

     R-SQUARED:
     ------------------------------------------------------------------------------
     R-Squared of OLS model is 1.0
     ------------------------------------------------------------------------------
     R-Squared of Ridge model is 0.999999917874719
     ------------------------------------------------------------------------------
     R-Squared of Lasso model is 0.9999998132931261
     ------------------------------------------------------------------------------
```

Fig 2 - Three accuracies

Progress (8th Mid Sem)

- Updated Dataset with **higher datapoints** and non linear data
- **9 algorithms** were taken into consideration.
- **Comprehensive** analysis of these algorithms on the dataset was carried.
- Found **best training ratio**, added more features and **three metric evaluation**.
- Execution time was studied for the shortlisted algorithms
- **Xtreme Gradient Boosting** provided the accurate result compared to other algortihsm

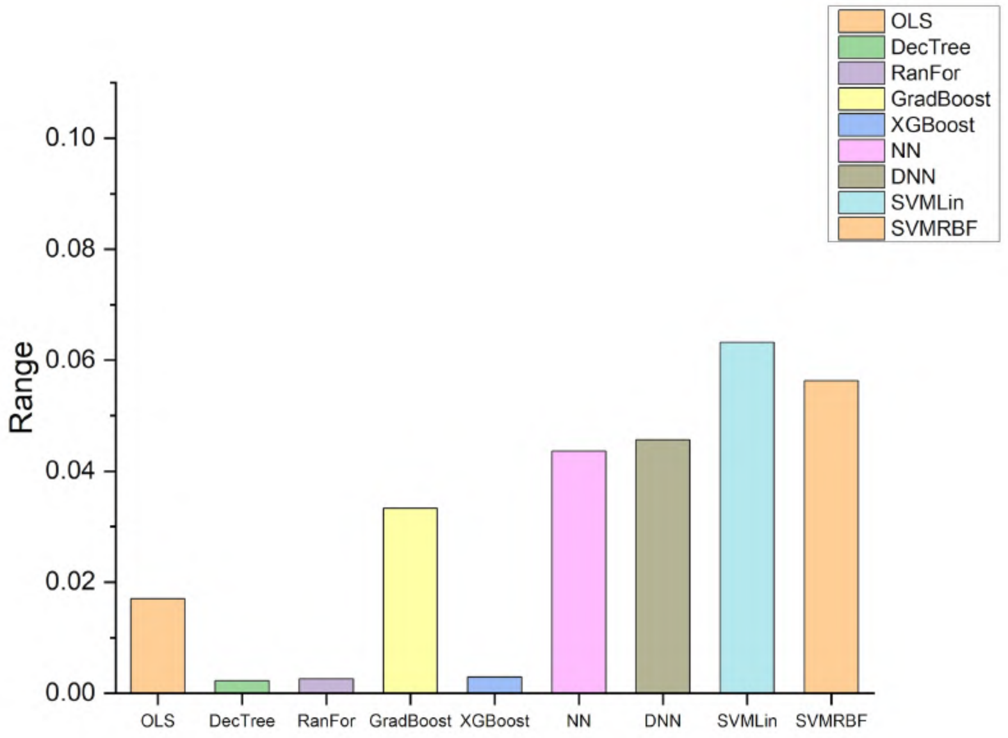

Fig 3 - MAE at 80:20 Ratio

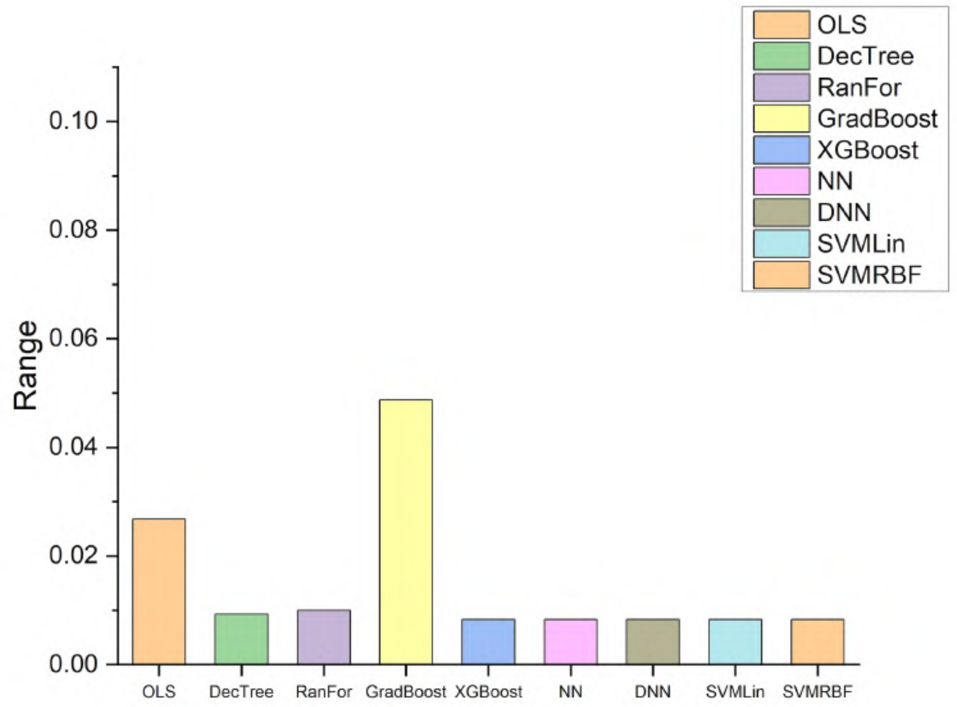

Fig 4 - RMSE at 80:20 Ratio

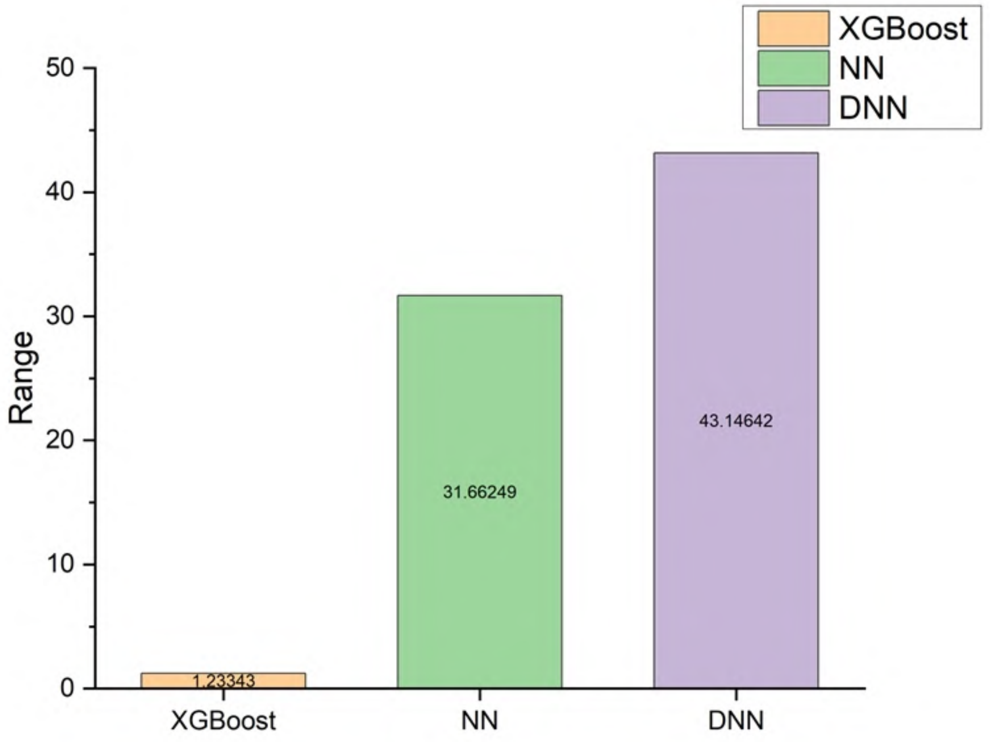

Fig 5 - Execution time for three algorithms

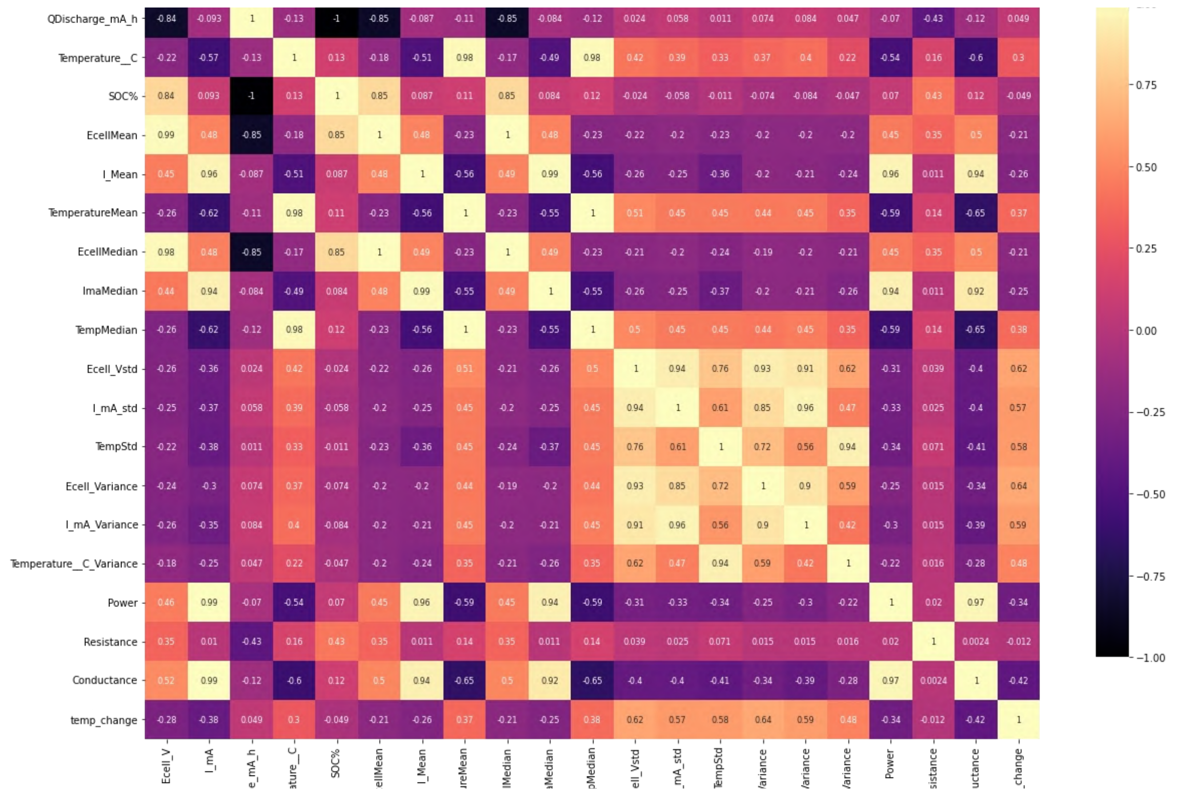

Fig 6 - Feature Correlation Map

Try Pitch

Circuit Diagram

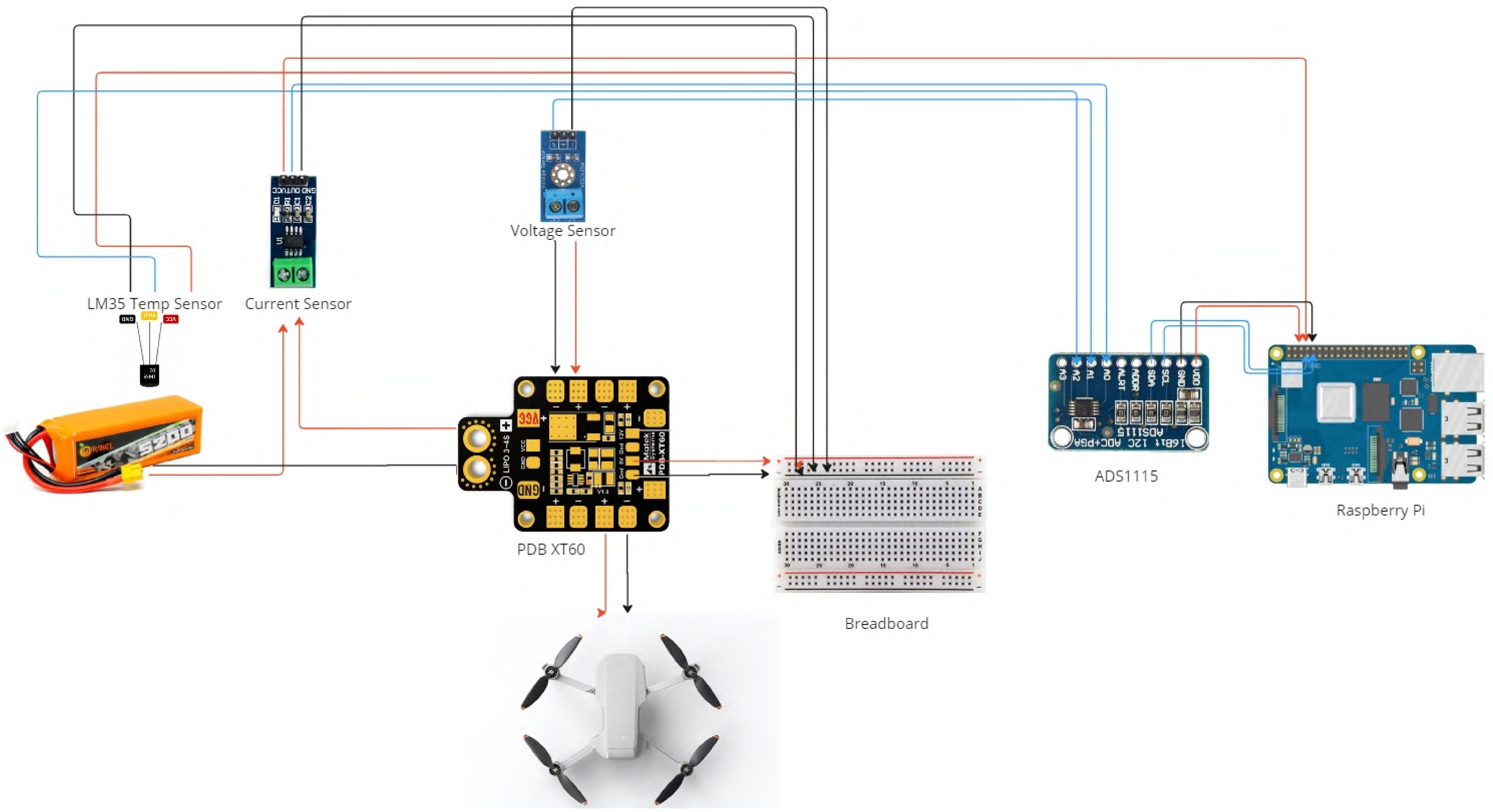

Fig 11 - BMS Circuit Diagram

Experimental Module

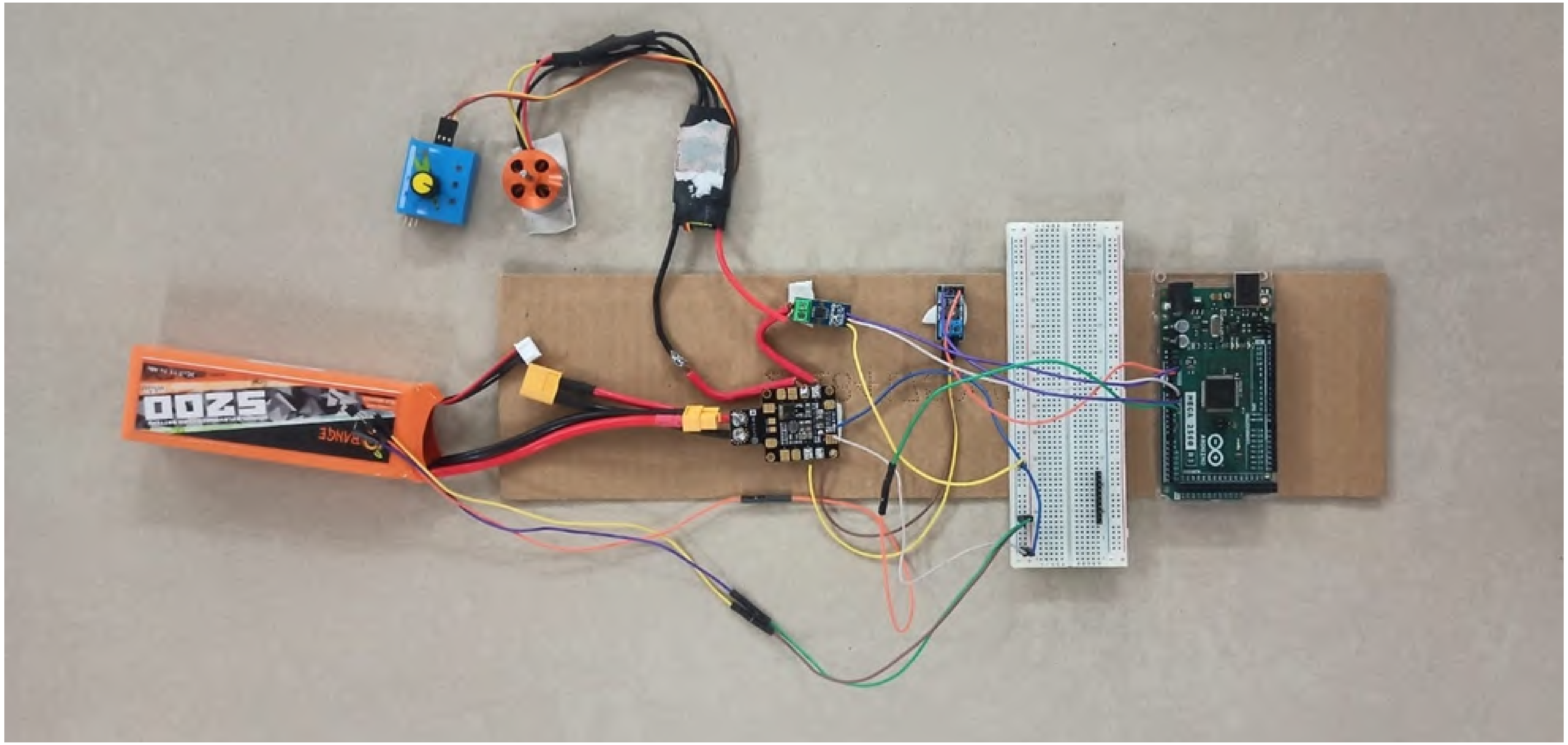

Fig 12 - Experimental Module

Data Collection

- Performed these condition while collecting data
