Renew Power Hiring Hackathon

Approach Presented By:

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Introduction

- In this hackathon, ReNew Power shared minute-wise normalized data of wind speed, power and temperature data for multiple components of a wind turbine.
- The company is looking to create a model to get an ideally functioning turbine's expected rotor bearing temperature.
- It will then use the model to check the deviation of the actual rotor bearing temperature of the faulty turbine from the expected temperature.

Data Description

- Dataset is divided into 15 features and one Target variable
- 15 features can be broadly classified into 4 factors:
  - Power factor:- Active Power, Reactive Power (both raw and converted), generator speed and Average Power for 10 minutes.
  - Temperature factor:- Ambient Temperature, Nacelle Temperature(both inside and outside) and wire winding temperature
  - Wind factor:- Wind speed, wind direction, wind speed Turbulence
  - Other:- Timestamp and Turbine Id

  - We have to predict Rotor bearing Temperature.

Feature Engineering

Hypothesis 1: *Wind Speed and Ambient Temperature are Time and season specific. Hence, there is a need to extract time and season features from timestamp variable*

New Features created: - Hour (Time specific), Month(Season specific)

Hypothesis 2 :- *Rotor Bearing Temperature is dependent on power loss*

New Features created: - Active Power loss, Reactive Power loss and Apparent Power(Active+Reactive)

Feature Engineering

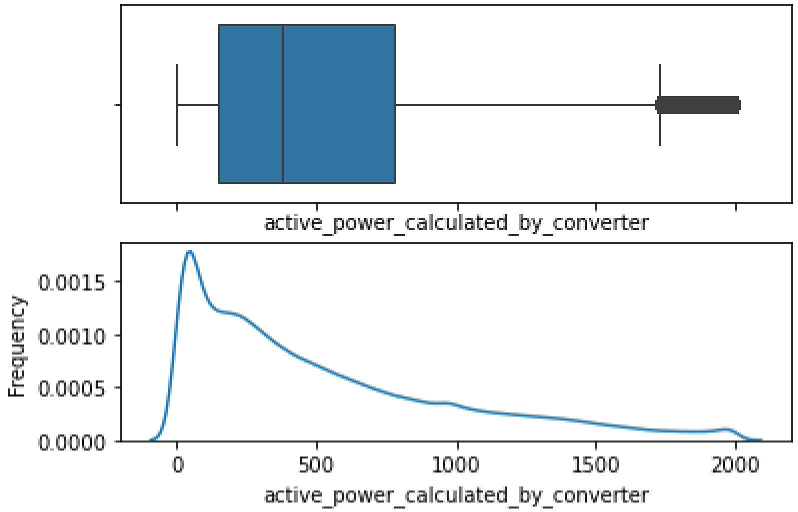
- ```
  train['hour']=pd.to_datetime(train['timestamp']).dt.hour
  test['hour']=pd.to_datetime(test['timestamp']).dt.hour
  ```
  ```
  train['month']=pd.to_datetime(train['timestamp']).dt.month
  test['month']=pd.to_datetime(test['timestamp']).dt.month
  ```

