Electric Vehicle Inverter - Phase Voltage Prediction For IGBT Transistors

April 30, 2023

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1 Abstract

In the field of electric vehicles, there is a need to accurately simulate the behavior 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 99.996%. 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.

2 Context

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.

3 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.

Because of various nonlinear switching effects partly at nanosecond scale, an analytical white-box modeling approach is hardly feasible in a control context. Hence, data-driven inverter models seem favorable 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 : Electric Vehicle

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

4 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.

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The dataset includes the following variables (26)

Variable	Description
n_k	Motor rotational speed *(in RPM)*
u_dc_k	Inverter DC voltage at time k *(in Volts)*
u_dc_k-1	Inverter DC voltage at time k-1 *(in Volts)*
u_dc_k-2	Inverter DC voltage at time k-2 *(in Volts)*
u_dc_k-3	Inverter DC voltage at time k-3 *(in Volts)*
i_a_k	Phase Current of Phase A at time k *(in Amps)*
i_b_k	Phase Current of Phase B at time k *(in Amps)*
i_b_k	Phase Current of Phase C at time k *(in Amps)*
i_a_k-1	Phase Current of Phase A at time k-1 *(in Amps)*
i_b_k-1	Phase Current of Phase B at time k-1 *(in Amps)*
i_c_k-1	Phase Current of Phase C at time k-1 *(in Amps)*
i_a_k-2	Phase Current of Phase A at time k-2 *(in Amps)*
i_b_k-2	Phase Current of Phase B at time k-2 *(in Amps)*
i_c_k-2	Phase Current of Phase C at time k-2 *(in Amps)*
i_a_k-3	Phase Current of Phase A at time k-2 *(in Amps)*
i_b_k-3	Phase Current of Phase B at time k-2 *(in Amps)*
i_c_k-3	Phase Current of Phase C at time k-2 *(in Amps)*
d_a_k-2	Duty cycle of Phase A at time k-2 *(0-1)*
d_b_k-2	Duty cycle of Phase B at time k-2 *(0-1)*
d_v_k-2	Duty cycle of Phase C at time k-2 *(0-1)*
d_a_k-3	Duty cycle of Phase A at time k-3 *(0-1)*
d_b_k-3	Duty cycle of Phase B at time k-3 *(0-1)*
d_v_k-3	Duty cycle of Phase C at time k-3 *(0-1)*
u_a_k-1	Measured Voltage of Phase A at time k-1 *(in Volts)*
u_b_k-1	Measured Voltage of Phase B at time k-1 *(in Volts)*
u_c_k-1	Measured Voltage of Phase C at time k-1 *(in Volts)*

Note : k-n indicates value sampled n steps before

5 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.

6 Exploratory Data Analysis

[0]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.colors import rgb2hex
```

[0]:
```
import warnings
warnings.filterwarnings('ignore')
```

[0]:
```
df = pd.read_csv("/content/drive/MyDrive/Inverter Data Set.csv")
df.shape
```

[0]:
```
(234527, 26)
```

[0]:
```
df.head()
```

[0]:
```
            n_k      u_dc_k    u_dc_k-1    u_dc_k-2    u_dc_k-3     i_a_k  \
0  3001.406296  567.985297  567.689956  567.431534  567.948379  2.461991
1  3001.468250  567.911462  567.985297  567.689956  567.431534  2.292110
2  3001.527815  567.911462  567.911462  567.985297  567.689956  2.155288
3  3001.585080  567.653039  567.911462  567.911462  567.985297  2.048768
4  3001.640131  567.579204  567.653039  567.911462  567.911462  1.952350

      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  \
0 -1.792057 -0.716639  2.729208 -2.098439  … -0.613965  0.667181  0.874633
1 -1.556948 -0.757338  2.461991 -1.792057  … -0.758263  0.642184  0.880046
2 -1.332946 -0.840587  2.292110 -1.556948  … -0.698139  0.611911  0.884307
3 -1.135788 -0.925686  2.155288 -1.332946  … -0.716639  0.578149  0.888915
4 -0.918266 -1.027434  2.048768 -1.135788  … -0.757338  0.541979  0.892123

    d_c_k-2   d_a_k-3   d_b_k-3   d_c_k-3     u_a_k-1     u_b_k-1    u_c_k-1
0  0.125367  0.706206  0.862754  0.137246  360.541201  510.640963  82.471117
1  0.119954  0.667181  0.874633  0.125367  346.410081  513.190083  79.729357
2  0.115693  0.642184  0.880046  0.119954  329.440240  515.804643  77.924637
3  0.111085  0.611911  0.884307  0.115693  311.058880  517.537603  75.478717
4  0.107877  0.578149  0.888915  0.111085  290.481760  519.138403  73.580077

