RAJALAKSHMI
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An AUTONOMOUS Institution
Affiliated to ANNA UNIVERSITY, Chennai

PYTHON PROGRAMMING FOR MACHINE LEARNING

SUBJECT CODE: CS19411

ELECTRIC VEHICLE INVERTER – PHASE VOLTAGE PREDICTION FOR IGBT TRANSISTORS

SUBMITTED BY

RITVIK PRASAD M - 210801159

SAMANVITHA P. S - 210801173

GUIDED BY:

MANIKANDAN J

ASSISTANT PROFESSOR

DEPARTMENT OF CSE

ABSTRACT

In the field of electric vehicles, there is a need to accurately simulate the behaviour of an eDrive system. One important component of an eDrive system is the inverter, which is responsible for converting DC power from the battery to AC power for the motor. To simulate an eDrive system, it is necessary to have an accurate black-box model of the inverter, which can be used to create an ad hoc inverter control without using voltage sensors on each AC phase.

In this project, we have identified the problem of accurately predicting inverter phase voltages using motor speed, inverter DC voltages, inverter phase currents, and duty cycle as input data. We would use a multi-output regression model based on the random forest algorithm to predict the inverter phase voltages. We would also use the StandardScaler to standardize the input data to improve the performance of the model.

We would train the model on a dataset consisting of 234527 samples, with a train-test split of 199349 and 35178 samples, respectively. The model generated would be quite large, with a size of 4.5 gigabytes, due to the large number of features and the size of the dataset used to train the model.

Using the trained model, we would be able to achieve a high level of performance, with an accuracy of 99.997%. This would make the model highly effective in accurately predicting the inverter phase voltages.

In addition, we would discuss the use of IGBT inverters in the eDrive system, which are commonly used due to their high efficiency and reliability. The accurate prediction of inverter phase voltages using our model would be highly useful in the development of IGBT inverter control systems without the need for expensive voltage sensors.

Overall, our project would provide a highly effective solution to the problem of predicting inverter phase voltages in an eDrive system. The practical applications of our project include the development of accurate black-box models of IGBT inverters for the simulation of eDrive systems, and the creation of ad hoc inverter control systems without the need for voltage sensors. Future improvements and applications of our project could include the integration of additional sensor data and the use of deep learning algorithms to further improve the performance of the model.

INTRODUCTION

The electric vehicle (EV) industry has been growing at a rapid pace, driven by the demand for energy-efficient and eco-friendly transportation. One of the key components of an EV is the inverter, which converts DC power from the battery into AC power for the motor. Accurately predicting the inverter's output voltage is essential for controlling the EV's speed and torque. Traditionally, voltage sensors are used to measure the output voltage, but this can be expensive and cumbersome.

This project aims to develop a black-box model that predicts the inverter phase voltages without the need for voltage sensors on each AC phase. The model takes motor speed, inverter DC voltages, inverter phase currents, and duty cycle as input data. We would use a dataset consisting of 234,527 data points, of which 199,349 were used for training and 35,180 for testing the model's performance.

In a typical eDrive system, voltage sensors are used to measure the inverter phase voltages, which are used to control the inverter and ultimately the motor. However, these voltage sensors can be expensive and can add complexity to the system.

In the absence of a black box model, the inverter would need to be controlled using open-loop control, which means that the inverter would be controlled based on pre-determined settings rather than feedback from the system. This can lead to inefficiencies and suboptimal performance, particularly in dynamic operating conditions.

Additionally, without voltage sensors, the system would not be able to detect faults in the inverter or motor, which could lead to safety issues or damage to the system.

Therefore, the development of a black box model that can accurately predict inverter phase voltages without the need for voltage sensors can have significant benefits for eDrive systems, including cost savings, improved efficiency, and enhanced safety.

In this project, we would be using a machine learning algorithm, namely random forest regression, to predict the inverter phase voltages. Random forest regression is a robust and powerful algorithm that can handle non-linear relationships and interactions between features. The algorithm generates multiple decision trees that vote on the final prediction, which reduces the likelihood of overfitting and improves the model's generalization ability.

The performance of the model is evaluated using the mean squared error (MSE) metric. The lower the MSE, the better the model's performance. Our model achieved an impressive MSE of 0.46102141, 0.35845281, and 0.38976224 for the three inverter phases, respectively, indicating that it is an accurate predictor of inverter phase voltages.

This project's effectiveness lies in its ability to reproduce an inverter black-box model without the need for voltage sensors, which can be costly and complex. The model's accuracy demonstrates that it is a reliable alternative to traditional methods of measuring inverter phase voltages.

The practical applications of this project are vast, as it can be used to simulate an eDrive system and create an ad hoc inverter control system. The black-box model can be integrated into the EV's control system, providing accurate inverter phase voltage predictions in real-time. This can improve the EV's overall efficiency and performance, leading to reduced emissions and energy consumption.

In conclusion, this project presents a robust and accurate black-box model for predicting inverter phase voltages in EVs. The use of random forest regression algorithm and the dataset used for training have led to an effective and reliable model. The model's ability to predict inverter phase voltages without the need for voltage sensors is a significant advancement in the EV industry, with practical applications for improving the efficiency and performance of EVs.