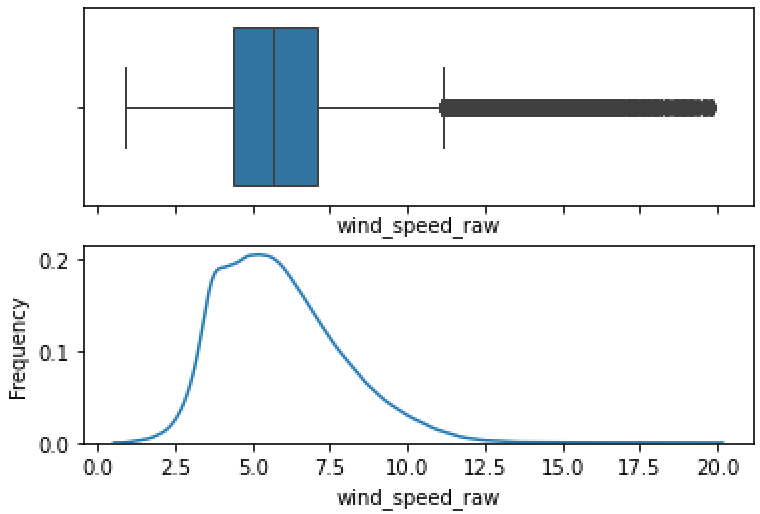
- ```
  train['active_power_loss']=train['active_power_raw']-train['active_power_calculated_by_converter']
  train['reactive_power_loss']=train['reactive_power']-train['reactice_power_calculated_by_converter']
  ```
  ```
  test['active_power_loss']=test['active_power_raw']-test['active_power_calculated_by_converter']
  test['reactive_power_loss']=test['reactive_power']-test['reactice_power_calculated_by_converter']
  ```

- ```
  train['apparent_power']=np.sqrt(train['active_power_calculated_by_converter'].values**2
                                  +train['reactice_power_calculated_by_converter'].values**2)
  ```
  ```