  - **Take Off (50Secs)**
  - **Cruise (Rest)**
  - **Landing (50Secs)**
- **Tested** the collected data
- Ran for **two** and **three** motors to check the non linearity
- Three motor data collection was done for **more iterations**
- At the noted time and varying speeds (Low, Meduim and High)

Results (0.05 SD)

- To take the **dynamic** condition, we added **three** types of noise.
- Gaussian Noise at **0.025SD**, **0.0125 SD**, and **0.05 SD**.
- **Random Forest**, **XGBoost** and **DNN** were good performing models

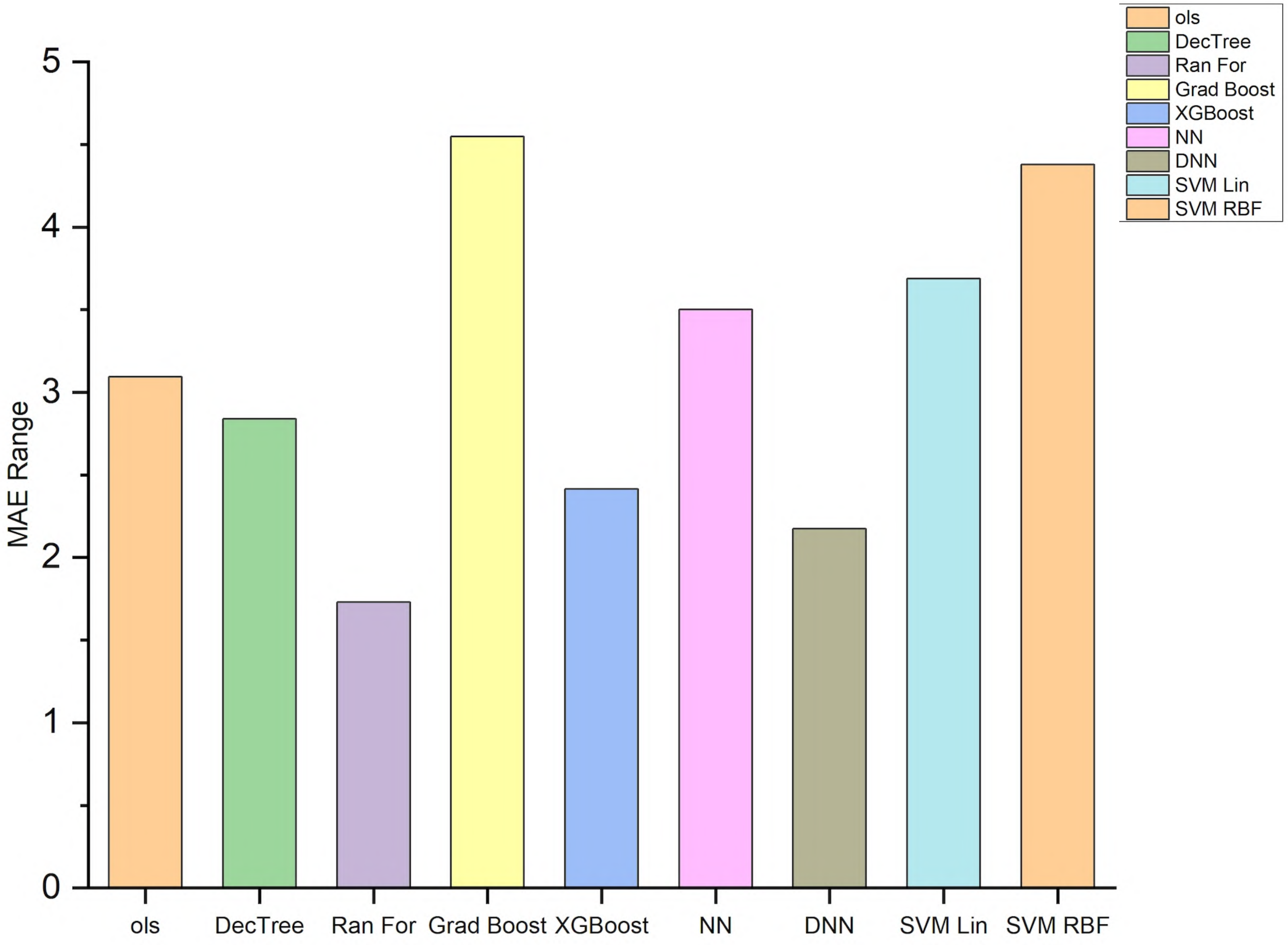

Fig 9- MAE at 0.05 SD Noise

Results (0.025 SD)

- To take the **dynamic** condition, we added **three** types of noise.
- Gaussian Noise at **0.025SD**, **0.0125 SD**, and **0.05 SD**.