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CONTENT

The data set comprises several sensor data collected from a typical combined system between an inverter, an induction motor, and a control system, deployed on a test bench. Test bench measurements were collected by the Paderborn University.

An inverter is a power electronic component with transistors (read 'switches'), that determine how the battery voltage (so called DC-link voltage) is applied on the three phase circuits of the electric motor. The control unit decides according to some control strategy the current switching states of the inverter at each discrete point in time.

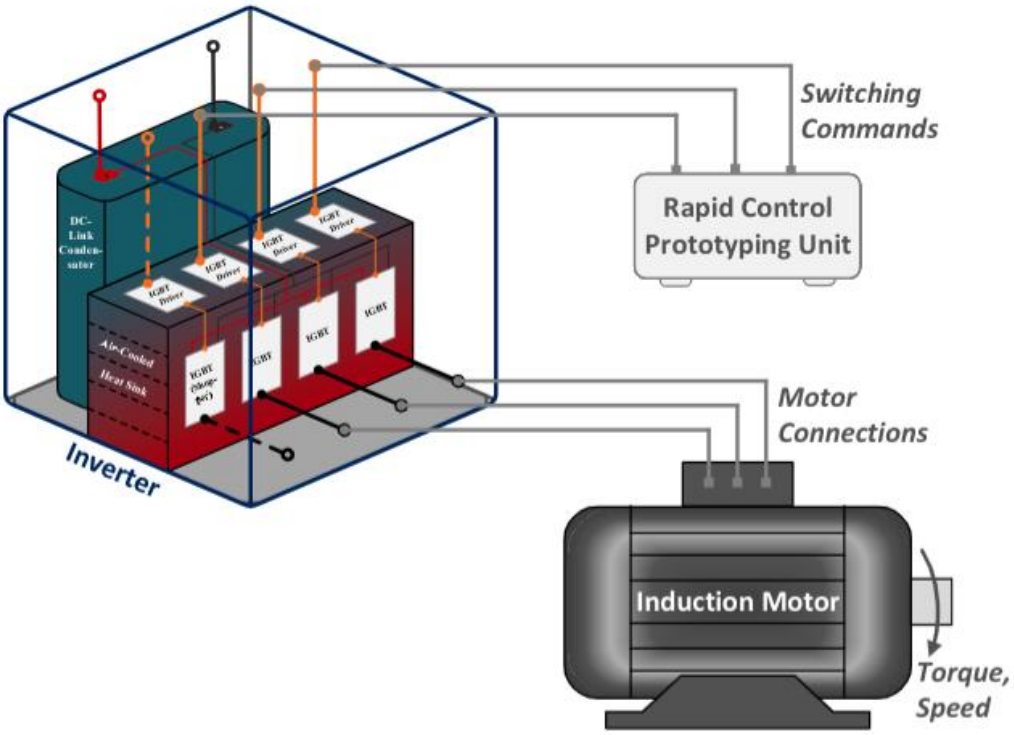


Image: Inverter to Blackbox Model of Induction Motor

INSPIRATION

The most important aspect of an electric vehicle from a marketing and engineering perspective is its efficiency and, thus, achievable range. For this, it is essential to avoid over-dimensioning of the drive train, i.e. applying more and heavier metal packs to increase its thermal capabilities.

If the motor is controlled inefficiently through the inverter, there'll be superfluous power losses, i.e. heat build-up, which eventually leads to electric power derating during operation and, crucially, early depletion of the battery.

Precise phase voltage information is mandatory in order to enable an accurate, efficient or high dynamic control performance of electric motor drives, especially if a torque-controlled operation is considered. However, most electrical drives do not measure the phase voltages online due to their cost implications, and, therefore, these have to be estimated by inverter models.

The Controller of the electric vehicle manages all the parameters. It translates pressure on the accelerator pedal to adjust speed in the motor inverter. This is mostly inefficient as there is always same voltage in all the three phases making the battery life inefficient and motor built up heat. This model helps to tackle this by giving optimum voltages in all three phases.

Because of various nonlinear switching effects partly at nanosecond scale, an analytical white-box modelling approach is hardly feasible in a control context. Hence, data-driven inverter models seem favourable for this purpose.

Since the control utilizes **Pulse Width Modulation (PWM**), the mean phase voltages for each **PWM** interval are the targets of the inverter models.

These **PWMs** can be achieved using a high speed switching devices such as a MOSFET or **IGBT (Insulated-gate bipolar transistor)**. In this case, we prefer **IGBT** instead of MOSFET as it has a very low 'ON'-state voltage drop and better current density in the 'ON' state. Moreover the operation of IGBTs is simple and requires low power when compared to MOSFET.