  test['apparent_power']=np.sqrt(test['active_power_calculated_by_converter'].values**2
                                 +test['reactice_power_calculated_by_converter'].values**2)
  ```
  ```

Exploratory Data Analysis-Univariate Analysis

- Most of the Features are right-skewed having high presence of outliers





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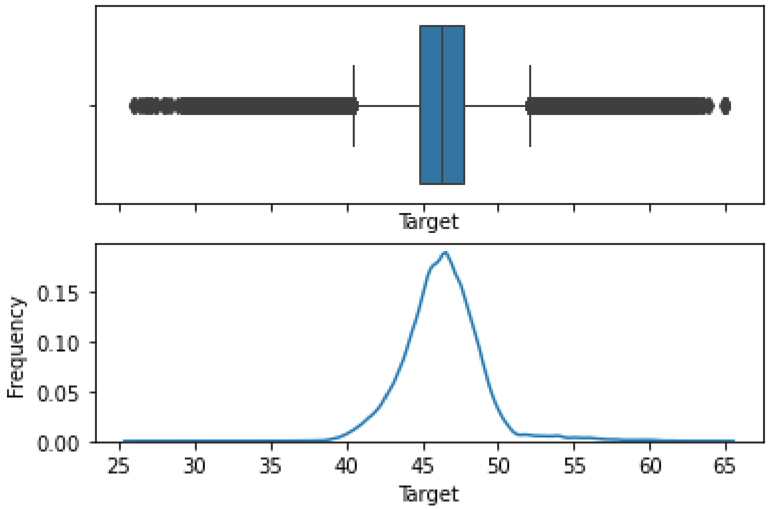
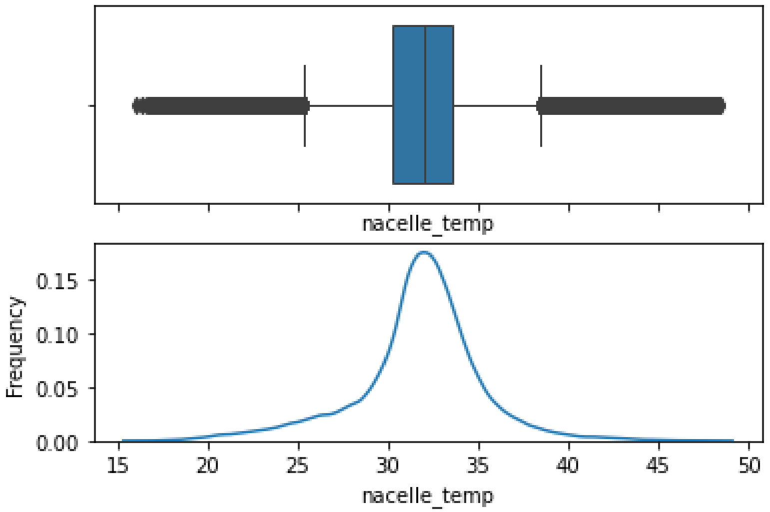
Exploratory Data Analysis-Univariate Analysis

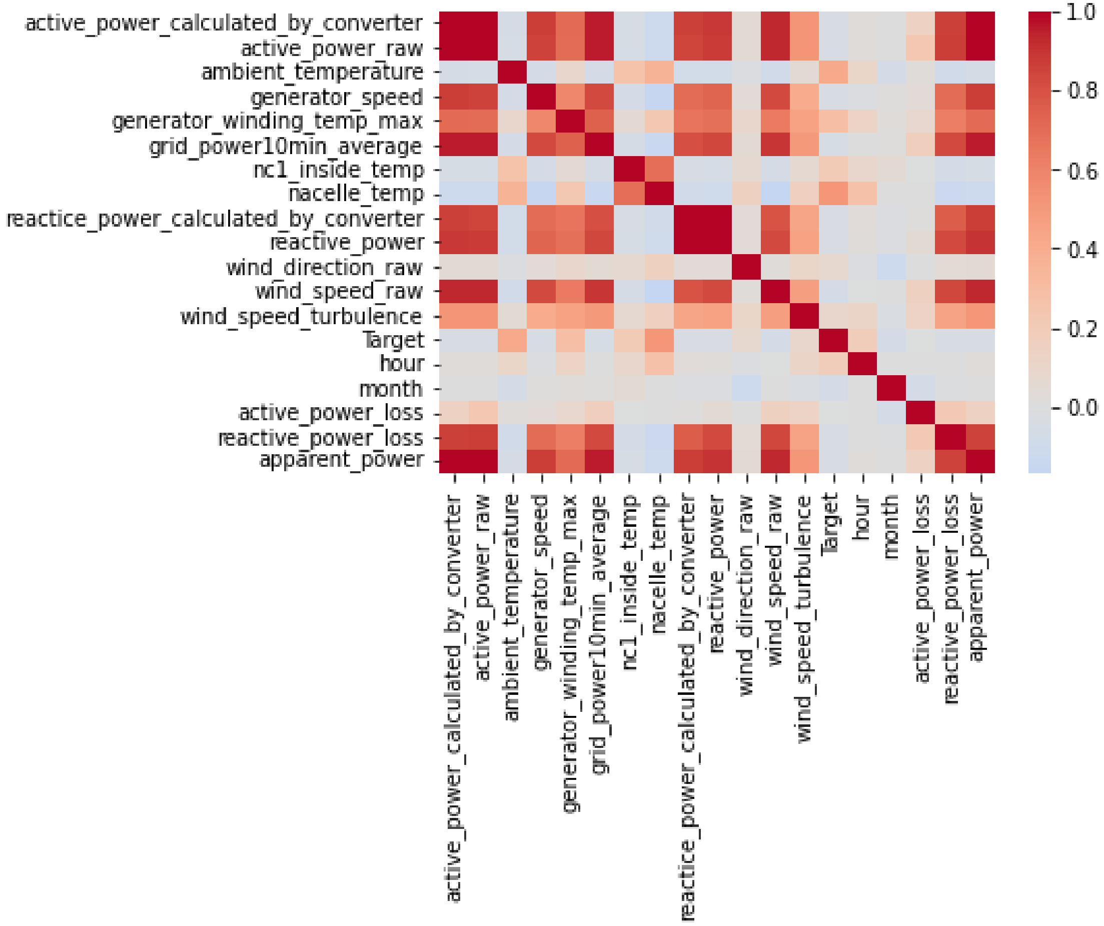
- Target Variable is normally distributed having outliers present on both sides. It shares similarity with nacelle temperature





Bivariate Analysis:- Correlation