- **Random Forest**, **XGBoost** and **DNN** were good performing models

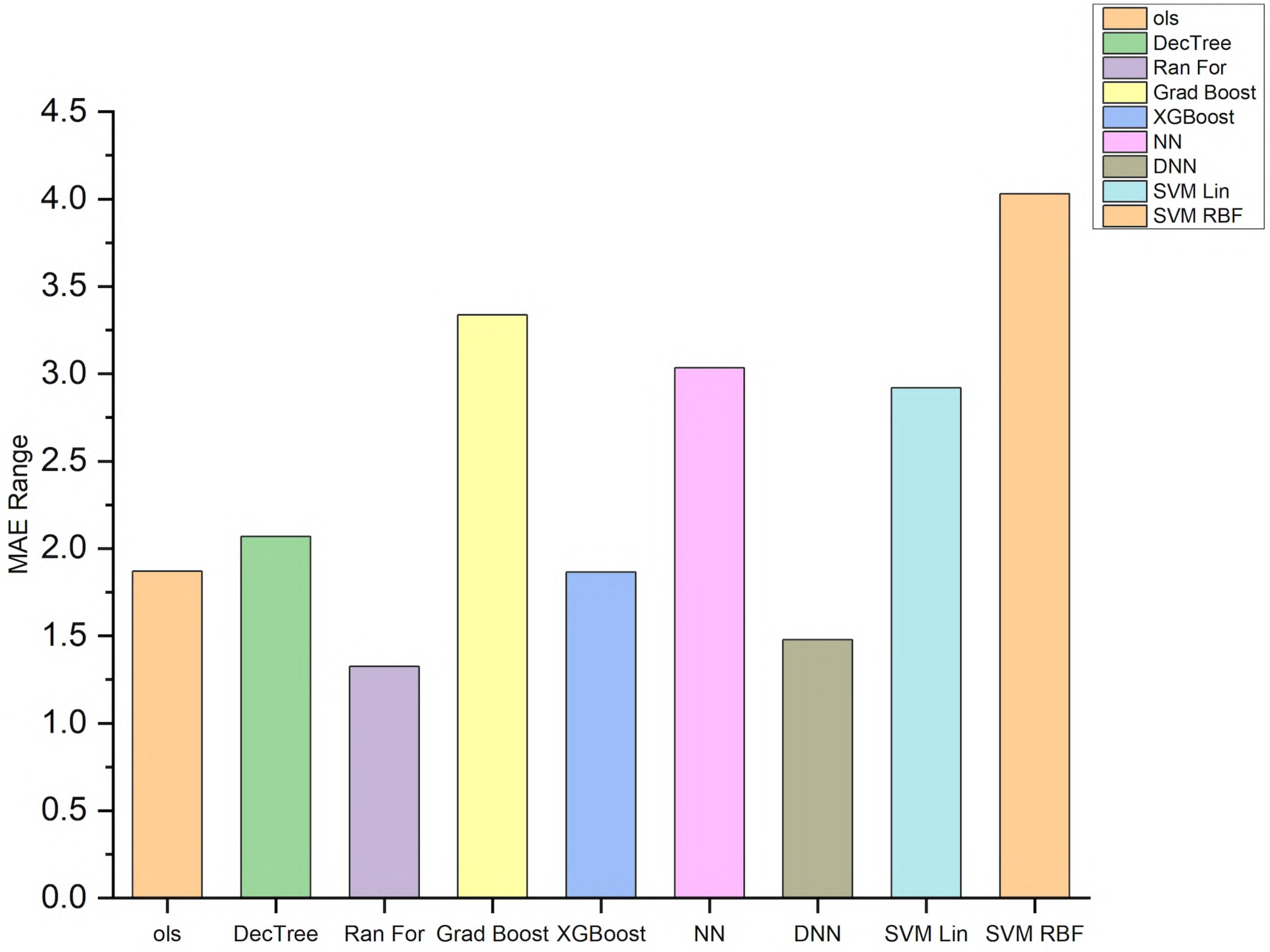

Fig 8- MAE at 0.025 SD Noise

Results (0.0125 SD)

- To take the **dynamic** condition, we added **three** types of noise.
- Gaussian Noise at **0.025SD**, **0.0125 SD**, and **0.05 SD**.
- **MAE** for **OLS, Decision Tree and Random Forest** were close to 0.
- The **0.0125 SD** showed **great accuracy** compared to others

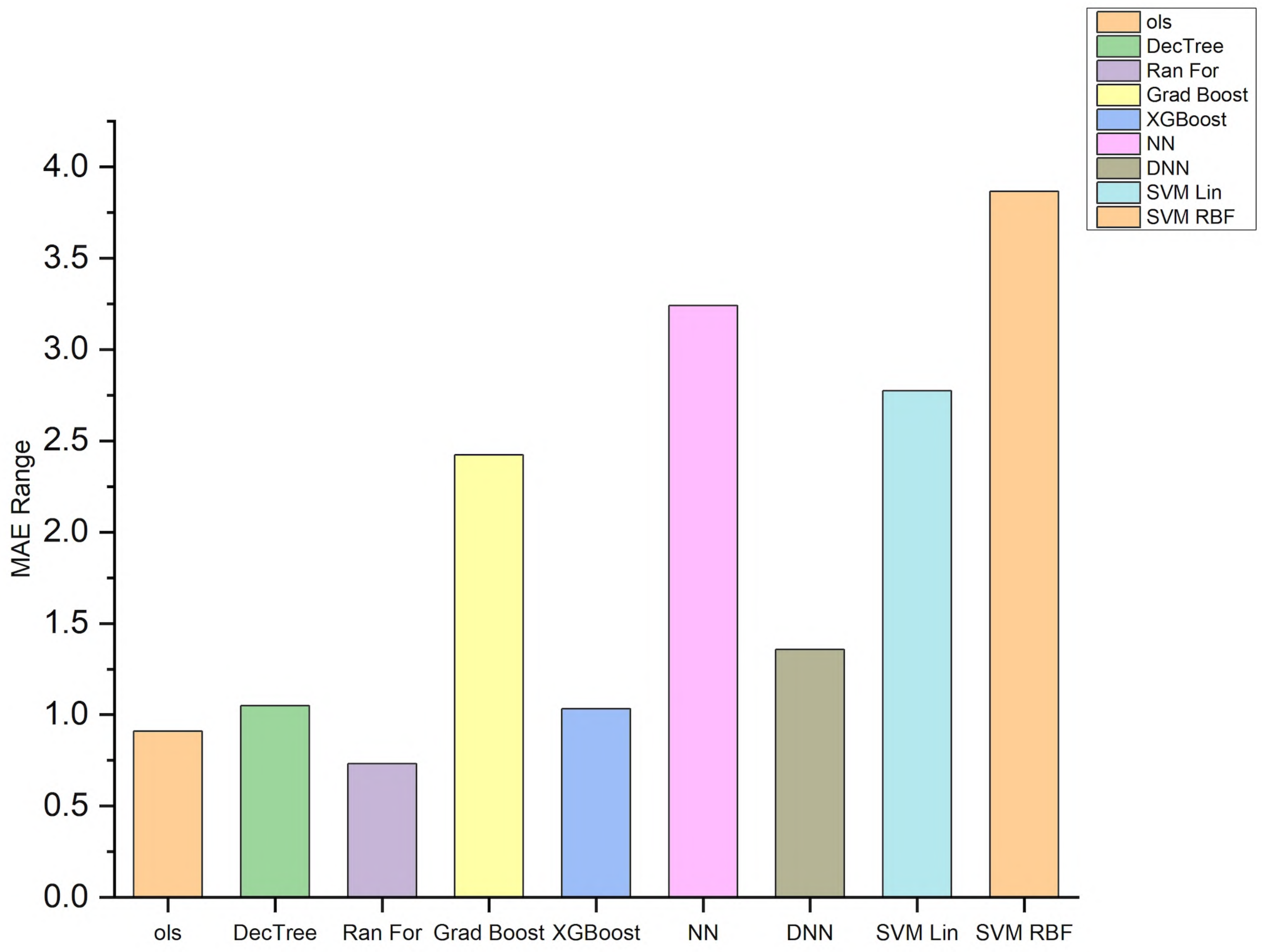

Fig 7 - MAE at 0.0125 SD Noise

Results (Time Analysis)

- Execution time analysis was performed.