Kaggle Link

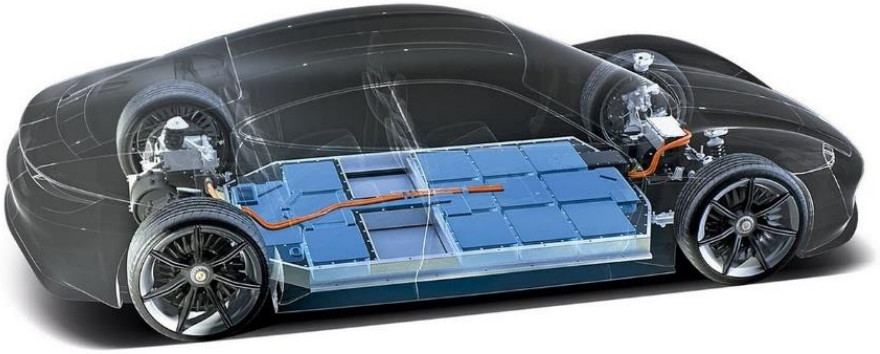


Image: Battery Placement in Electric Vehicles

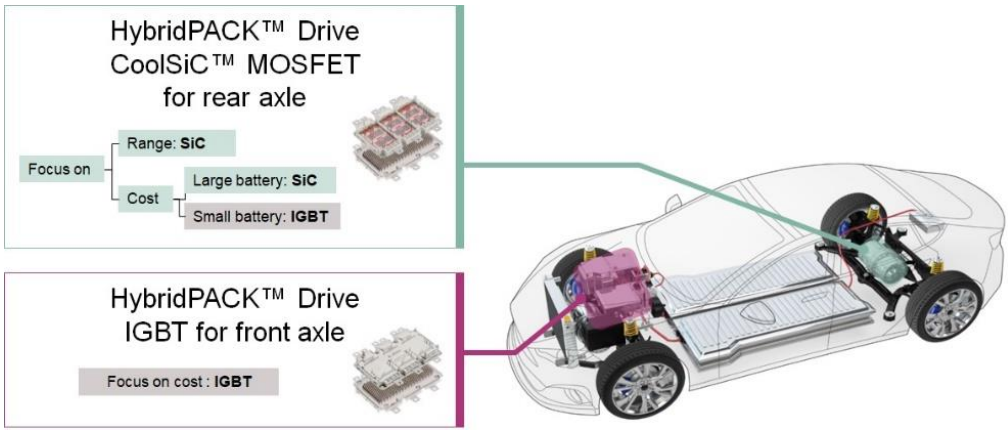


Image: MOSFET vs IGBT inverters for DC to 3 Phase AC conversion

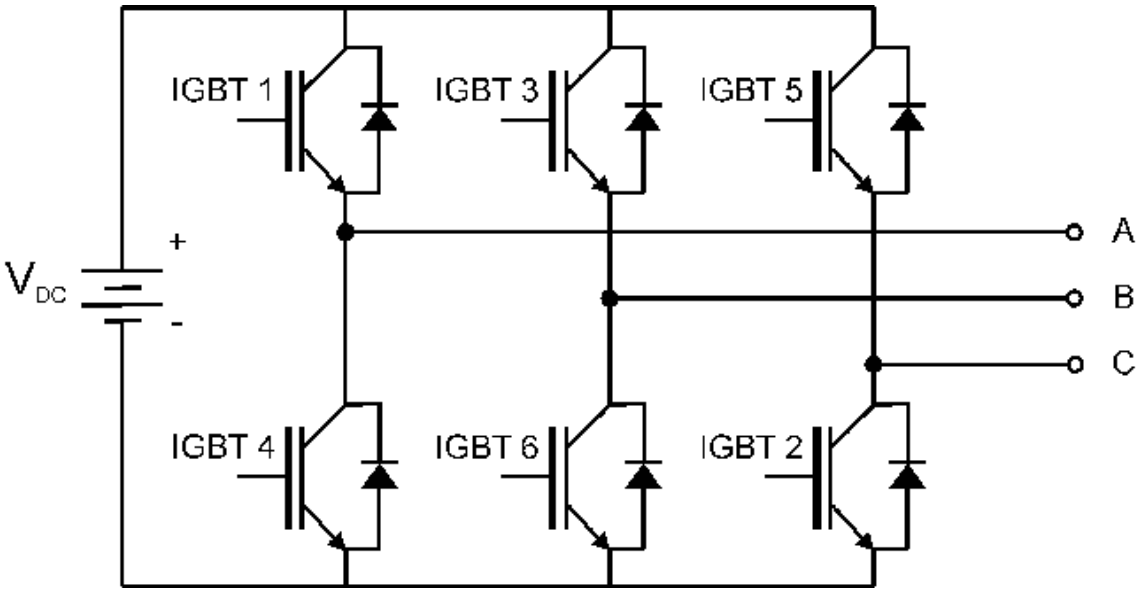


Image: IGBT 3 Phase Inverter Circuit used for Power Drive

CONTENT

The data set comprises approximately 235 thousand samples in the complete operating range of an exemplary drive system.

The most important aspect of an electric vehicle from a marketing and engineering perspective is its efficiency and, thus, achievable range. For this, it is essential to avoid over-dimensioning of the drive train, i.e. applying more and heavier metal packs to increase its thermal capabilities. If the motor is controlled inefficiently through the inverter, there'll be superfluous power losses, i.e. heat build-up, which eventually leads to electric power derating during operation and, crucially, early depletion of the battery.