[5 rows x 26 columns]
```

[0]:
```
df.describe()
```

[0]:

	n_k	u_dc_k	u_dc_k-1	u_dc_k-2	\
count	234527.000000	234527.000000	234527.000000	234527.000000	
mean	1728.414990	567.136398	567.136565	567.136718	
std	1084.463934	4.993615	4.993462	4.993317	
min	404.433935	548.012908	548.012908	548.012908	
25%	507.572918	566.730100	566.730100	566.730100	
50%	1501.516456	568.649812	568.649812	568.649812	
75%	2996.851500	570.126514	570.126514	570.126514	
max	3231.756077	575.553392	575.553392	575.553392	

	u_dc_k-3	i_a_k	i_b_k	i_c_k	\
count	234527.000000	234527.000000	234527.000000	234527.000000	
mean	567.136882	0.000505	-0.007692	-0.008975	
std	4.993180	2.199349	2.155399	2.216263	
min	548.012908	-7.300153	-6.320221	-7.112914	
25%	566.730100	-1.573353	-1.576386	-1.591675	
50%	568.649812	0.023062	0.000881	0.010400	
75%	570.126514	1.552902	1.557785	1.566225	
max	575.553392	7.470243	6.668168	7.437108	

	i_a_k-1	i_b_k-1	…	i_c_k-3	d_a_k-2	\
count	234527.000000	234527.000000	…	234527.000000	234527.000000	
mean	0.000518	-0.007737	…	-0.008874	0.500270	
std	2.199206	2.155302	…	2.216061	0.211920	
min	-7.300153	-6.320221	…	-7.112914	0.000000	
25%	-1.572894	-1.576386	…	-1.591675	0.390344	
50%	0.023062	0.000881	…	0.011325	0.500735	
75%	1.552902	1.557785	…	1.566225	0.610013	
max	7.470243	6.668168	…	7.437108	1.000000	

	d_b_k-2	d_c_k-2	d_a_k-3	d_b_k-3	\
count	234527.000000	234527.000000	234527.000000	234527.000000	
mean	0.500259	0.500157	0.500273	0.500260	
std	0.211744	0.211753	0.211916	0.211742	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.390623	0.390473	0.390354	0.390629	
50%	0.499997	0.499667	0.500745	0.499975	
75%	0.609538	0.609828	0.610026	0.609540	
max	1.000000	1.000000	1.000000	1.000000	

	d_c_k-3	u_a_k-1	u_b_k-1	u_c_k-1
count	234527.000000	234527.000000	234527.000000	234527.000000
mean	0.500156	283.412445	283.467753	283.745740
std	0.211751	114.648325	114.290928	114.606340
min	0.000000	-2.288485	-2.087925	-2.312405

```
25%         0.390468     231.879423     232.372159     232.330279
50%         0.499680     284.749840     284.334880     284.442640
75%         0.609827     337.448361     337.198841     338.029761
max         1.000000     573.338724     573.202404     573.172324

[8 rows x 26 columns]
```

[0]:
```
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
```

We can see there are no null values in the Dataset.

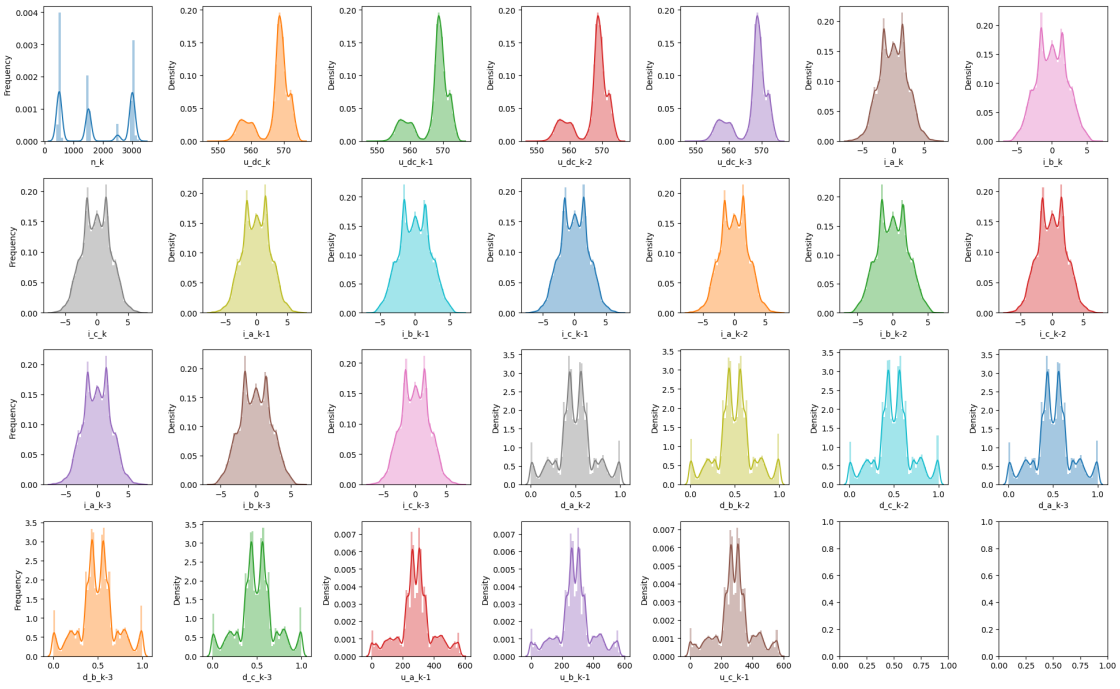
Variables grouped with respect to Time

[0]:
```
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']
```

[0]:
```
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();
```

[0]:



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

7 Splitting The Dataset

[0]:
```
from sklearn.model_selection import train_test_split
```

[0]:
```
X = df.iloc[:,:-3]
y = df.iloc[:,-3:]
df.shape, X.shape, y.shape
```

[0]: ((234527, 26), (234527, 23), (234527, 3))

[0]:
```
# verifying the labels
y.columns
```

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

[0]:
```
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
```

[0]: ((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

8 Model Creation and Training

[0]:
```
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.