- Based on this, it was concluded that for the fast prediction without compromising the results, **XGBoost** was perfect for this scenario
- **XGBoost - 0.05 Secs**
- **Ran Forest - 0.5Secs**
- **DNN - Around 3.5 Secs**

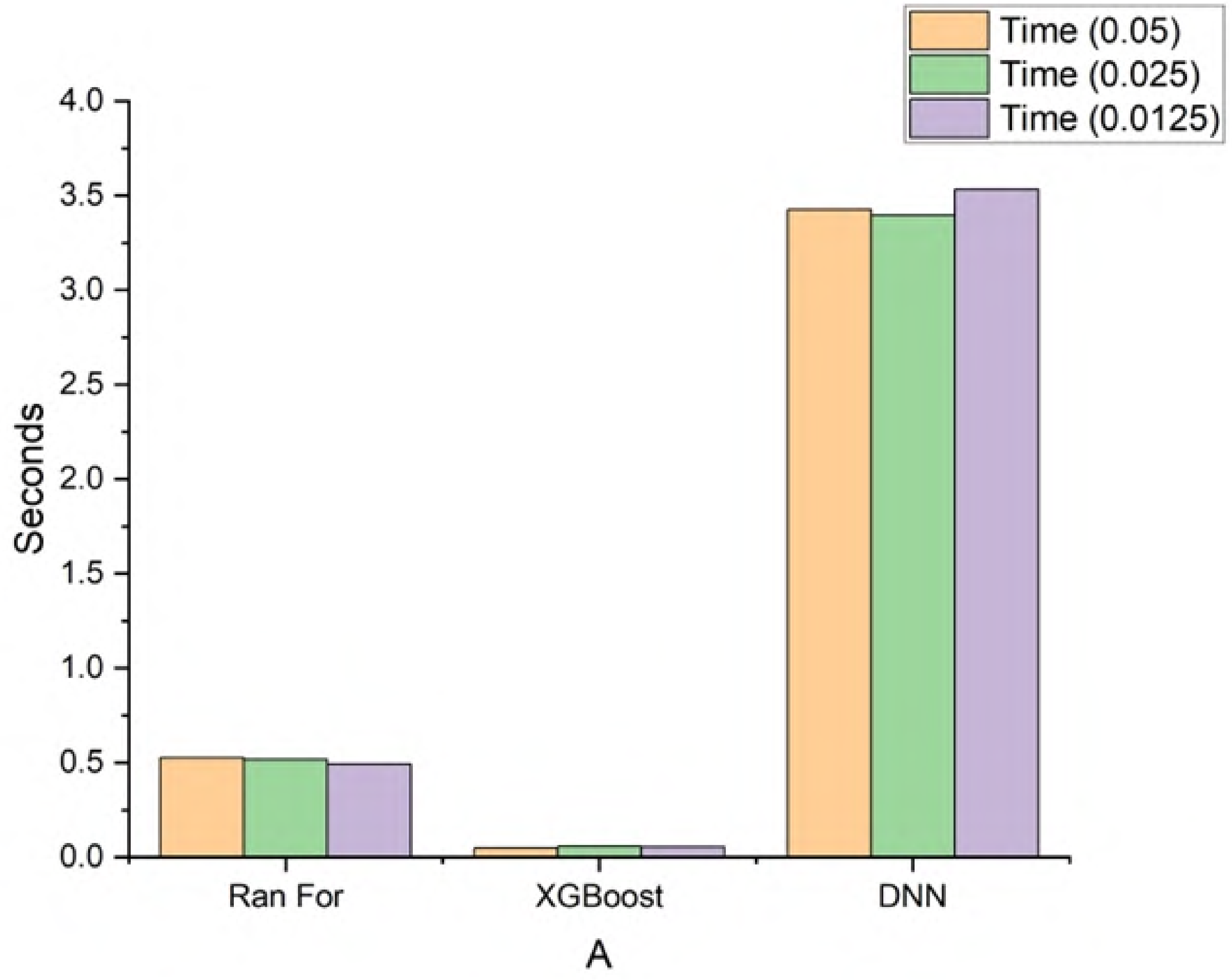

Fig 10 - Execution time of three algorithms

Real-time Monitoring

Concept

- **Continuous** & **up-to-date** information
- Data collection & **Analyzed** Real-time
- Raspberry Pi's **GPIO Pin Layout**
- Pi uses an external ADC
- Communication via **I2C**
- Connected as
  - **VDD — 5V**
  - **GND — Gnd**
  - **SCL — GPIO 3**
  - **SDA — GPIO 2**

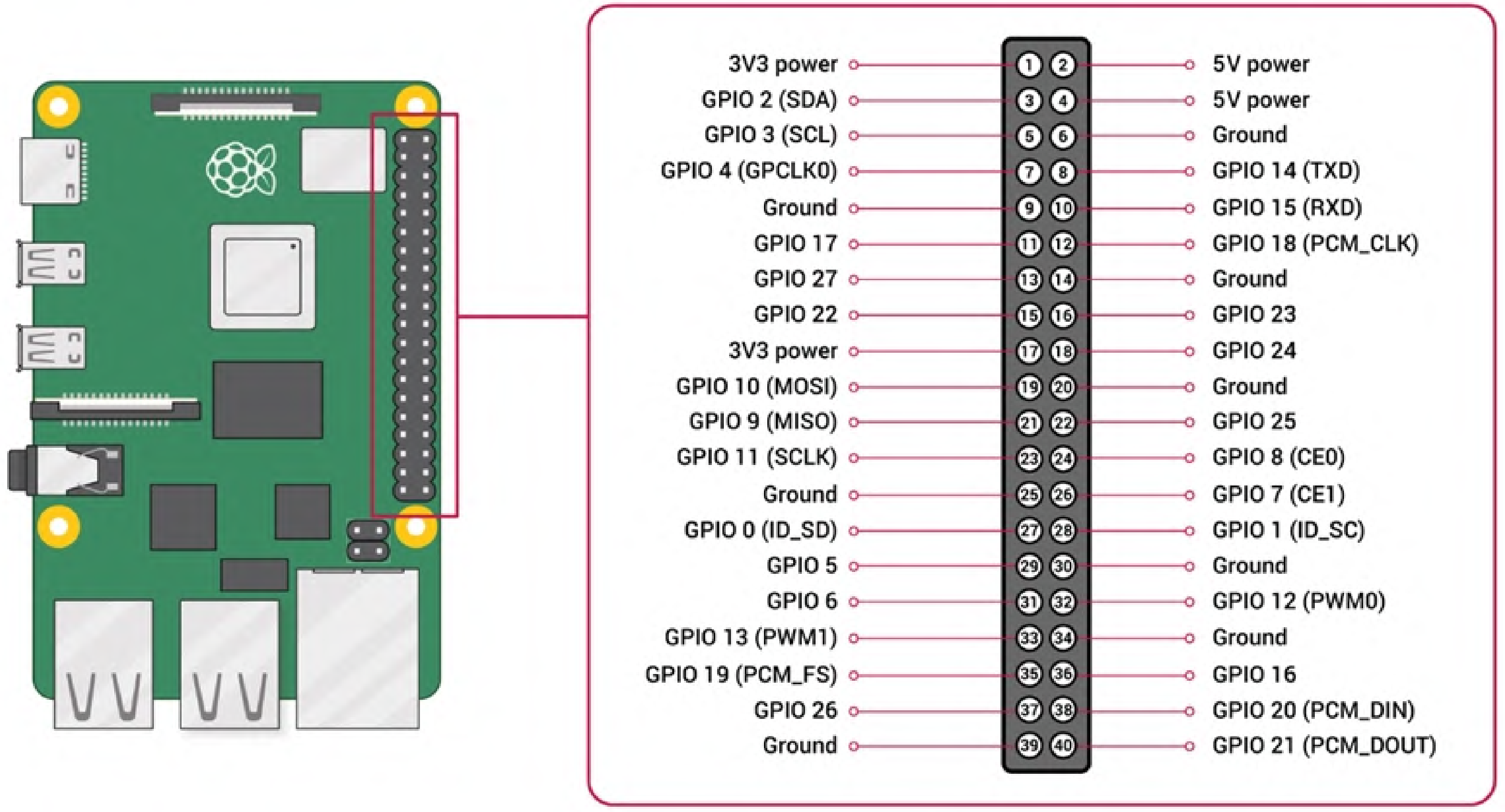

Fig 12 - Raspberry Pi GPIO