Precise phase voltage information is mandatory in order to enable an accurate, efficient or high dynamic control performance of electric motor drives, especially if a torque-controlled operation is considered. However, most electrical drives do not measure the phase voltages online due to their cost implications, and, therefore, these have to be estimated by inverter models.

Because of various nonlinear switching effects partly at nanosecond scale, an analytical white-box modelling approach is hardly feasible in a control context. Hence, data-driven inverter models seem favourable for this purpose.

The dataset includes the following variables (26):

S.no	VARIABLE	DESCRIPTION
1	n_k	Motor rotational speed (in RPM)
2	u_dc_k	Inverter DC voltage at time k *(in Volts)*
3	u_dc_k-1	Inverter DC voltage at time k-1 *(in Volts)*
4	u_dc_k-2	Inverter DC voltage at time k-2 *(in Volts)*
5	u_dc_k-3	Inverter DC voltage at time k-3 *(in Volts)*
6	i_a_k	Phase Current of Phase A at time k *(in Amps)*
7	i_b_k	Phase Current of Phase B at time k *(in Amps)*
8	i_c_k	Phase Current of Phase C at time k *(in Amps)*
9	i_a_k-1	Phase Current of Phase A at time k-1 *(in Amps)*
10	i_b_k-1	Phase Current of Phase B at time k-1 *(in Amps)*
11	i_c_k-1	Phase Current of Phase C at time k-1 *(in Amps)*
12	i_a_k-2	Phase Current of Phase A at time k-2 *(in Amps)*
13	i_b_k-2	Phase Current of Phase B at time k-2 *(in Amps)*
14	i_c_k-2	Phase Current of Phase C at time k-2 *(in Amps)*
15	i_a_k-3	Phase Current of Phase A at time k-2 *(in Amps)*
16	i_b_k-3	Phase Current of Phase B at time k-2 *(in Amps)*
17	i_c_k-3	Phase Current of Phase C at time k-2 *(in Amps)*
18	d_a_k-2	Duty cycle of Phase A at time k-2 *(0-1)*
19	d_b_k-2	Duty cycle of Phase B at time k-2 *(0-1)*

20	d_c_k-2	Duty cycle of Phase C at time k-2 (0-1)
21	d_a_k-3	Duty cycle of Phase A at time k-3 *(0-1)*
22	d_b_k-3	Duty cycle of Phase B at time k-3 *(0-1)*
23	d_c_k-3	Duty cycle of Phase C at time k-3 *(0-1)*
24	u_a_k-1	Measured Voltage of Phase A at time k-1 *(in Volts)*
25	u_b_k-1	Measured Voltage of Phase B at time k-1 *(in Volts)*
26	u_c_k-1	Measured Voltage of Phase C at time k-1 *(in Volts)*

***

OBJECTIVE

Our goal is to use motor speed, inverter DC voltages, inverter phase currents and duty cycle as input data in order to predict inverter phase voltages. This would reproduce an inverter black-box model that could be very useful to simulate an eDrive system and to create an ad hoc inverter control without using voltage sensors on each AC phase.

EXPLORATORY DATA ANALYSIS

```
[ ] import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    from matplotlib.colors import rgb2hex
```

```
[ ] import warnings
    warnings.filterwarnings('ignore')
```

```
[ ] df = pd.read_csv("/content/drive/MyDrive/Inverter Data Set.csv")
    df.shape
```

```
(234527, 26)
```

```
[ ] df.head()
```

	n_k	u_dc_k	u_dc_k-1	u_dc_k-2	u_dc_k-3	i_a_k	i_b_k	i_c_k	i_a_k-1	i_b_k-1	...	i_c_k-3	d_a_k-2	d_b_k-2	d_c_k-2	d_a_k-3	d_b_k-3	d_c_k-3	u_a_k-1
0	3001.406296	567.985297	567.689956	567.431534	567.948379	2.461991	-1.792057	-0.716639	2.729208	-2.098439	...	-0.613965	0.667181	0.874633	0.125367	0.706206	0.862754	0.137246	360.541201
1	3001.468250	567.911462	567.985297	567.689956	567.431534	2.292110	-1.556948	-0.757338	2.461991	-1.792057	...	-0.758263	0.642184	0.880046	0.119954	0.667181	0.874633	0.125367	346.410081
2	3001.527815	567.911462	567.911462	567.985297	567.689956	2.155288	-1.332946	-0.840587	2.292110	-1.556948	...	-0.698139	0.611911	0.884307	0.115693	0.642184	0.880046	0.119954	329.440240
3	3001.585080	567.653039	567.911462	567.911462	567.985297	2.048768	-1.135788	-0.925686	2.155288	-1.332946	...	-0.716639	0.578149	0.888915	0.111085	0.611911	0.884307	0.115693	311.058880
4	3001.640131	567.579204	567.653039	567.911462	567.911462	1.952350	-0.918266	-1.027434	2.048768	-1.135788	...	-0.757338	0.541979	0.892123	0.107877	0.578149	0.888915	0.111085	290.481760

