Importing Libraries

In [ ]:

```
!pip install plotly shap
```

```
Requirement already satisfied: plotly in /usr/local/lib/python3.7/dist-packages (5.5.0)
Collecting shap
  Downloading shap-0.40.0-cp37-cp37m-manylinux2010_x86_64.whl (564 kB)
     |████████████████████████████████| 564 kB 27.6 MB/s
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.7/dist-packages (from plotly)
(8.0.1)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from plotly) (1.15.0)
Requirement already satisfied: numba in /usr/local/lib/python3.7/dist-packages (from shap) (0.51.2)
Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.7/dist-packages (from shap) (2
1.3)
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages (from shap) (1.3.5)
Requirement already satisfied: tqdm>4.25.0 in /usr/local/lib/python3.7/dist-packages (from shap) (4.6
4.0)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from shap) (1.4.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from shap) (1.21.6)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.7/dist-packages (from shap) (1.3.
0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-packages (from shap) (1.
0.2)
Collecting slicer==0.0.7
  Downloading slicer-0.0.7-py3-none-any.whl (14 kB)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /usr/local/lib/python3.7/dist-packages (fro
m packaging>20.9->shap) (3.0.8)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (from numba->shap)
(57.4.0)
Requirement already satisfied: llvmlite<0.35,>=0.34.0.dev0 in /usr/local/lib/python3.7/dist-packages
(from numba->shap) (0.34.0)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (from pandas->sh
ap) (2022.1)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-packages (from
pandas->shap) (2.8.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from sc
ikit-learn->shap) (3.1.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-lea
rn->shap) (1.1.0)
Installing collected packages: slicer, shap
Successfully installed shap-0.40.0 slicer-0.0.7
```

In [ ]:

```
# packages
import time
import random
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib.dates as mdates
import collections
import ast
import seaborn as sns
import scipy.stats as stats
from pandas.plotting import autocorrelation_plot
from statsmodels.tsa.stattools import adfuller
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, mean_absolute_percentag
from scipy.ndimage.filters import gaussian_filter
import plotly.graph_objects as go
import plotly.express as px
import plotly.io as pio
from datetime import datetime,timedelta
from tqdm import tqdm
from keras.models import Sequential, load_model
from keras.layers import Dense
from keras.layers import LSTM, GRU
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
import xgboost
import os
import shap
import tensorflow as tf
tf.compat.v1.disable_v2_behavior()
```

```python
import warnings
warnings.filterwarnings('ignore')
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.te
sting is deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/python/compat/v2_compat.py:1
07: disable_resource_variables (from tensorflow.python.ops.variable_scope) is deprecated and will be r
emoved in a future version.
Instructions for updating:
non-resource variables are not supported in the long term
```

Data Loading

In [ ]:

```python
df_mt3 = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Research/electricity_321.csv', parse_date
df_mt3 = df_mt3.iloc[:, [0,4]]
df_mt3.head()
```

Out[ ]:

	timestamp	MT_3
0	2012-01-01 00:00:00	415.0
1	2012-01-01 01:00:00	556.0
2	2012-01-01 02:00:00	560.0
3	2012-01-01 03:00:00	443.0
4	2012-01-01 04:00:00	346.0

In [ ]:

```python
df_mt3 = df_mt3.dropna()
df_mt3 = df_mt3[df_mt3.MT_3 != 0]
df_mt3.shape
```

Out[ ]:

```
(21065, 2)
```

Visualization

In [ ]:

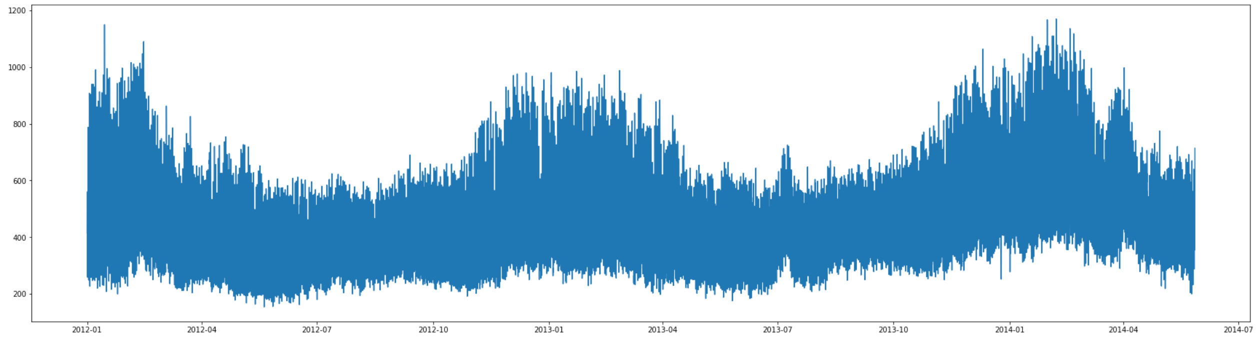
```python
df_viz = df_mt3.copy()
df_viz.set_index(df_viz.timestamp, inplace=True)
df_viz.drop('timestamp', axis=1, inplace=True)
df_viz.head()
```

Out[ ]:

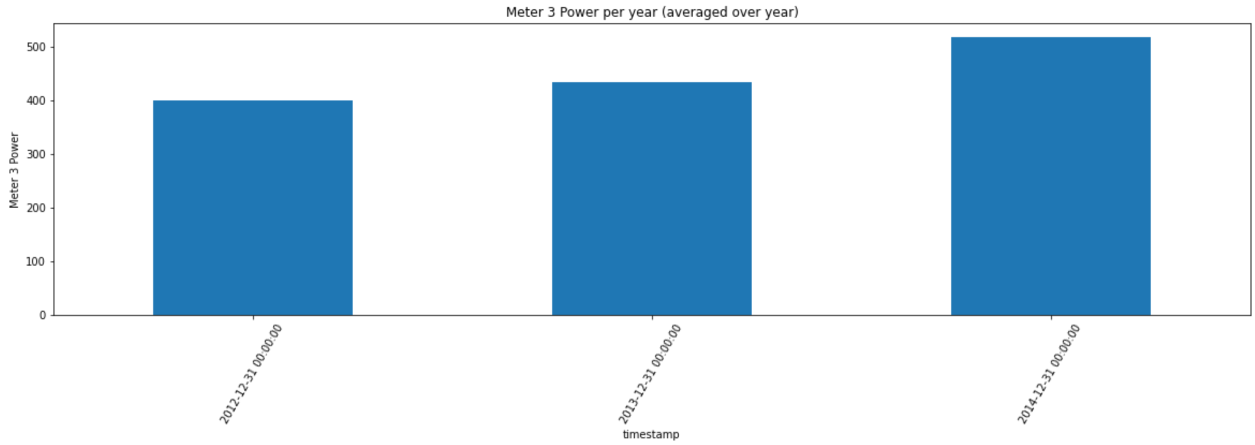
	MT_3
timestamp	
2012-01-01 00:00:00	415.0
2012-01-01 01:00:00	556.0
2012-01-01 02:00:00	560.0
2012-01-01 03:00:00	443.0
2012-01-01 04:00:00	346.0

In [ ]:

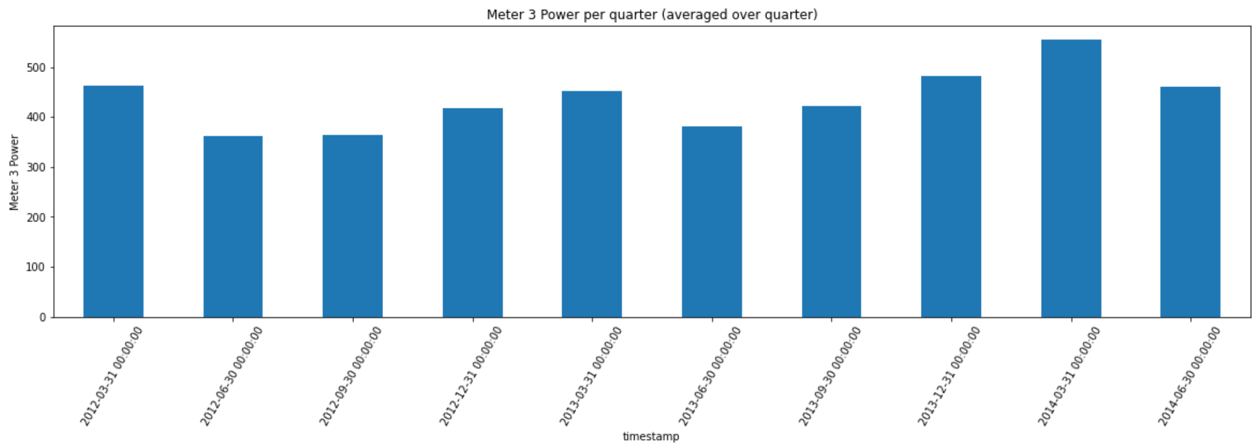
```python
plt.figure(figsize=(30,8))
plt.plot(df_viz.index, df_viz['MT_3'])
plt.show()
```



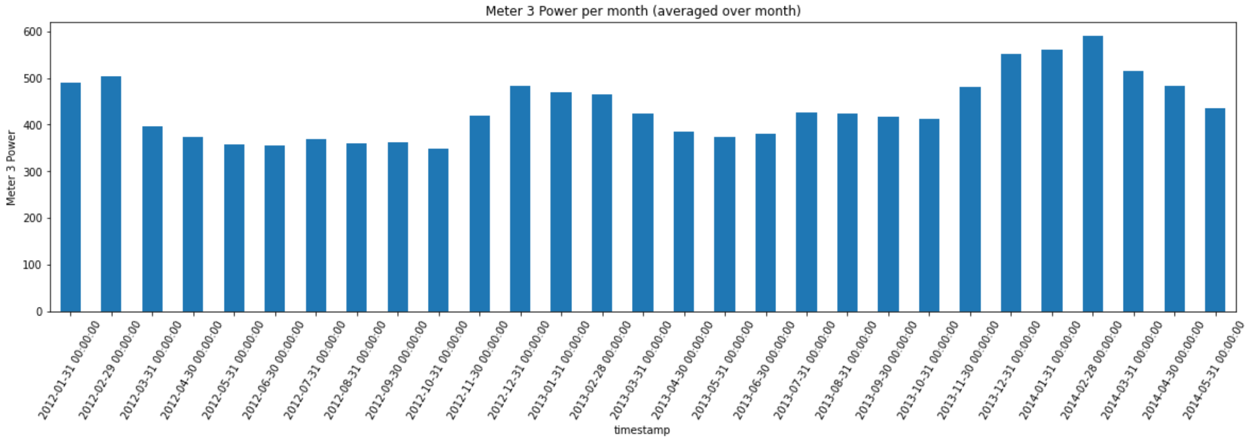
In [ ]:
```
plt.figure(figsize=(20,5))
df_viz.MT_3.resample('Y').mean().plot(kind='bar')
plt.xticks(rotation=60)
plt.ylabel('Meter 3 Power')
plt.title('Meter 3 Power per year (averaged over year)')
plt.show()
```



In [ ]:
```
plt.figure(figsize=(20,5))
df_viz.MT_3.resample('Q').mean().plot(kind='bar')
plt.xticks(rotation=60)
plt.ylabel('Meter 3 Power')
plt.title('Meter 3 Power per quarter (averaged over quarter)')
plt.show()
```

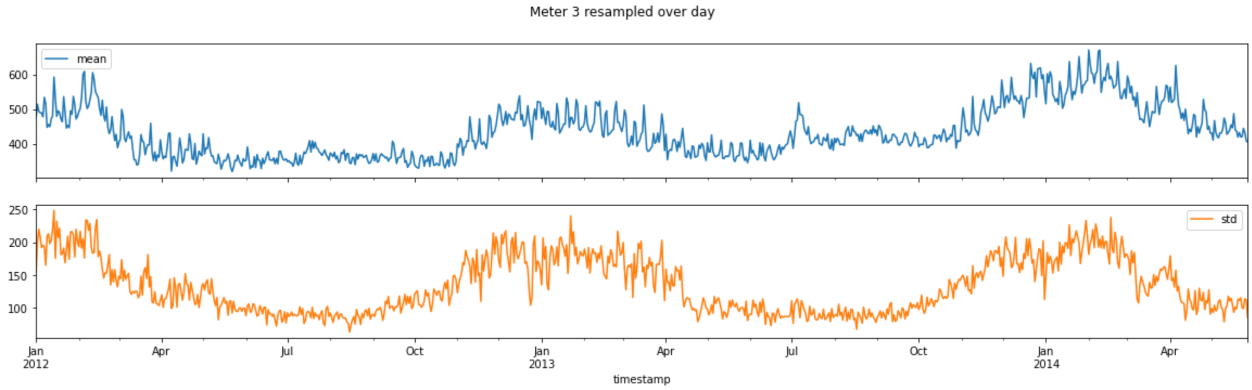


In [ ]:
```
plt.figure(figsize=(20,5))
df_viz.MT_3.resample('M').mean().plot(kind='bar')
plt.xticks(rotation=60)
plt.ylabel('Meter 3 Power')
plt.title('Meter 3 Power per month (averaged over month)')
plt.rcParams["figure.figsize"] = (20,5)
plt.show()
```



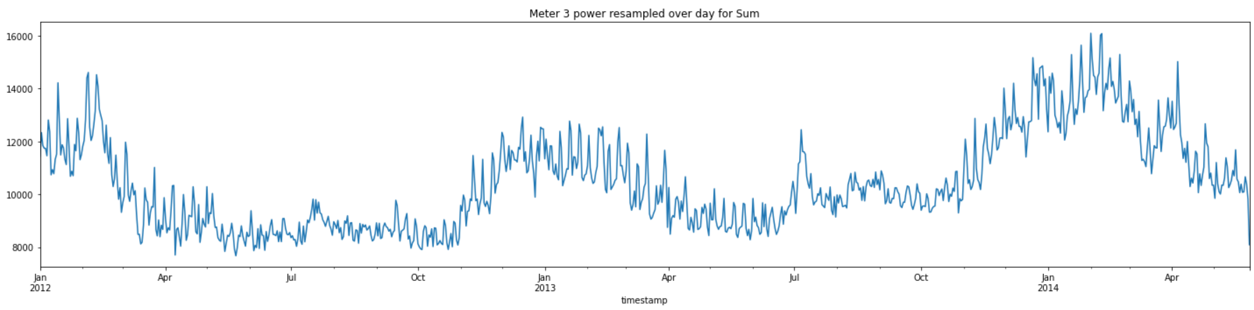
In [ ]:

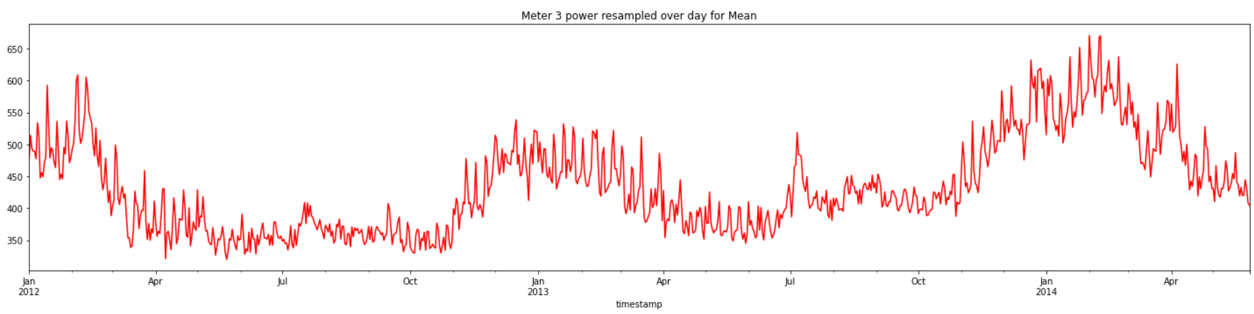
```
r = df_viz.MT_3.resample('D').agg(['mean', 'std'])
r.plot(subplots = True, title='Meter 3 resampled over day')
plt.show()
```



In [ ]:

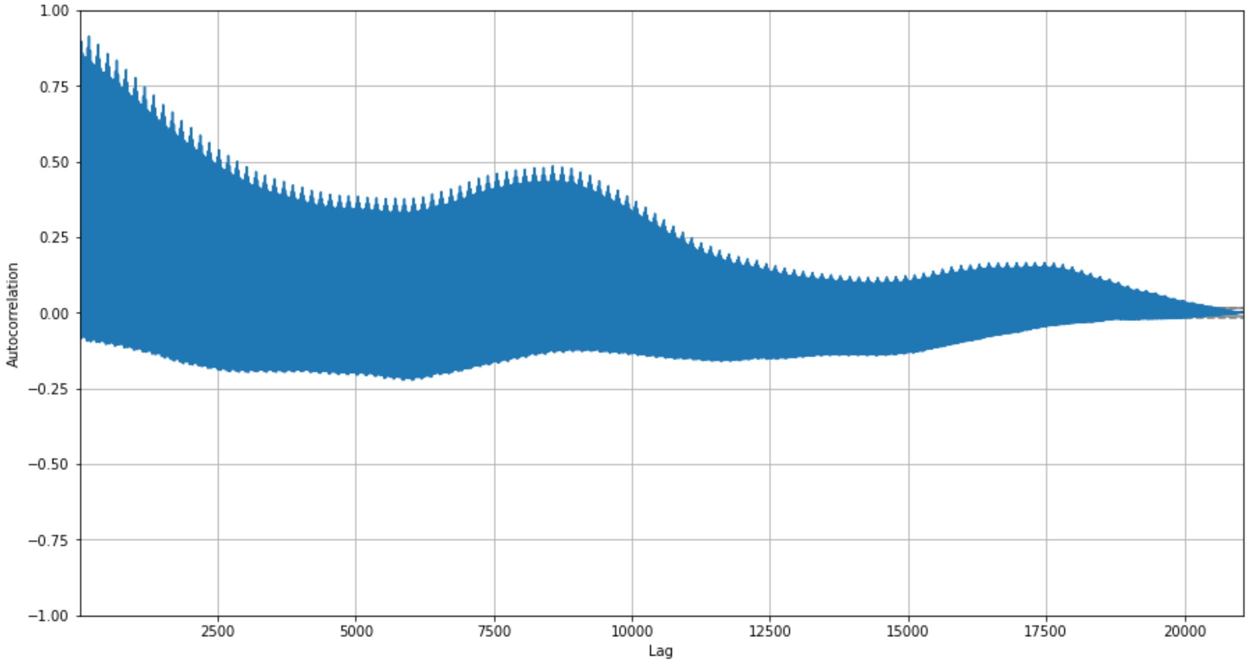
```
df_viz.MT_3.resample('D').sum().plot(title='Meter 3 power resampled over day for Sum')
plt.tight_layout()
plt.show()

df_viz.MT_3.resample('D').mean().plot(title='Meter 3 power resampled over day for Mean', color='r')
plt.tight_layout()
plt.show()
```





In [ ]:

```
plt.figure(figsize=(15,8))
autocorrelation_plot(df_viz['MT_3'])
plt.show()
```



ADF Test

In [ ]:
```
result = adfuller(df_mt3.MT_3.dropna())
print('p-value: %f' % result[1])
```

```
p-value: 0.000003
```

As p-value is <= 0.05, the data is stationary

Feature Engineering/Extraction

In [ ]:
```
# Extracts features and returns new dataframe
def extract_ts_features(df, primary=True, cyclic=True):
  if primary:
    df['hour'] = [i.hour for i in df['timestamp']]
    df['month'] = [i.month for i in df['timestamp']]
    df['year'] = [i.year for i in df['timestamp']]
    df['day_of_week'] = [i.dayofweek for i in df['timestamp']]
    df['day_of_year'] = [i.dayofyear for i in df['timestamp']]

  if cyclic:
    # turn time data to be cyclic
    df['dow_sin'] = np.sin(df.day_of_week * (2 * np.pi / 7))
    df['dow_cos'] = np.cos(df.day_of_week * (2 * np.pi / 7))
    df['hour_sin'] = np.sin(df.hour * (2 * np.pi / 24))
    df['hour_cos'] = np.cos(df.hour * (2 * np.pi / 24))

  return df
```

In [ ]:
```
df_mt3 = extract_ts_features(df_mt3)
df_mt3.shape
```

Out[ ]:
```
(21065, 11)
```

In [ ]:
```
data_split = 0.85
```

In [ ]:
```
Dataset = df_mt3.copy()
Dataset_time = df_mt3['timestamp']
```

In [ ]:
```
df_mt3.drop('timestamp', axis=1, inplace=True)
```

```
df_mt3
```

Out[ ]:

	MT_3	hour	month	year	day_of_week	day_of_year	dow_sin	dow_cos	hour_sin	hour_cos
0	415.0	0	1	2012	6	1	-0.781831	0.62349	0.000000	1.000000e+00
1	556.0	1	1	2012	6	1	-0.781831	0.62349	0.258819	9.659258e-01
2	560.0	2	1	2012	6	1	-0.781831	0.62349	0.500000	8.660254e-01
3	443.0	3	1	2012	6	1	-0.781831	0.62349	0.707107	7.071068e-01
4	346.0	4	1	2012	6	1	-0.781831	0.62349	0.866025	5.000000e-01
...	...	...	...	...	...	...	...	...	...	...
21063	376.0	15	5	2014	1	147	0.781831	0.62349	-0.707107	-7.071068e-01
21064	368.0	16	5	2014	1	147	0.781831	0.62349	-0.866025	-5.000000e-01
21065	394.0	17	5	2014	1	147	0.781831	0.62349	-0.965926	-2.588190e-01
21066	469.0	18	5	2014	1	147	0.781831	0.62349	-1.000000	-1.836970e-16
21067	714.0	19	5	2014	1	147	0.781831	0.62349	-0.965926	2.588190e-01

21065 rows × 10 columns

Correlation Plots

In [ ]:

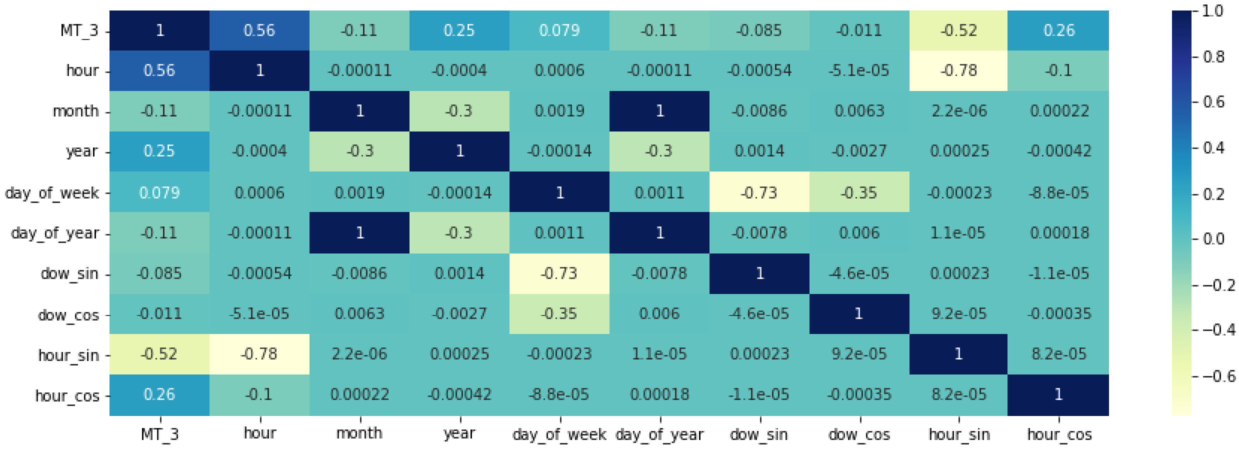
```
df_mt3.corr()
```

Out[ ]:

	MT_3	hour	month	year	day_of_week	day_of_year	dow_sin	dow_cos	hour_sin	hour
MT_3	1.000000	0.561902	-0.108570	0.249339	0.078679	-0.109273	-0.084768	-0.010733	-0.521830	0.257
hour	0.561902	1.000000	-0.000109	-0.000400	0.000598	-0.000110	-0.000542	-0.000051	-0.775965	-0.102
month	-0.108570	-0.000109	1.000000	-0.296503	0.001911	0.996558	-0.008598	0.006338	0.000002	0.000
year	0.249339	-0.000400	-0.296503	1.000000	-0.000139	-0.299818	0.001436	-0.002702	0.000253	-0.000
day_of_week	0.078679	0.000598	0.001911	-0.000139	1.000000	0.001078	-0.733880	-0.353799	-0.000234	-0.000
day_of_year	-0.109273	-0.000110	0.996558	-0.299818	0.001078	1.000000	-0.007818	0.006025	0.000011	0.000
dow_sin	-0.084768	-0.000542	-0.008598	0.001436	-0.733880	-0.007818	1.000000	-0.000046	0.000231	-0.000
dow_cos	-0.010733	-0.000051	0.006338	-0.002702	-0.353799	0.006025	-0.000046	1.000000	0.000092	-0.000
hour_sin	-0.521830	-0.775965	0.000002	0.000253	-0.000234	0.000011	0.000231	0.000092	1.000000	0.000
hour_cos	0.257580	-0.102221	0.000219	-0.000420	-0.000088	0.000176	-0.000011	-0.000350	0.000082	1.000

In [ ]:

```
plt.figure(figsize=(15,5))
sns.heatmap(df_mt3.corr(), cmap="YlGnBu", annot=True)
plt.show()
```



No Lag

LSTM

In [ ]:

```
X_scaler = MinMaxScaler()
Y_scaler = MinMaxScaler()
X_data = X_scaler.fit_transform(df_mt3.iloc[:,1:])
Y_data = Y_scaler.fit_transform(df_mt3['MT_3'].to_numpy().reshape(-1,1))

data_series = Dataset["MT_3"].copy()
n_train = int(len(df_mt3) * data_split)
n_test = (len(df_mt3) - n_train)
print(n_train, n_test)

X_train = X_data[:-n_test]
y_train = Y_data[:-n_test]
train_dates_lstm = Dataset_time[:-n_test]

X_test = X_data[-n_test:]
y_test_LSTM = Y_data[-n_test:]
test_dates_lstm = Dataset_time[-n_test:]

X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)

print(X_train.shape, y_train.shape, X_test.shape, y_test_LSTM.shape)
```

```
17905 3160
(17905, 9, 1) (17905, 1) (3160, 9, 1) (3160, 1)
```

In [ ]:

```
model = Sequential()
model.add(LSTM(200, activation='relu', return_sequences=True, input_shape=(X_train.shape[1],X_train.sh
model.add(LSTM(100, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mae')
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 9, 200)            161600

 lstm_1 (LSTM)               (None, 100)               120400

 dense (Dense)               (None, 1)                 101

=================================================================
Total params: 282,101
Trainable params: 282,101
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
batch_size = 256
```

```
buffer_size = 150
train_data = tf.data.Dataset.from_tensor_slices((X_train, y_train))
train_data = train_data.cache().shuffle(buffer_size).batch(batch_size).repeat()
val_data = tf.data.Dataset.from_tensor_slices((X_test, y_test_LSTM))
val_data = val_data.batch(batch_size).repeat()
```

In [ ]:

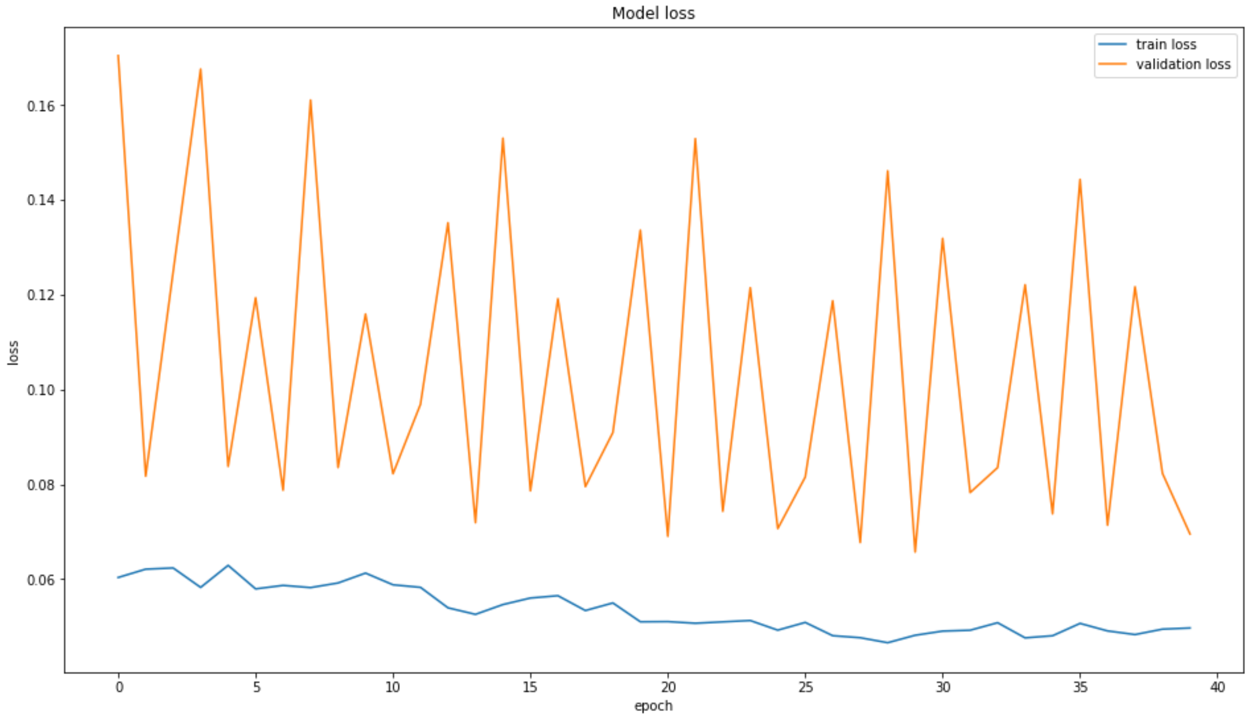
```
model_path = 'LSTM_Multivariate_No_Lag.h5'
early_stopings = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0, patience=10, verbos
checkpoint =  tf.keras.callbacks.ModelCheckpoint(model_path, monitor='val_loss', save_best_only=True,
callbacks=[early_stopings,checkpoint]
history = model.fit(train_data,epochs=100,steps_per_epoch=100,validation_data=val_data,validation_step
```

```
Epoch 1/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0604 - val_loss: 0.1703
Epoch 2/100
100/100 [==============================] - 8s 75ms/step - loss: 0.0621 - val_loss: 0.0817
Epoch 3/100
100/100 [==============================] - 8s 75ms/step - loss: 0.0624 - val_loss: 0.1248
Epoch 4/100
100/100 [==============================] - 8s 77ms/step - loss: 0.0583 - val_loss: 0.1675
Epoch 5/100
100/100 [==============================] - 8s 75ms/step - loss: 0.0629 - val_loss: 0.0838
Epoch 6/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0579 - val_loss: 0.1193
Epoch 7/100
100/100 [==============================] - 8s 77ms/step - loss: 0.0587 - val_loss: 0.0787
Epoch 8/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0582 - val_loss: 0.1610
Epoch 9/100
100/100 [==============================] - 8s 77ms/step - loss: 0.0592 - val_loss: 0.0835
Epoch 10/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0613 - val_loss: 0.1159
Epoch 11/100
100/100 [==============================] - 8s 78ms/step - loss: 0.0588 - val_loss: 0.0822
Epoch 12/100
100/100 [==============================] - 7s 75ms/step - loss: 0.0583 - val_loss: 0.0969
Epoch 13/100
100/100 [==============================] - 7s 74ms/step - loss: 0.0540 - val_loss: 0.1351
Epoch 14/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0526 - val_loss: 0.0719
Epoch 15/100
100/100 [==============================] - 7s 73ms/step - loss: 0.0546 - val_loss: 0.1529
Epoch 16/100
100/100 [==============================] - 7s 73ms/step - loss: 0.0560 - val_loss: 0.0786
Epoch 17/100
100/100 [==============================] - 7s 74ms/step - loss: 0.0565 - val_loss: 0.1191
Epoch 18/100
100/100 [==============================] - 7s 73ms/step - loss: 0.0534 - val_loss: 0.0795
Epoch 19/100
100/100 [==============================] - 7s 74ms/step - loss: 0.0550 - val_loss: 0.0909
Epoch 20/100
100/100 [==============================] - 7s 72ms/step - loss: 0.0510 - val_loss: 0.1335
Epoch 21/100
100/100 [==============================] - 7s 74ms/step - loss: 0.0511 - val_loss: 0.0690
Epoch 22/100
100/100 [==============================] - 7s 73ms/step - loss: 0.0507 - val_loss: 0.1528
Epoch 23/100
100/100 [==============================] - 7s 74ms/step - loss: 0.0510 - val_loss: 0.0743
Epoch 24/100
100/100 [==============================] - 7s 74ms/step - loss: 0.0513 - val_loss: 0.1214
Epoch 25/100
100/100 [==============================] - 8s 75ms/step - loss: 0.0493 - val_loss: 0.0707
Epoch 26/100
100/100 [==============================] - 7s 74ms/step - loss: 0.0509 - val_loss: 0.0815
Epoch 27/100
100/100 [==============================] - 8s 77ms/step - loss: 0.0481 - val_loss: 0.1187
Epoch 28/100
100/100 [==============================] - 8s 78ms/step - loss: 0.0477 - val_loss: 0.0677
Epoch 29/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0466 - val_loss: 0.1460
Epoch 30/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0482 - val_loss: 0.0657
Epoch 31/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0491 - val_loss: 0.1318
Epoch 32/100
100/100 [==============================] - 7s 74ms/step - loss: 0.0492 - val_loss: 0.0782
Epoch 33/100
100/100 [==============================] - 8s 77ms/step - loss: 0.0508 - val_loss: 0.0835
Epoch 34/100
```

```
100/100 [==============================] - 8s 76ms/step - loss: 0.0476 - val_loss: 0.1220
Epoch 35/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0481 - val_loss: 0.0738
Epoch 36/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0507 - val_loss: 0.1442
Epoch 37/100
100/100 [==============================] - 8s 77ms/step - loss: 0.0491 - val_loss: 0.0714
Epoch 38/100
100/100 [==============================] - 8s 76ms/step - loss: 0.0483 - val_loss: 0.1216
Epoch 39/100
100/100 [==============================] - 8s 77ms/step - loss: 0.0495 - val_loss: 0.0823
Epoch 40/100
100/100 [==============================] - 7s 75ms/step - loss: 0.0497 - val_loss: 0.0695
Epoch 40: early stopping
```

In [ ]:

```
plt.figure(figsize=(16,9))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train loss', 'validation loss'])
plt.show()
```



In [ ]:

```
model = load_model('/content/drive/MyDrive/Colab Notebooks/Research/LSTM_Multivariate_No_Lag.h5')
model.evaluate(X_test, y_test_LSTM)
```

Out[ ]: 0.06552249668519708

In [ ]:

```
y_pred_LSTM = model.predict(X_test)
pred_Inverse_LSTM = Y_scaler.inverse_transform(np.reshape(y_pred_LSTM, (y_pred_LSTM.shape[0], y_pred_L
y_test_inverse_LSTM = np.array(df_mt3.iloc[-n_test:,0])
```

Deep SHAP

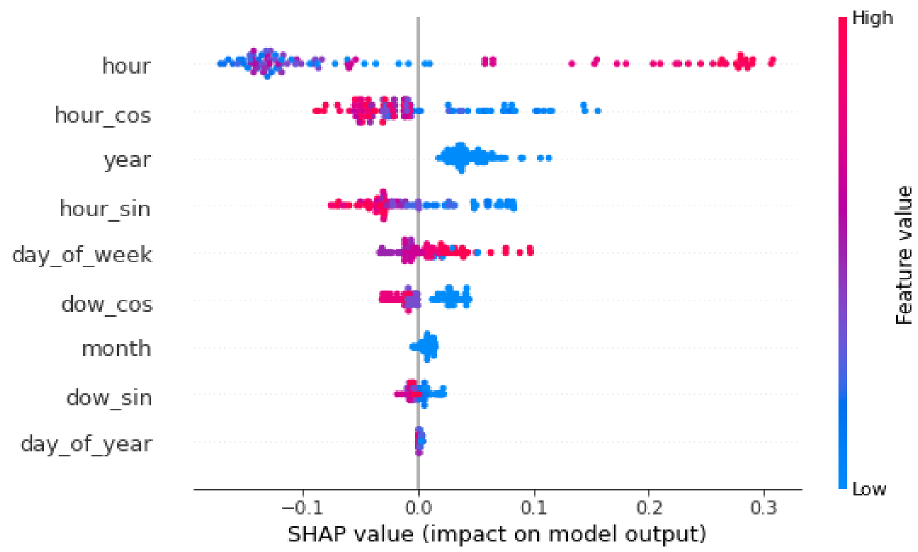
In [ ]:

```
explainer = shap.DeepExplainer(model, X_train[:1000])
shap_values = explainer.shap_values(X_test[:100], check_additivity=False)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/shap/explainers/tf_utils.py:28: The nam
e tf.keras.backend.get_session is deprecated. Please use tf.compat.v1.keras.backend.get_session instea
d.
```