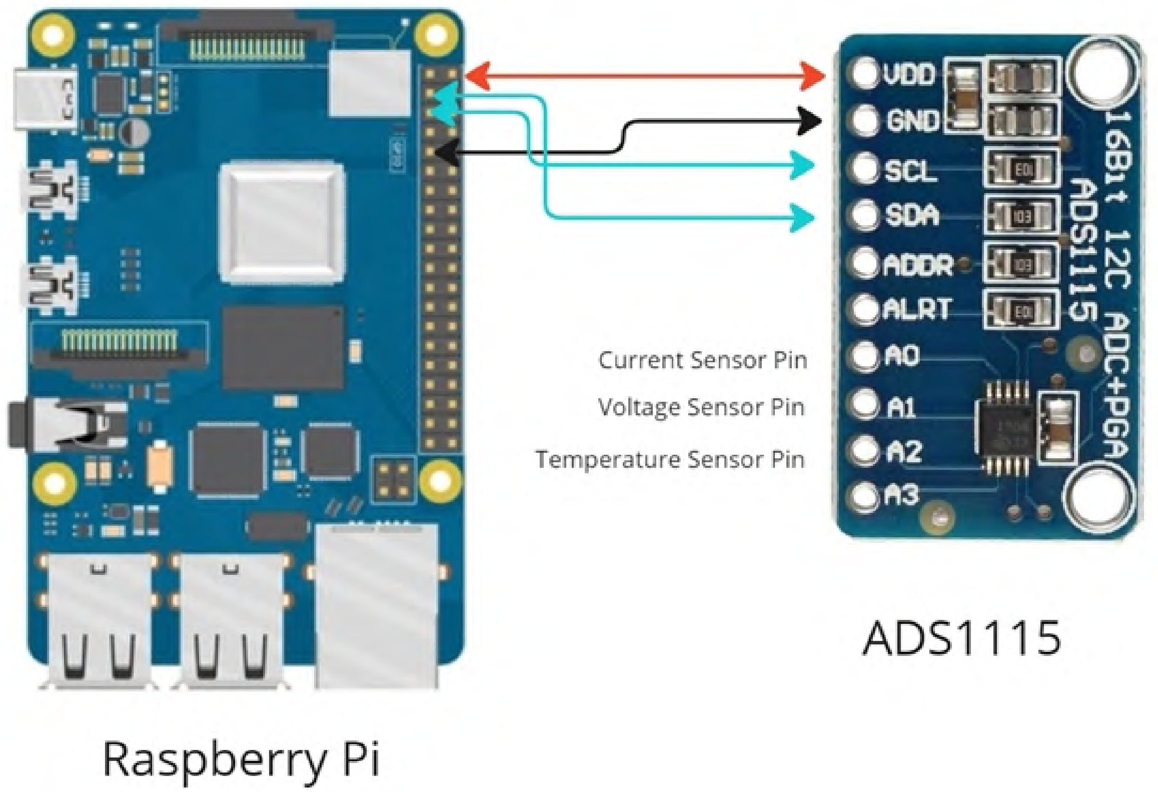

Fig 13 - Pi with ADS1115

Real-time Monitoring

Prediction Results

- **Positive** results were seen for the predictions
- Collected SOC Data for this **three conditions** for analysis of the error

- Real-time test for three conditions
  - **High Speed** Predictions
  - **Cruise Speed** Predictions
  - **Variable Speed** Predictions

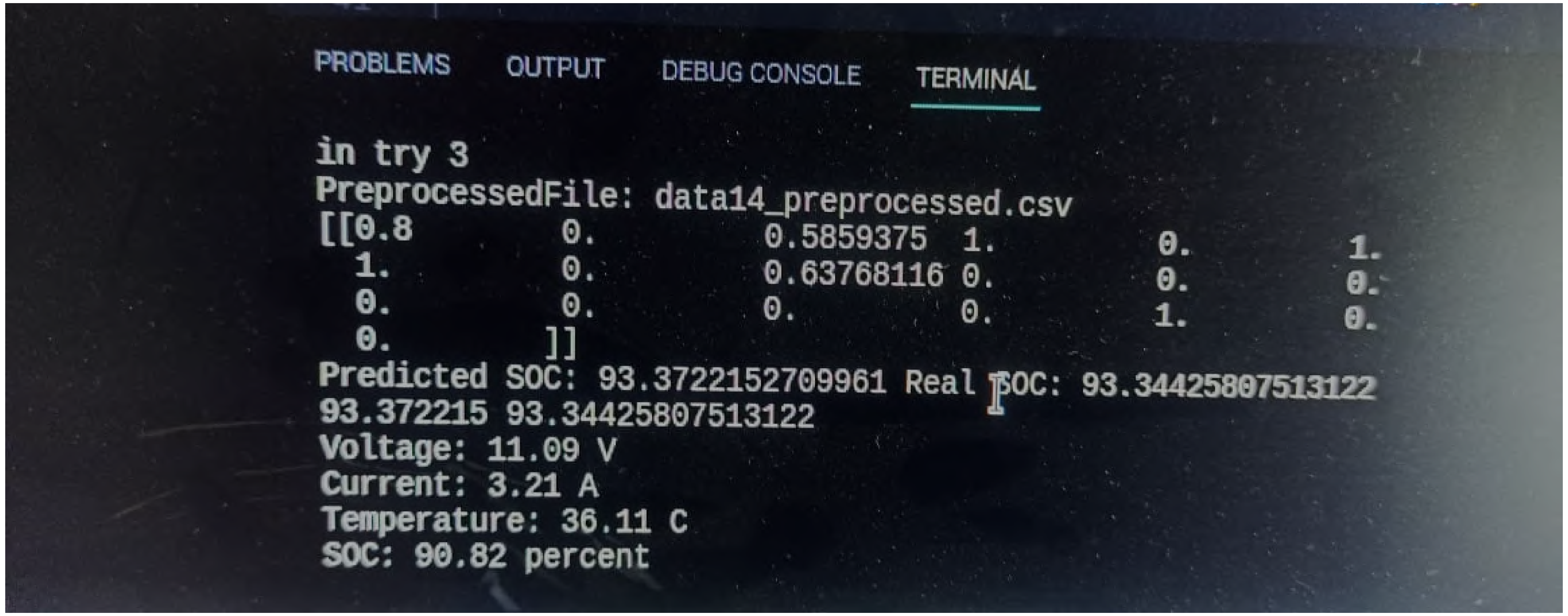

Fig 14 - Predicted and Real SOC on three motors

Variable Condition

Error Analysis

- Fig15 shows the error of **output** for **variable condition**
- As real **SOC decreases** the **error increases.**