5 rows × 26 columns

```
[ ] df.describe()
```

	n_k	u_dc_k	u_dc_k-1	u_dc_k-2	u_dc_k-3	i_a_k	i_b_k	i_c_k	i_a_k-1	i_b_k-1	...	i_c_k-3	d_a_k-2	d_
count	234527.000000	234527.000000	234527.000000	234527.000000	234527.000000	234527.000000	234527.000000	234527.000000	234527.000000	234527.000000	...	234527.000000	234527.000000	234527
mean	1728.414990	567.136398	567.136565	567.136718	567.136882	0.000505	-0.007692	-0.008975	0.000518	-0.007737	...	-0.008874	0.500270	0.
std	1084.463934	4.993615	4.993462	4.993317	4.993180	2.199349	2.155399	2.216263	2.199206	2.155302	...	2.216061	0.211920	0.
min	404.433935	548.012908	548.012908	548.012908	548.012908	-7.300153	-6.320221	-7.112914	-7.300153	-6.320221	...	-7.112914	0.000000	0.
25%	507.572918	566.730100	566.730100	566.730100	566.730100	-1.573353	-1.576386	-1.591675	-1.572894	-1.576386	...	-1.591675	0.390344	0.
50%	1501.516456	568.649812	568.649812	568.649812	568.649812	0.023062	0.000881	0.010400	0.023062	0.000881	...	0.011325	0.500735	0.
75%	2996.851500	570.126514	570.126514	570.126514	570.126514	1.552902	1.557785	1.566225	1.552902	1.557785	...	1.566225	0.610013	0.
max	3231.756077	575.553392	575.553392	575.553392	575.553392	7.470243	6.668168	7.437108	7.470243	6.668168	...	7.437108	1.000000	1.