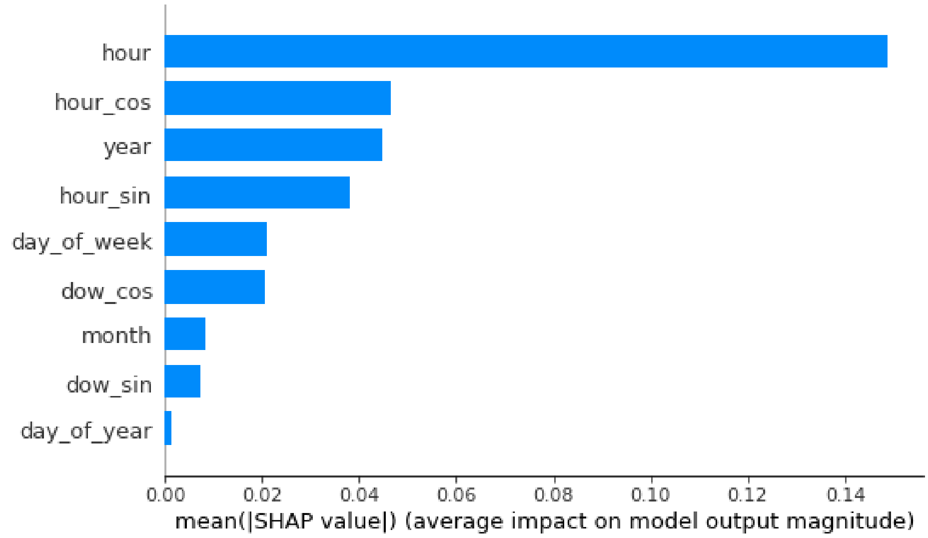
In [ ]:

```
shap.summary_plot(np.array(shap_values[0]).reshape(100,9), features=np.array(X_test[:100]).reshape(100
```



In [ ]:

```
shap.summary_plot(np.array(shap_values[0]).reshape(100,9), features=np.array(X_test[:100]).reshape(100
```



GRU

In [ ]:

```
model = Sequential()
model.add(GRU(200, activation='relu', return_sequences=True, input_shape=(X_train.shape[1],X_train.sha
model.add(GRU(100, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mae')
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 gru (GRU)                   (None, 9, 200)            121800

 gru_1 (GRU)                 (None, 100)               90600

 dense_1 (Dense)             (None, 1)                 101

=================================================================
Total params: 212,501
Trainable params: 212,501
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
batch_size = 256
buffer_size = 150
train_data = tf.data.Dataset.from_tensor_slices((X_train, y_train))
```

```
train_data = train_data.cache().shuffle(buffer_size).batch(batch_size).repeat()
val_data = tf.data.Dataset.from_tensor_slices((X_test, y_test_LSTM))
val_data = val_data.batch(batch_size).repeat()
```

In [ ]:

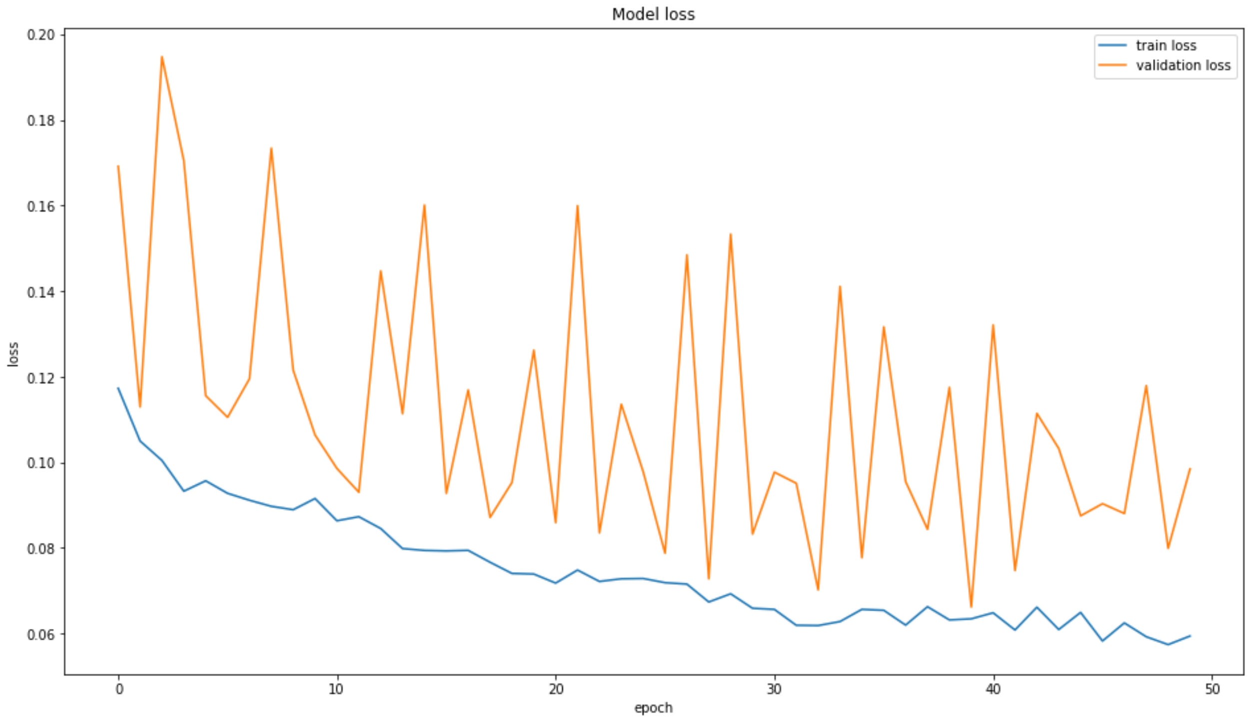
```
model_path = 'GRU_Multivariate_No_Lag.h5'
early_stopings = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0, patience=10, verbos
checkpoint =  tf.keras.callbacks.ModelCheckpoint(model_path, monitor='val_loss', save_best_only=True,
callbacks=[early_stopings,checkpoint]
history = model.fit(train_data,epochs=100,steps_per_epoch=100,validation_data=val_data,validation_step
```

```
Train on 100 steps, validate on 50 steps
Epoch 1/100
100/100 [==============================] - 11s 102ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.11
73 - val_loss: 0.1691
Epoch 2/100
100/100 [==============================] - 11s 114ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.10
50 - val_loss: 0.1129
Epoch 3/100
100/100 [==============================] - 14s 137ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.10
05 - val_loss: 0.1947
Epoch 4/100
100/100 [==============================] - 14s 137ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.09
33 - val_loss: 0.1704
Epoch 5/100
100/100 [==============================] - 15s 150ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.09
57 - val_loss: 0.1156
Epoch 6/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.09
28 - val_loss: 0.1105
Epoch 7/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.09
12 - val_loss: 0.1195
Epoch 8/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.08
97 - val_loss: 0.1734
Epoch 9/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.08
89 - val_loss: 0.1215
Epoch 10/100
100/100 [==============================] - 10s 99ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.091
6 - val_loss: 0.1064
Epoch 11/100
100/100 [==============================] - 10s 99ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.086
4 - val_loss: 0.0986
Epoch 12/100
100/100 [==============================] - 10s 100ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.08
73 - val_loss: 0.0930
Epoch 13/100
100/100 [==============================] - 10s 100ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.08
46 - val_loss: 0.1447
Epoch 14/100
100/100 [==============================] - 10s 99ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.079
9 - val_loss: 0.1114
Epoch 15/100
100/100 [==============================] - 11s 111ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
94 - val_loss: 0.1601
Epoch 16/100
100/100 [==============================] - 11s 111ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
93 - val_loss: 0.0928
Epoch 17/100
100/100 [==============================] - 11s 111ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
94 - val_loss: 0.1169
Epoch 18/100
100/100 [==============================] - 11s 111ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
67 - val_loss: 0.0871
Epoch 19/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
41 - val_loss: 0.0953
Epoch 20/100
100/100 [==============================] - 11s 111ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
39 - val_loss: 0.1262
Epoch 21/100
100/100 [==============================] - 15s 153ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
18 - val_loss: 0.0859
Epoch 22/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
48 - val_loss: 0.1600
Epoch 23/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
```

```
22 - val_loss: 0.0835
Epoch 24/100
100/100 [==============================] - 11s 113ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
28 - val_loss: 0.1136
Epoch 25/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
29 - val_loss: 0.0978
Epoch 26/100
100/100 [==============================] - 10s 100ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
19 - val_loss: 0.0788
Epoch 27/100
100/100 [==============================] - 10s 100ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.07
16 - val_loss: 0.1484
Epoch 28/100
100/100 [==============================] - 11s 113ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
74 - val_loss: 0.0728
Epoch 29/100
100/100 [==============================] - 11s 113ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
93 - val_loss: 0.1533
Epoch 30/100
100/100 [==============================] - 11s 110ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
59 - val_loss: 0.0833
Epoch 31/100
100/100 [==============================] - 10s 100ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
57 - val_loss: 0.0977
Epoch 32/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
20 - val_loss: 0.0951
Epoch 33/100
100/100 [==============================] - 10s 100ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
19 - val_loss: 0.0702
Epoch 34/100
100/100 [==============================] - 10s 99ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.062
8 - val_loss: 0.1411
Epoch 35/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
57 - val_loss: 0.0777
Epoch 36/100
100/100 [==============================] - 11s 113ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
54 - val_loss: 0.1316
Epoch 37/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
20 - val_loss: 0.0955
Epoch 38/100
100/100 [==============================] - 11s 111ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
63 - val_loss: 0.0844
Epoch 39/100
100/100 [==============================] - 11s 111ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
32 - val_loss: 0.1175
Epoch 40/100
100/100 [==============================] - 11s 110ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
35 - val_loss: 0.0662
Epoch 41/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
49 - val_loss: 0.1321
Epoch 42/100
100/100 [==============================] - 11s 114ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
08 - val_loss: 0.0747
Epoch 43/100
100/100 [==============================] - 10s 101ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
62 - val_loss: 0.1114
Epoch 44/100
100/100 [==============================] - 10s 101ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
10 - val_loss: 0.1032
Epoch 45/100
100/100 [==============================] - 10s 101ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
50 - val_loss: 0.0875
Epoch 46/100
100/100 [==============================] - 11s 112ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.05
83 - val_loss: 0.0903
Epoch 47/100
100/100 [==============================] - 11s 113ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.06
25 - val_loss: 0.0881
Epoch 48/100
100/100 [==============================] - 11s 113ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.05
93 - val_loss: 0.1179
Epoch 49/100
100/100 [==============================] - 11s 114ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.05
74 - val_loss: 0.0799
Epoch 50/100
100/100 [==============================] - 11s 113ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.05
```

```
94 - val_loss: 0.0985
Epoch 50: early stopping
```

In [ ]:
```
plt.figure(figsize=(16,9))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train loss', 'validation loss'])
plt.show()
```



In [ ]:
```
model = load_model('/content/drive/MyDrive/Colab Notebooks/Research/GRU_Multivariate_No_Lag.h5')
model.evaluate(X_test, y_test_LSTM)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/python/ops/init_ops.py:93: c
alling GlorotUniform.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will
be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/python/ops/init_ops.py:93: c
alling Orthogonal.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will be
removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
WARNING:tensorflow:From /usr/local/lib/python3.7/dist-packages/tensorflow/python/ops/init_ops.py:93: c
alling Zeros.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will be remov
ed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
```

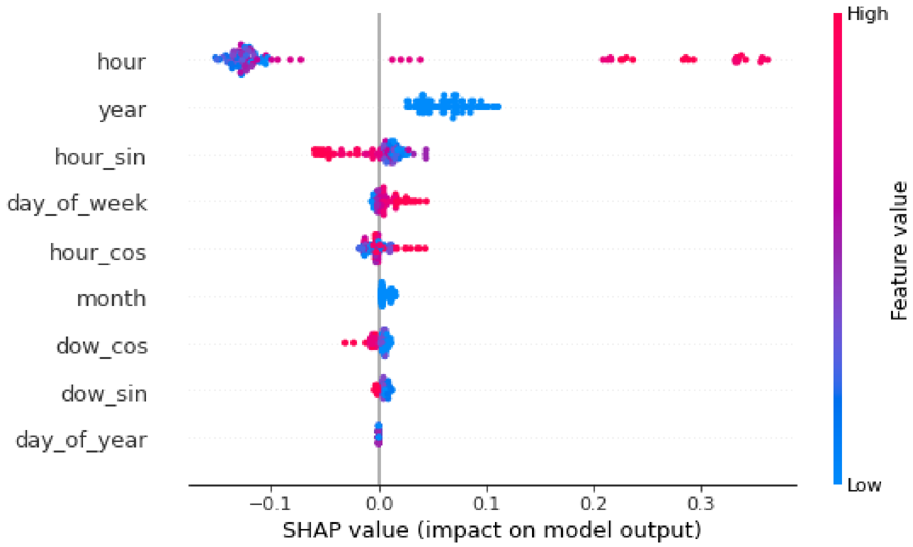
Out[ ]:
```
0.06593464015971257
```

In [ ]:
```
y_pred_GRU = model.predict(X_test)
pred_Inverse_GRU = Y_scaler.inverse_transform(np.reshape(y_pred_GRU, (y_pred_GRU.shape[0], y_pred_GRU.
y_test_inverse_GRU = np.array(df_mt3.iloc[-n_test:,0])
```