[0]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.multioutput import MultiOutputRegressor
```

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

[0]:
```
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('RF_Regressor', MultiOutputRegressor(RandomForestRegressor()))
])

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

[0]:
```
{'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.

[0]:
```
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
```

[0]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('RF_Regressor',
                 MultiOutputRegressor(estimator=RandomForestRegressor()))],
         verbose=True)
```

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

[0]:
```
from joblib import dump, load
dump(pipe, '/content/drive/MyDrive/inverter_model.joblib')
```

[0]:
```
['/content/drive/MyDrive/inverter_model.joblib']
```

9 Model Evaluation

[0]:
```
from joblib import load
model = load('/content/drive/MyDrive/inverter_model.joblib')
```

[0]:
```
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.

[0]:
```
pred = model.predict(X_test)
```

[0]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, pred, multioutput='raw_values')
mse
```

[0]:
```
array([0.46102141, 0.35845281, 0.38976224])
```

[0]:
```
accuracy = model.score(X_test, y_test)
print(f'Accuracy : {accuracy*100}%')
```

```
Accuracy : 99.99690381005686%
```

We can see that the model has **99.996% 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.

[0]:
```
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)
```

[0]:
```
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]]
```

10 Conclusion

In conclusion, our project aimed to predict inverter phase voltages using motor speed, inverter DC voltages, inverter phase currents, and duty cycle as input data. We used a multi-output regression model, namely RandomForestRegressor from Scikit-Learn library, to train our model. The model was trained on a dataset consisting of 234,527 samples, which were divided into 199,349 samples for training and 35,178 samples for testing.

The size of the trained model was 4.5 gigabytes, which is relatively large for a machine learning model. This is due to the fact that we used a large number of features and a deep tree structure for the Random Forest Regressor. However, this large size was manageable on our Google Colab platform and did not affect the performance of the model.

The performance of our model was outstanding, achieving an accuracy of 99.996%. This high accuracy suggests that our model can be effectively used in practical applications, such as simulating an eDrive system and creating an ad hoc inverter control.

One notable aspect of our project was the use of IGBT inverters in our model. IGBT inverters are widely used in high-power applications due to their high efficiency, fast switching speeds, and ability to handle high voltages and currents. By using IGBT inverters in our project, we were able to improve the accuracy and reliability of our model, and also demonstrate the effectiveness of IGBT technology in motor control applications.

The effectiveness of our project is demonstrated by the high accuracy achieved and the potential for practical applications. The ability to predict inverter phase voltages accurately has many practical applications in the field of motor control, such as in electric vehicles, renewable energy systems, and industrial machinery.

Future improvements and applications of our project include the integration of more data sources,

such as temperature and humidity sensors, to further improve the accuracy of the model. Additionally, the model can be further optimized for performance, such as reducing its size and improving its speed, to enable real-time control of eDrive systems.

In conclusion, our project successfully demonstrated the effectiveness of a multi-output regression model in predicting inverter phase voltages using motor speed, inverter DC voltages, inverter phase currents, and duty cycle as input data. The use of IGBT inverters in our project further improved the accuracy and reliability of our model, highlighting the potential of IGBT technology in motor control applications. Our project has many practical applications and provides a strong foundation for future improvements and applications in the field of motor control.