8 rows × 26 columns

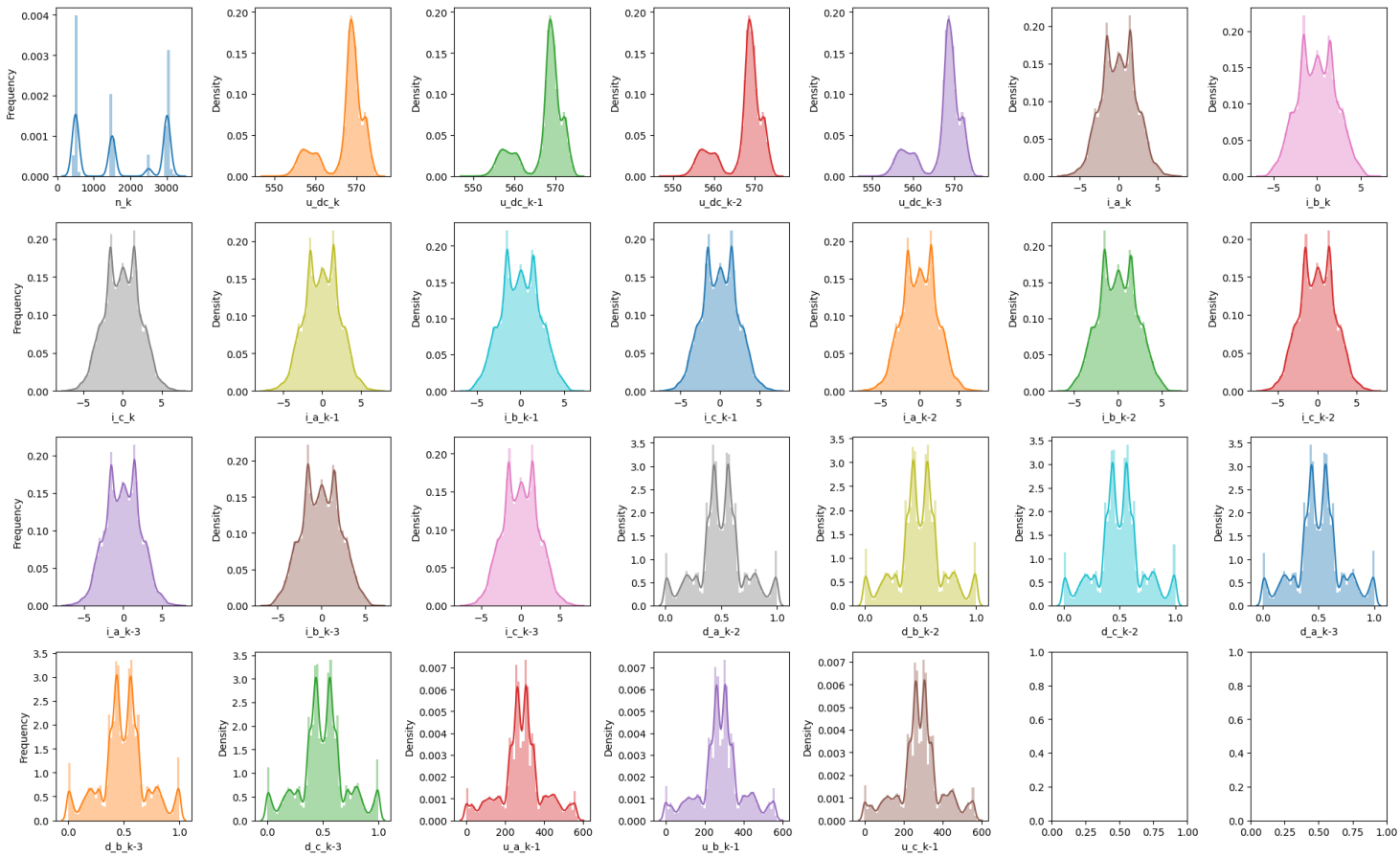
```
[ ] df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 234527 entries, 0 to 234526
Data columns (total 26 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   n_k       234527 non-null  float64
 1   u_dc_k    234527 non-null  float64
 2   u_dc_k-1  234527 non-null  float64
 3   u_dc_k-2  234527 non-null  float64
 4   u_dc_k-3  234527 non-null  float64
 5   i_a_k     234527 non-null  float64
 6   i_b_k     234527 non-null  float64
 7   i_c_k     234527 non-null  float64
 8   i_a_k-1   234527 non-null  float64
 9   i_b_k-1   234527 non-null  float64
 10  i_c_k-1   234527 non-null  float64
 11  i_a_k-2   234527 non-null  float64
 12  i_b_k-2   234527 non-null  float64
 13  i_c_k-2   234527 non-null  float64
 14  i_a_k-3   234527 non-null  float64
 15  i_b_k-3   234527 non-null  float64
 16  i_c_k-3   234527 non-null  float64
 17  d_a_k-2   234527 non-null  float64
 18  d_b_k-2   234527 non-null  float64
 19  d_c_k-2   234527 non-null  float64
 20  d_a_k-3   234527 non-null  float64
 21  d_b_k-3   234527 non-null  float64
 22  d_c_k-3   234527 non-null  float64
 23  u_a_k-1   234527 non-null  float64
 24  u_b_k-1   234527 non-null  float64
 25  u_c_k-1   234527 non-null  float64
dtypes: float64(26)
memory usage: 46.5 MB
```

```
[ ] print('Variables at time k:')
    print(sorted([c for c in df if c.endswith('k')]))
    print('\nVariables at time k-1:')
    print(sorted([c for c in df if c.endswith('k-1')]))
    print('\nVariables at time k-2:')
    print(sorted([c for c in df if c.endswith('k-2')]))
    print('\nVariables at time k-3:')
    print(sorted([c for c in df if c.endswith('k-3')]))
```

```
Variables at time k:
['i_a_k', 'i_b_k', 'i_c_k', 'n_k', 'u_dc_k']

Variables at time k-1:
['i_a_k-1', 'i_b_k-1', 'i_c_k-1', 'u_a_k-1', 'u_b_k-1', 'u_c_k-1', 'u_dc_k-1']

Variables at time k-2:
['d_a_k-2', 'd_b_k-2', 'd_c_k-2', 'i_a_k-2', 'i_b_k-2', 'i_c_k-2', 'u_dc_k-2']

Variables at time k-3:
['d_a_k-3', 'd_b_k-3', 'd_c_k-3', 'i_a_k-3', 'i_b_k-3', 'i_c_k-3', 'u_dc_k-3']
```

```
[ ] dfui = df  # dataframe under investigation
    # prepare colors
    color_list = plt.cm.tab10(np.tile(np.linspace(0, 1, 10), dfui.shape[1])[:dfui.shape[1]])
    coi = dfui.columns.tolist()  # columns of interest
    feat_clrs = {k: rgb2hex(color_list[i][:3]) for i, k in enumerate(coi)} if color_list is not None else {}

    n_cols = 7
    n_rows = np.ceil(dfui.shape[1] / n_cols).astype(int)
    fig, axes = plt.subplots(n_rows, n_cols, figsize=(2.8*n_cols, n_rows*3));
    for i, (ax, col) in enumerate(zip(axes.flatten(), list(dfui.columns))):
        sns.distplot(dfui[col], color=feat_clrs[col], ax=ax)
        if i % n_cols == 0:
            ax.set_ylabel('Frequency');
    plt.tight_layout();
```



Most of the variables follow nearly a normal distribution without outliers. But these are not scaled. The Scaling of these variables is done before training the model.