- We can observe that variables are highly correlated. Specially power factor variables are highly correlated



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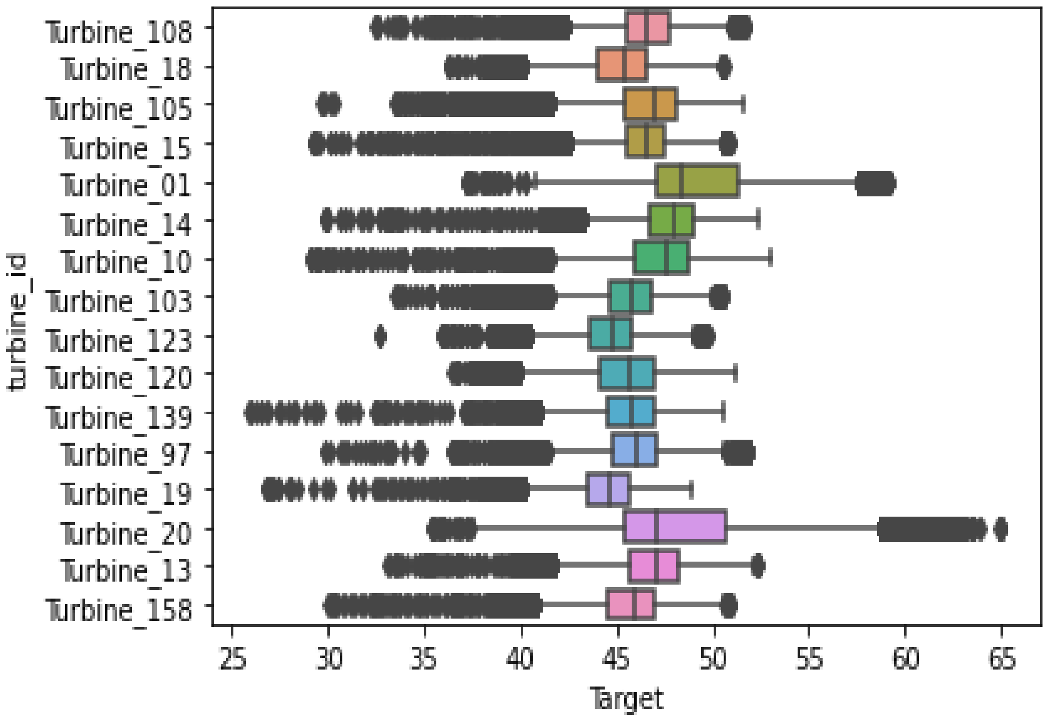
Bivariate Analysis: Turbine Id vs Target

- Target variation is significant w.r.t Turbine id
- We can observe that Turbine 20 and Turbine 1 shows high variability in Rotor bearing Temperature



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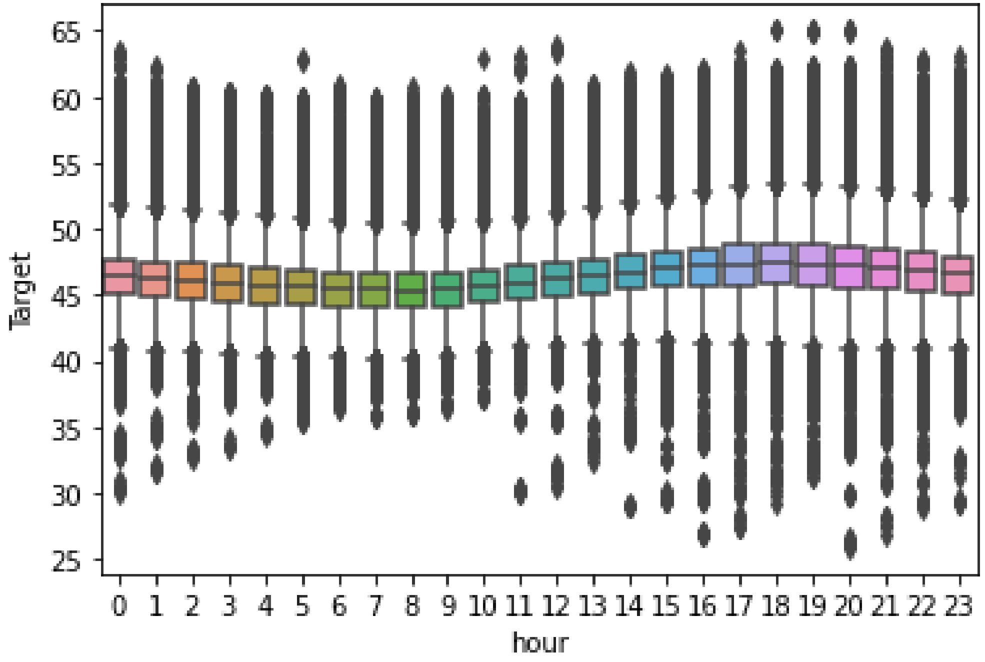
Bivariate Analysis: Hours vs Target

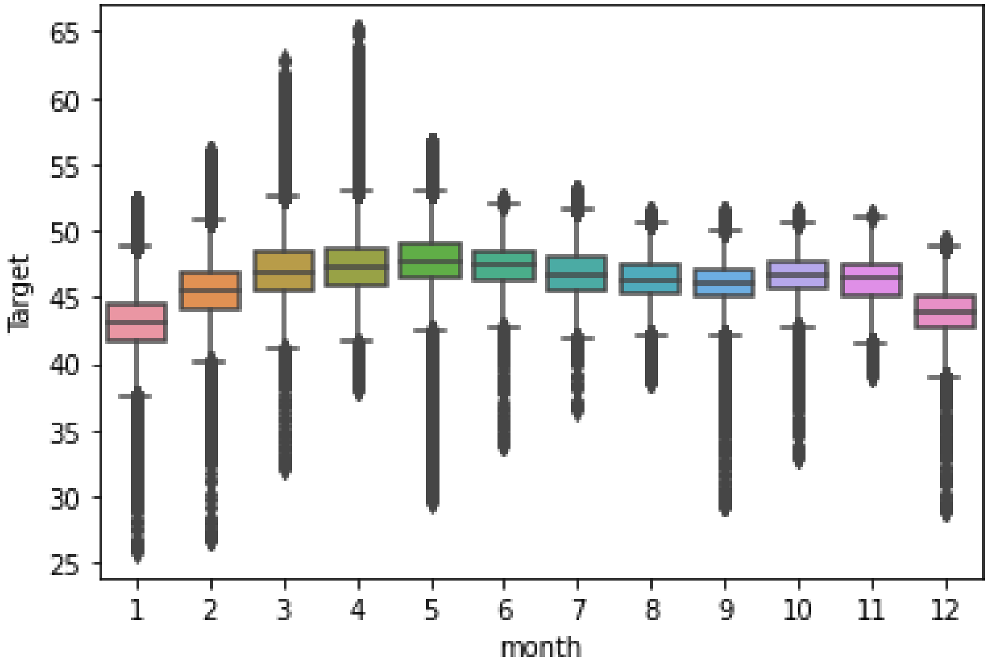
- We can observe that, Median Rotor Bearing Temperature do increase in the noon.



Bivariate Analysis: Months vs Target