- An error range of **4%** to **70%** is observed from maximum charging to lower charging levels

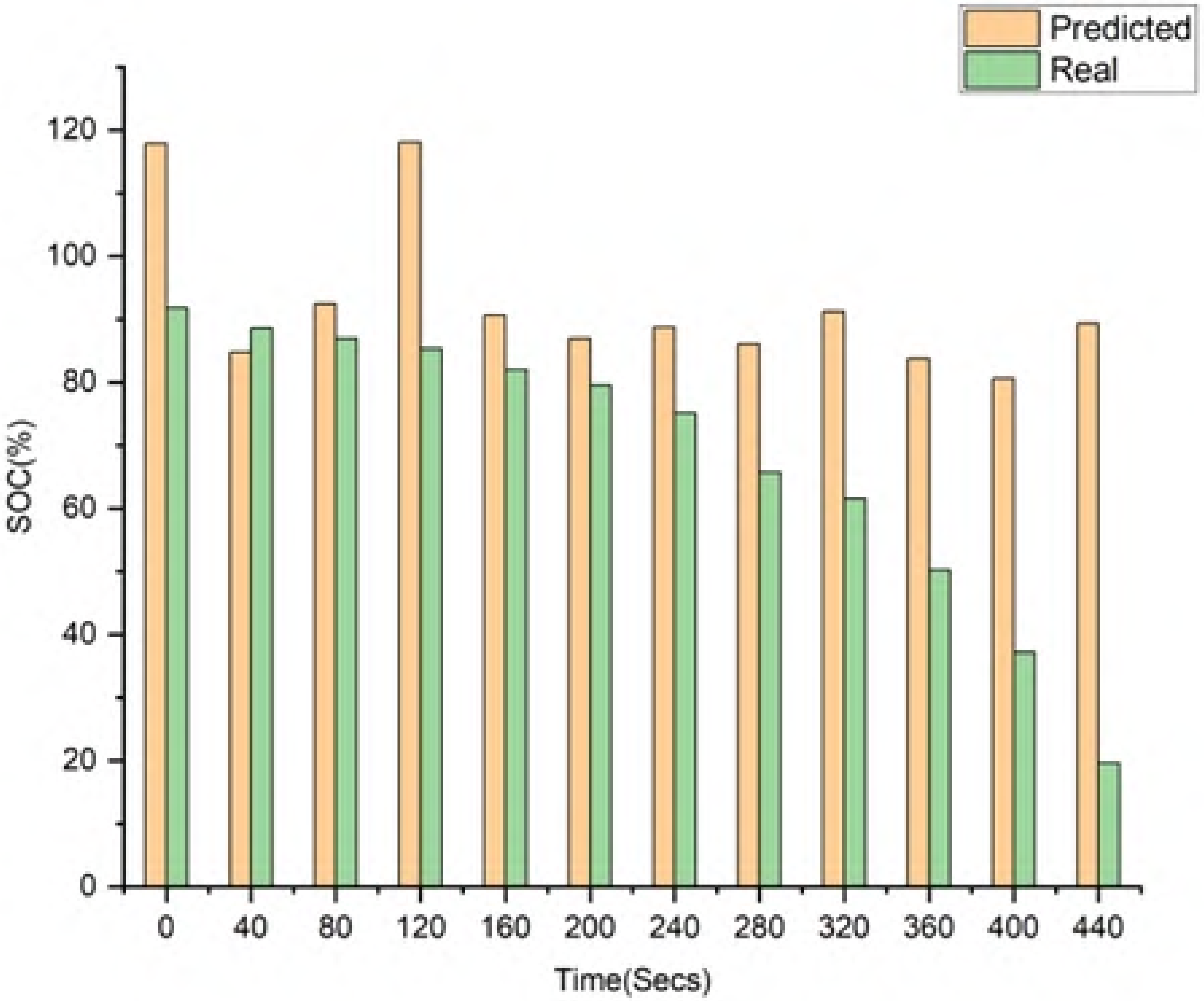

Fig 15 - Predicted and Real SOC on three motors at varied speed condition

Cruise Condition

Error Analysis

- **Similar** case with cruise condition
- As real **SOC decreases** the **error increases**.
- An error range of **5%** to **70%** is observed from maximum charging to lower charging levels

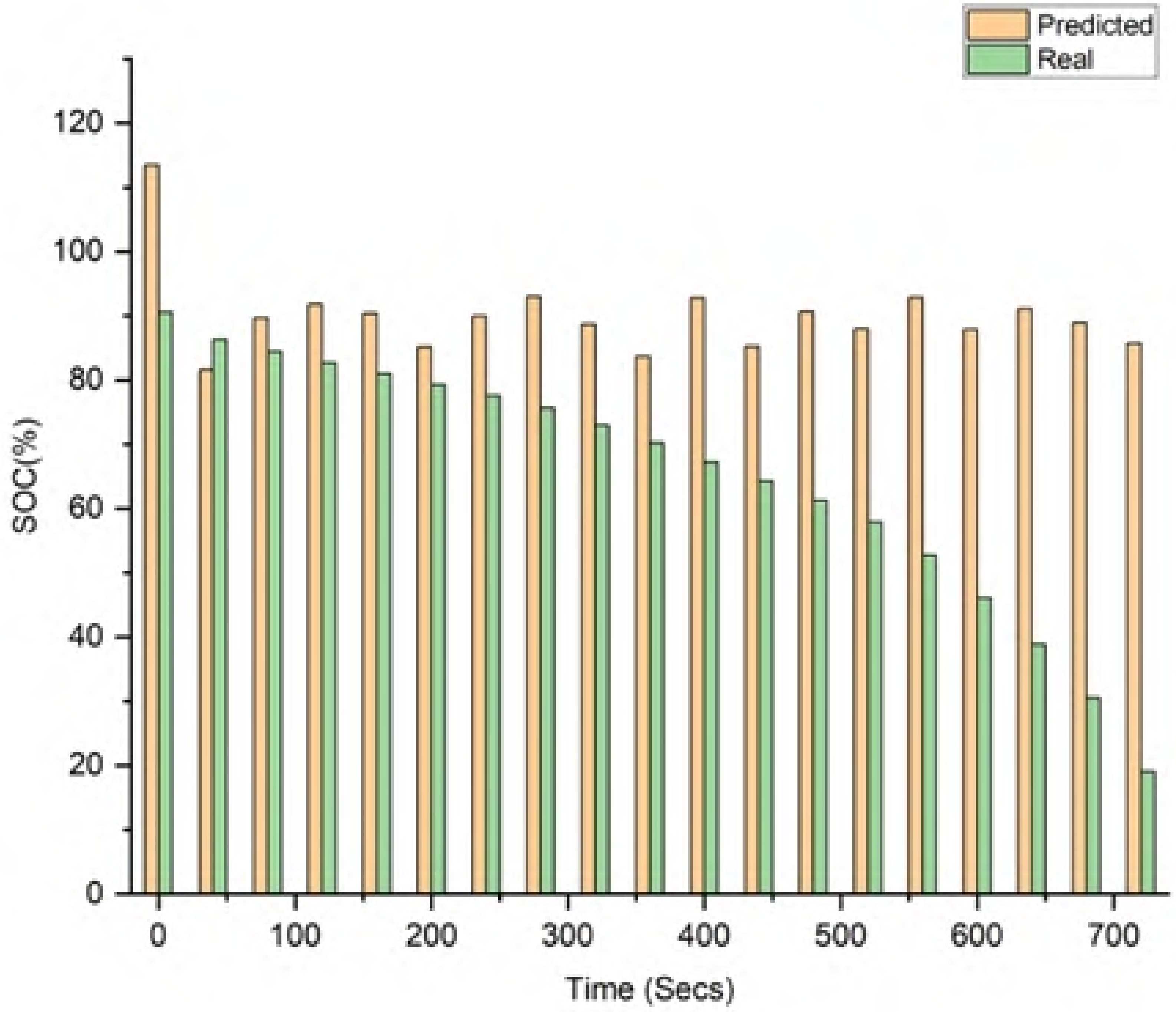

Fig 16 - Predicted and Real SOC on three motors at Cruise speed condition

High Speed Condition

Error Analysis

- With high speed condition, the error is **comparatively quite minimal**.
- As real SOC decreases the error increases.