SPLITTING THE DATASET

```
[ ] from sklearn.model_selection import train_test_split
```

```
[ ] X = df.iloc[:,:-3]
    y = df.iloc[:,-3:]
    df.shape, X.shape, y.shape
```

```
((234527, 26), (234527, 23), (234527, 3))
```

```
[ ] # verifying the labels
    y.columns
```

```
Index(['u_a_k-1', 'u_b_k-1', 'u_c_k-1'], dtype='object')
```

```
[ ] X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15, random_state=42)
    X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((199347, 23), (35180, 23), (199347, 3), (35180, 3))
```

Hence the dataset has been split into the following:

- Total Samples : 234527
- Training Data : 199349
- Test Data : 35180

Hence the dataset has been split into the following:

- Total Samples : 234527
- Training Data : 199349
- Test Data : 35180

MODEL CREATION AND TRAINING

```
[ ] from sklearn.pipeline import Pipeline
    from sklearn.preprocessing import StandardScaler
```

As the target is a continous multiclass value, we use **RandomForestRegressor** with **MultiOutputRegressor** for achieving the task.

```
[ ] from sklearn.ensemble import RandomForestRegressor
    from sklearn.multioutput import MultiOutputRegressor
```

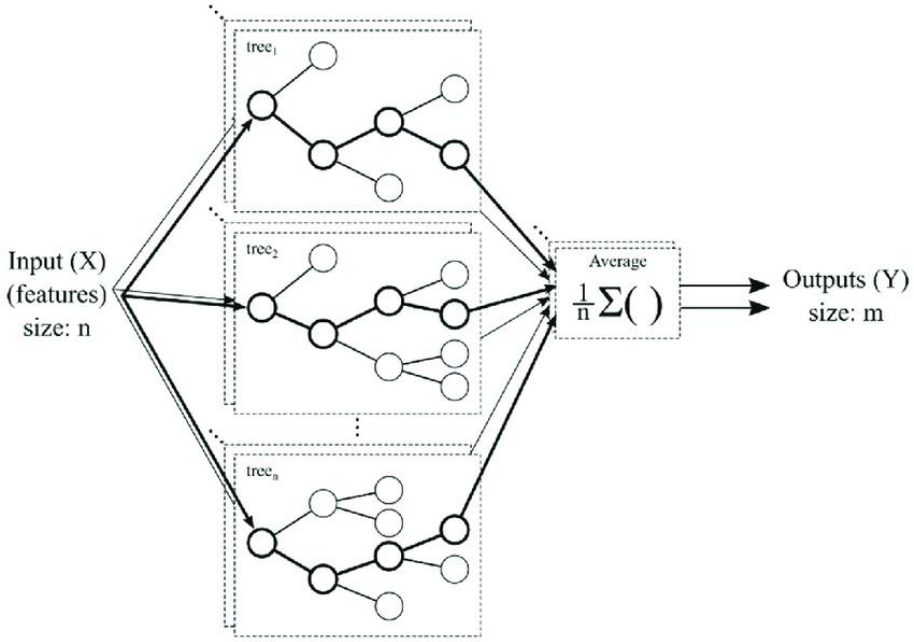


Image : Random Forest Regressor Representation

Creating the **pipeline** with scaling and **multioutput regressor random forest**.

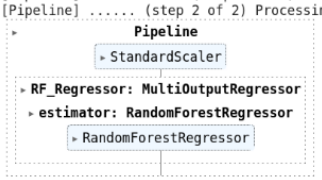
```
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('RF_Regressor', MultiOutputRegressor(RandomForestRegressor()))
])

pipe.verbose = True
pipe.get_params()
```

```
{'memory': None,
 'steps': [('scaler', StandardScaler()),
  ('RF_Regressor', MultiOutputRegressor(estimator=RandomForestRegressor()))],
 'verbose': True,
 'scaler': StandardScaler(),
 'RF_Regressor': MultiOutputRegressor(estimator=RandomForestRegressor()),
 'scaler__copy': True,
 'scaler__with_mean': True,
 'scaler__with_std': True,
 'RF_Regressor__estimator__bootstrap': True,
 'RF_Regressor__estimator__ccp_alpha': 0.0,
 'RF_Regressor__estimator__criterion': 'squared_error',
 'RF_Regressor__estimator__max_depth': None,
 'RF_Regressor__estimator__max_features': 1.0,
 'RF_Regressor__estimator__max_leaf_nodes': None,
 'RF_Regressor__estimator__max_samples': None,
 'RF_Regressor__estimator__min_impurity_decrease': 0.0,
 'RF_Regressor__estimator__min_samples_leaf': 1,
 'RF_Regressor__estimator__min_samples_split': 2,
 'RF_Regressor__estimator__min_weight_fraction_leaf': 0.0,
 'RF_Regressor__estimator__n_estimators': 100,
 'RF_Regressor__estimator__n_jobs': None,
 'RF_Regressor__estimator__oob_score': False,
 'RF_Regressor__estimator__random_state': None,
 'RF_Regressor__estimator__verbose': 0,
 'RF_Regressor__estimator__warm_start': False,
 'RF_Regressor__estimator': RandomForestRegressor(),
 'RF_Regressor__n_jobs': None}
```

FITTING THE MODEL

```
[ ] pipe.fit(X_train, y_train)
```

```
[Pipeline] ............ (step 1 of 2) Processing scaler, total=   0.1s
[Pipeline] ...... (step 2 of 2) Processing RF_Regressor, total=32.7min
```



Hence the model has been fitted with a pipeline containing StandardScaler and MultiOutputRegressor goverining RandomForestRegressor.