- Median Bearing Temperatures are higher in the month of March, April, May and June.

- March and April data shows High Variability.



Feature Selection

- Since, Highly correlated features are present in the dataset. Feature Selection has been done to reduce noise.
- Method Selected:-Forward Feature selection
- Estimator Used:- Decision Tree Regressor is chosen over Linear Regression due to presence of outliers.
- Scoring:- MAPE

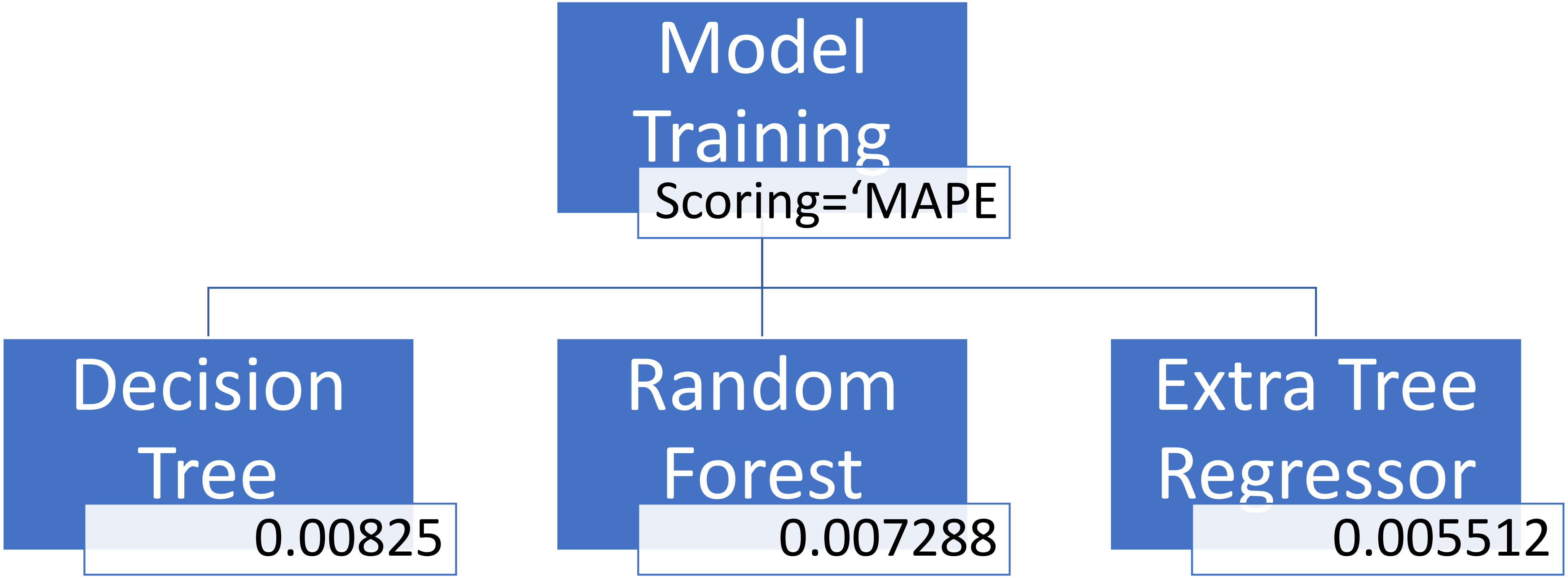
```
sfs1=sfs(k_features=8,forward=True,estimator=DecisionTreeRegressor(),verbose=1,
        scoring='neg_mean_absolute_percentage_error')
```

Feature Selection list

- Following were the features selected using forward feature selection:

```
['ambient_temperature',
 'generator_winding_temp_max',
 'grid_power10min_average',
 'nc1_inside_temp',
 'wind_direction_raw',
 'turbine_id',
 'hour',
 'month']
```

Model Training



Model selection

- Extra Tree Regressor model was performing better than other ensemble models. Hence it was selected for final prediction

```
etr_val=etr.predict(X_test)
```

```
mape(y_test,etr_val)
```

```
0.005512894500379294
```

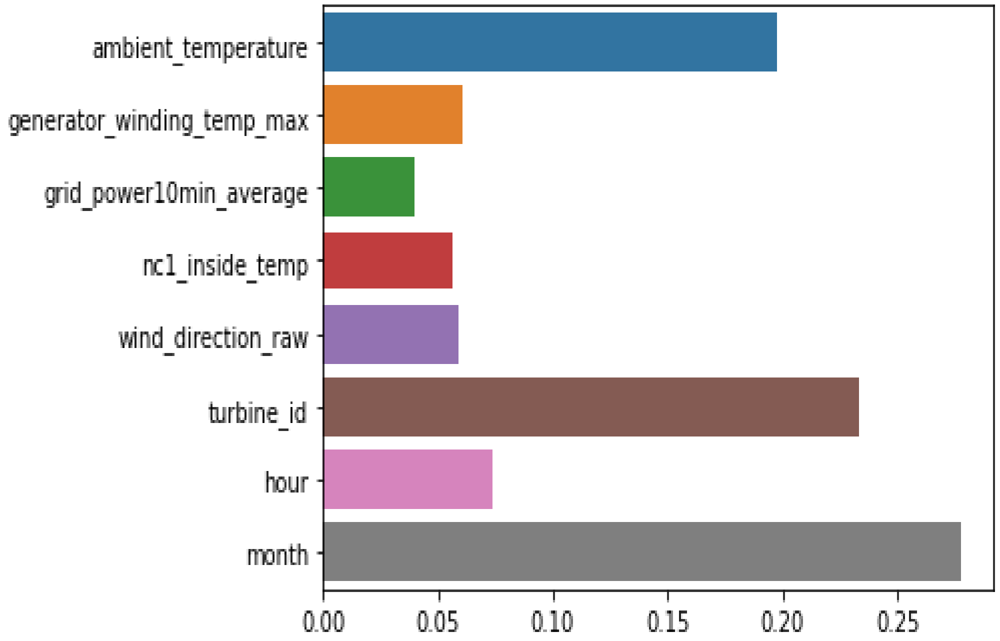
final predictions

```
test_pred=etr.predict(test1)
```

Feature Importance

- We can observe that in Extra tree Regressor model training, following are important features:-
- Ambient Temperature:- Explaining 20 % variability
- Turbine Id:- 23% variability
- Month:- 28% variability

```
array([0.19798046, 0.06091976, 0.04009326, 0.05659086, 0.05927591,
       0.23360787, 0.07355027, 0.27798162])
```



THANK YOU!!