- An error range of **1%** to **30%** is observed

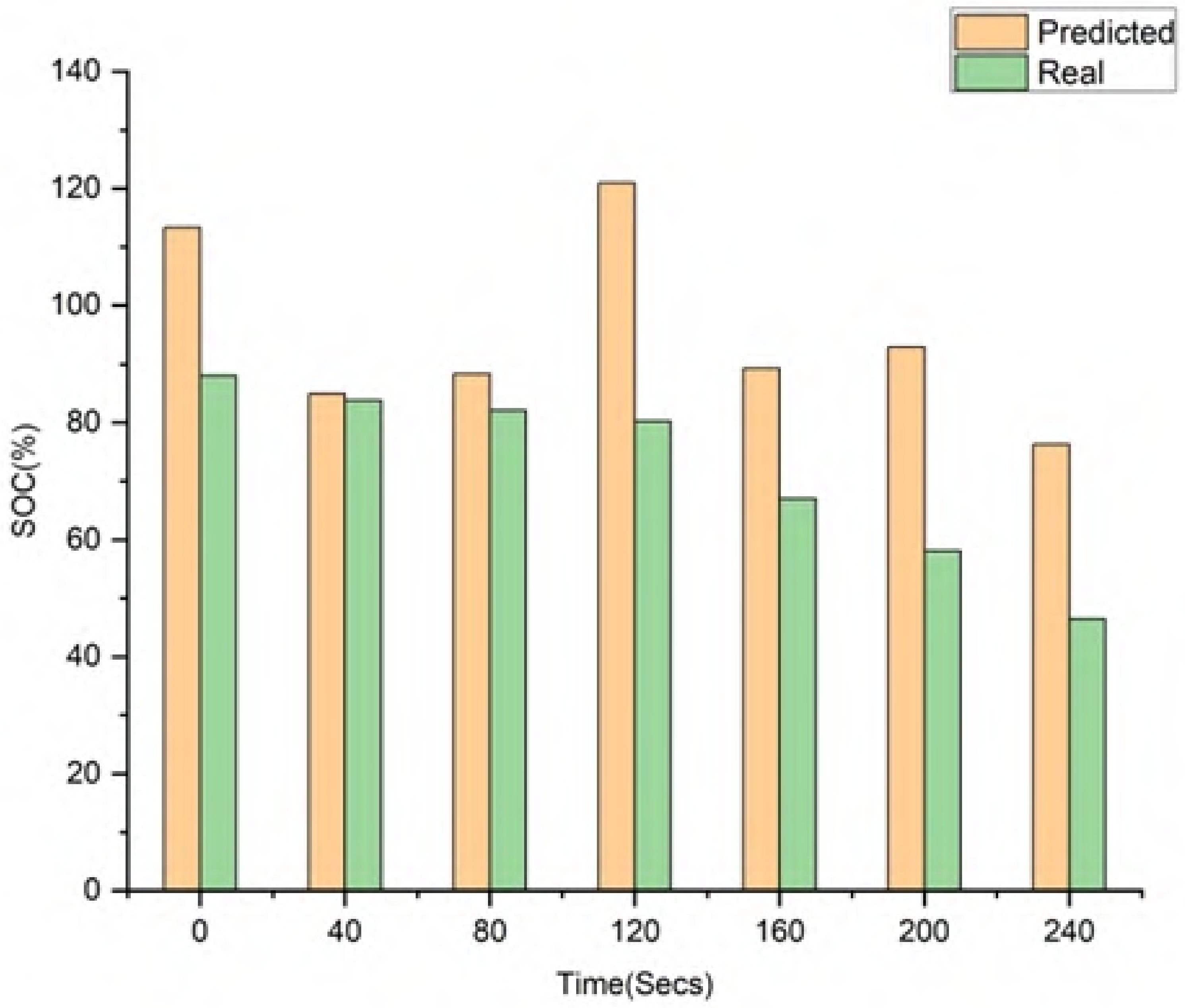

Fig 17- Predicted and Real SOC on three motors at High speed condition

All three condition error

Error Analysis

- **Error increases** with **lower percentage** of battery
- Three conditions' error for an entire discharge cycle
- All the conditions show the **same pattern**

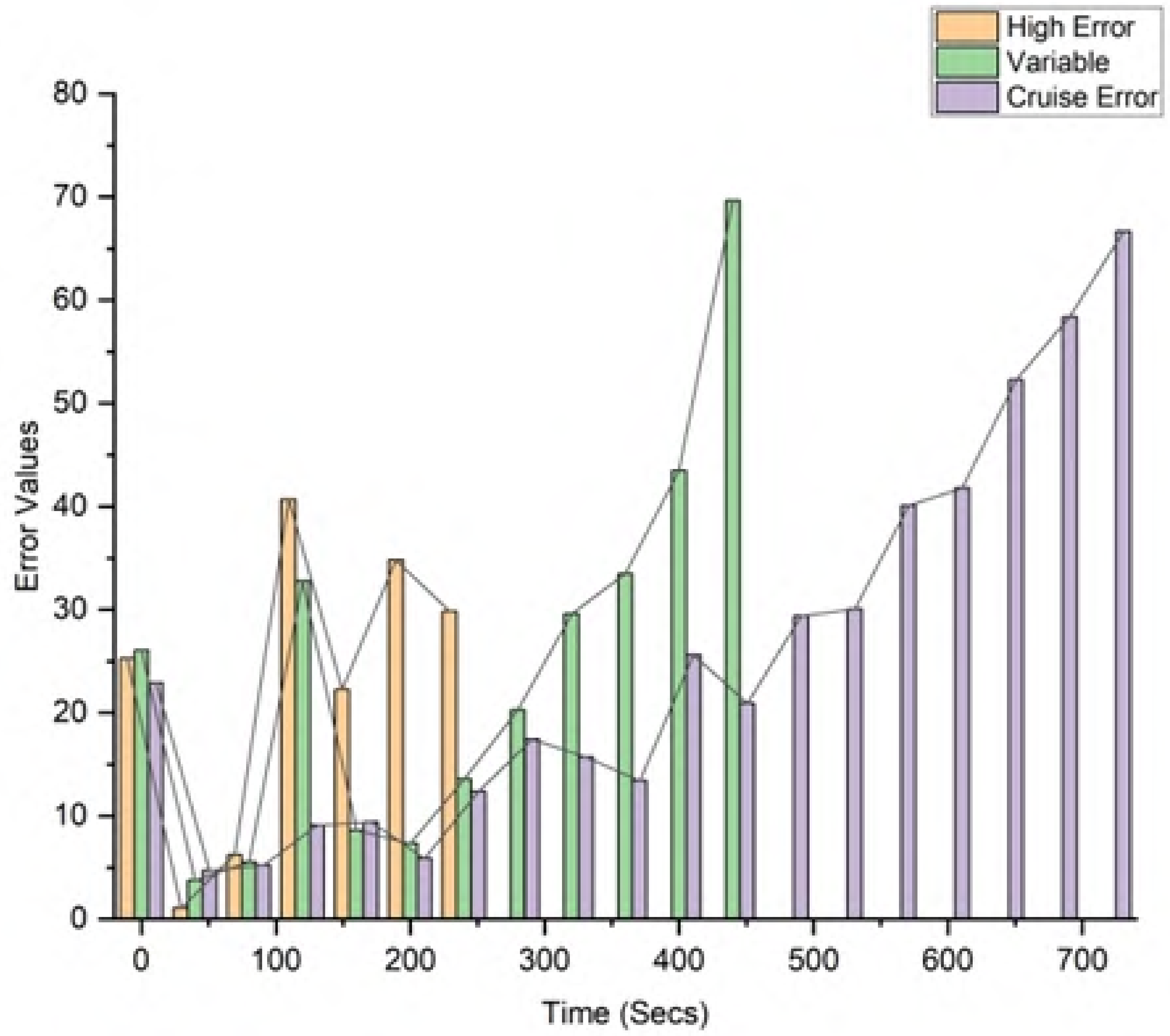

Fig 18 - Error comparison of the three condition predictions

Try Pitch

Conclusions

- A thorough analysis of the results revealed the **XGBoost algorithm** to be suitable.
- Predictions were **accurate** at **higher charging** levels but i**naccurate at lower levels**.
- **Robust** BMS Module was made
- It was observed that **heat is generated** from the components used in this setup
- Optimized prediction time of **40Secs**
- To use **4S and 2S** batteries more effectively, the current system needs to **expand** its dataset.

Future Improvements

Towards better & efficient system.

- ✓ **Heat Sink inside the BMS**
- ✓ **High Quality sensors for accurate measurements**
- ✓ **Increased set of data for real-time scenarios**
- ✓ **More data collection for 2S and 4S battery for versatile use**

References

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Thank you