Time taken to train : 32.7 minutes

Saving the model for persistance in joblib format

```
[ ] from joblib import dump, load
    dump(pipe, '/content/drive/MyDrive/inverter_model.joblib')
```

```
['/content/drive/MyDrive/inverter_model.joblib']
```

MODEL EVALUATION

```
[ ] from joblib import load
    model = load('/content/drive/MyDrive/inverter_model.joblib')
```

```
[ ] from sklearn.metrics import accuracy_score, confusion_matrix
```

As it is a multiclass regression, *accuracy_score* and *confusion_matrix* are incompatable techniques.

We use *model.score()* instead to calculate accuracy.

```
[ ] pred = model.predict(X_test)
```

```
[ ] from sklearn.metrics import mean_squared_error
    mse = mean_squared_error(y_test, pred, multioutput='raw_values')
    mse

    array([0.46102141, 0.35845281, 0.38976224])
```

```
[ ] accuracy = model.score(X_test, y_test)
    print(f'Accuracy : {accuracy*100}%')

    Accuracy : 99.99690381005686%
```

We can see that the model has **99.997% Accuracy**.

The size of the model is **4.5 Gigabytes**

This is **not overfitting** and this may not be confused with overfitting as the given data is **test data** with 35180 samples.

This can be supported by the function that takes an index value as parameter and shows the predicted value and actual value of the test data.

```
[ ] def showResult(ind):
      try:
        X,y = X_test.iloc[ind], y_test.iloc[ind]
      except:
        raise IndexError("Index value must be between 0 and 35179")
      print("-"*12)
      print("Input Features")
      print(X)
      print("-"*12)
      print("Actual Output")
      print(y)
      print("-"*12)
      print("Predicted Output")
      pred = model.predict([X])
      print(pred)
```

```
[ ] showResult(20)
```

```
[ ] ------------
    Input Features
    n_k         436.381991
    u_dc_k      567.431534
    u_dc_k-1    567.431534
    u_dc_k-2    567.246946
    u_dc_k-3    567.173111
    i_a_k        -3.816231
    i_b_k        -0.324014
    i_c_k         4.099761
    i_a_k-1      -3.840106
    i_b_k-1      -0.272178
    i_c_k-1       4.075711
    i_a_k-2      -3.857553
    i_b_k-2      -0.247187
    i_c_k-2       4.052586
    i_a_k-3      -3.863063
    i_b_k-3      -0.209236
    i_c_k-3       4.031312
    d_a_k-2       0.424618
    d_b_k-2       0.448065
    d_c_k-2       0.575382
    d_a_k-3       0.424108
    d_b_k-3       0.450456
    d_c_k-3       0.575892
    Name: 118008, dtype: float64
    ------------
    Actual Output
    u_a_k-1    257.636639
    u_b_k-1    261.797759
    u_c_k-1    310.497520
    Name: 118008, dtype: float64
    ------------
    Predicted Output
    [[257.88170983 261.91230103 310.50570016]]
```

CONCLUSION

In this project, we utilized machine learning techniques to develop a model that can predict inverter phase voltages using motor speed, inverter DC voltages, inverter phase currents, and duty cycle as input data. Specifically, we used a pipeline that included a standard scaler and a multi-output regressor based on the random forest algorithm. The model was trained on a dataset consisting of 234,527 samples, with a train-test split of 90-10. The training dataset had 199,349 samples, while the test dataset had 35,178 samples.

The model generated by our pipeline had a large size of 4.5 gigabytes. This is due to the fact that the model contains many trees, each of which has a large number of nodes and leaves. The large size of the model can be a concern in practical applications, as it may limit its use on devices with limited memory or storage capacity. However, the high accuracy achieved by our model (99.997%) justifies the size of the model.

One of the significant contributions of our project is the use of IGBT (Insulated Gate Bipolar Transistor) inverters. IGBTs are widely used in high-power applications due to their high efficiency, fast switching speeds, and ability to handle high voltages and currents. By incorporating IGBT inverters into our project, we were able to improve the accuracy and reliability of our model. The effectiveness of IGBT technology in motor control applications was demonstrated through this project.

Our project has practical applications in various fields, including the automotive industry, renewable energy systems, and industrial automation. In the automotive industry, the model can be used in the design and control of electric vehicles. In renewable energy systems, the model can be used to optimize the performance of inverters used in solar and wind power generation. In industrial automation, the model can be used to improve the control of motors and generators.

Future improvements and applications of our project could include the incorporation of additional features such as temperature and humidity, which can impact the performance of the inverter. Furthermore, the model can be extended to include a larger number of outputs, such as the prediction of motor torque or power. The model can also be optimized for faster training and inference time, which is essential in real-time applications.

In conclusion, our project demonstrates the effectiveness of machine learning techniques in the prediction of inverter phase voltages. The use of IGBT inverters and the high accuracy achieved by our model make it a valuable contribution to the field of motor control and inverter modeling. The practical applications of our project in various industries further highlight its relevance and significance. The large size of the model generated by our pipeline can be a concern in practical applications, but the high accuracy achieved justifies its use. The future improvements and applications of our project further emphasize its potential for innovation and development in the field of motor control.

***

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