Deep SHAP

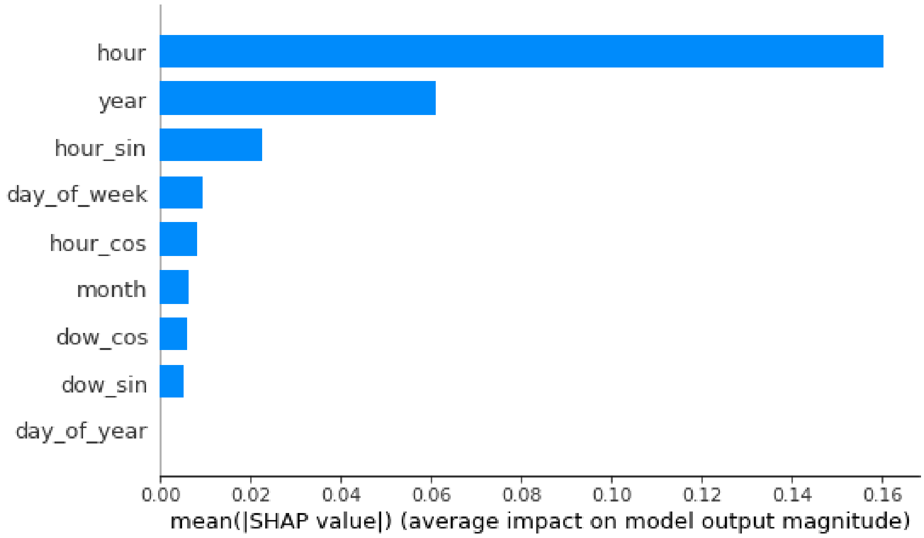
In [ ]:
```
explainer = shap.DeepExplainer(model, X_train[:1000])
shap_values = explainer.shap_values(X_test[:100], check_additivity=False)
```

In [ ]:
```
shap.summary_plot(np.array(shap_values[0]).reshape(100,9), features=np.array(X_test[:100]).reshape(10(
```



In [ ]:

```
shap.summary_plot(np.array(shap_values[0]).reshape(100,9), features=np.array(X_test[:100]).reshape(100
```



RF

In [ ]:

```
data_series = Dataset["MT_3"].copy()
n_train = int(len(Dataset.MT_3) * data_split)
n_test = (len(Dataset) - n_train)
# look_back = 2
n_train, n_test
```

Out[ ]: (17905, 3160)

In [ ]:

```
# creating target and features for training set
X_train = np.array(df_mt3[:-n_test].loc[:, df_mt3.columns != 'MT_3'])
y_train = np.array(df_mt3[:-n_test].iloc[:, 0])
train_dates = Dataset_time[:-n_test]

# creating target and features for test set
X_test = np.array(df_mt3[-n_test:].loc[:, df_mt3.columns != 'MT_3'])
y_test_RF = np.array(df_mt3[-n_test:].iloc[:, 0])
test_dates = Dataset_time[-n_test:]

print(X_train.shape, y_train.shape, X_test.shape, y_test_RF.shape)
```

(17905, 9) (17905,) (3160, 9) (3160,)

In [ ]:

```
RF_Model1 = RandomForestRegressor(n_estimators=1000, max_features=1, random_state=123)
```

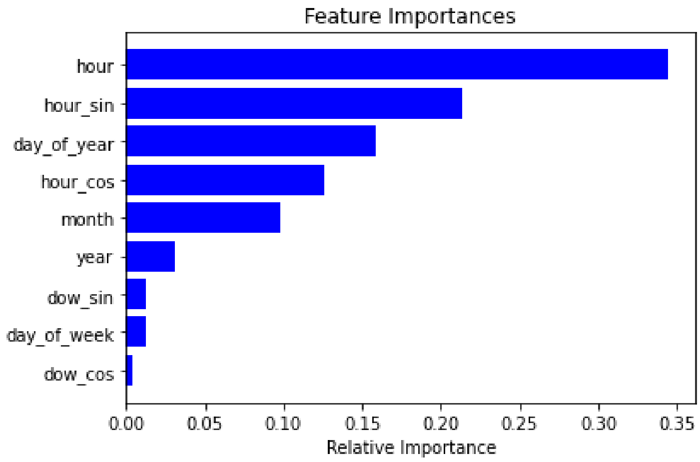
In [ ]:

```python
labels = y_train
features = X_train

# Fit the RF model with features and labels.
rgr=RF_Model1.fit(X_train, y_train)

# Now that we've run our models and fit it, let's create
# dataframes to look at the results
predictions_RF=rgr.predict(X_test)

# plot of predictions and actual values
fig = go.Figure()
fig.add_trace(go.Scatter(x=test_dates, y=y_test_RF, line_shape='linear',
              name = 'Ground Truth'))
fig.add_trace(go.Scatter(x=test_dates, y=predictions_RF, line_shape='linear',
              name = 'Prediction'))
fig.show()

# calculating RMSE metrics
error = np.sqrt(mean_squared_error(y_test_RF[:-1], y_test_RF[1:]))
print('Baseline RMSE: %.3f' % error)
error = np.sqrt(mean_squared_error(predictions_RF, y_test_RF))
print('Test RMSE: %.3f' % error)
print(error / np.mean(y_test_RF))
```

```
Baseline RMSE: 79.584
Test RMSE: 85.186
0.16538735232660562
```

In [ ]:

```python
features = df_mt3.columns[df_mt3.columns != 'MT_3']
importances = rgr.feature_importances_
indices = np.argsort(importances)

plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='b', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



GBR

In [ ]:

```
GBR_Model1 = GradientBoostingRegressor(n_estimators=3000, max_features='auto', criterion='squared_erro
```

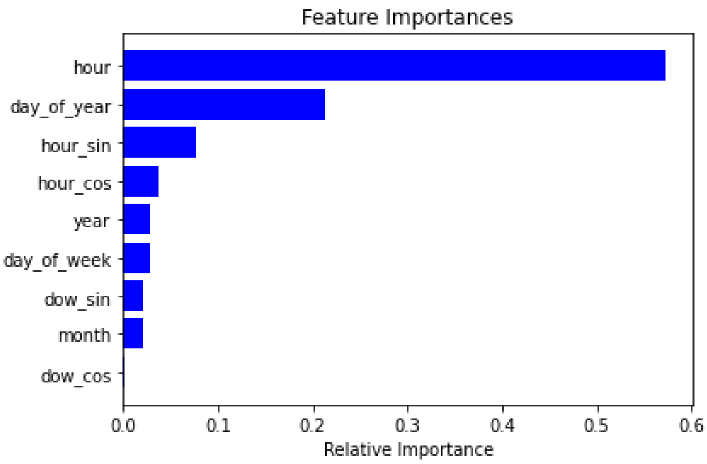
In [ ]:

```
# Fit the RF model with features and labels.
gbr=GBR_Model1.fit(X_train, y_train)

# Now that we've run our models and fit it, let's create
# dataframes to look at the results
predictions_GBR=gbr.predict(X_test)

# plot of predictions and actual values
fig = go.Figure()
fig.add_trace(go.Scatter(x=test_dates, y=y_test_RF, line_shape='linear',
              name = 'Ground Truth'))
fig.add_trace(go.Scatter(x=test_dates, y=predictions_GBR, line_shape='linear',
              name = 'Prediction'))
fig.show()

# calculating RMSE metrics
error = np.sqrt(mean_squared_error(y_test_RF[:-1], y_test_RF[1:]))
print('Baseline RMSE: %.3f' % error)
error = np.sqrt(mean_squared_error(predictions_GBR, y_test_RF))
print('Test RMSE: %.3f' % error)
print(error / np.mean(y_test_RF))
```

```
Baseline RMSE: 79.584
Test RMSE: 68.123
0.13225932991377962
```

In [ ]:

```
features = df_mt3.columns[df_mt3.columns != 'MT_3']
importances = gbr.feature_importances_
indices = np.argsort(importances)

plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='b', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



XGB

In [ ]:

```
import xgboost
```

In [ ]:

```
XGB_Model1 = xgboost.XGBRegressor(n_estimators=1000, max_features=1, random_state=123)
```

In [ ]:

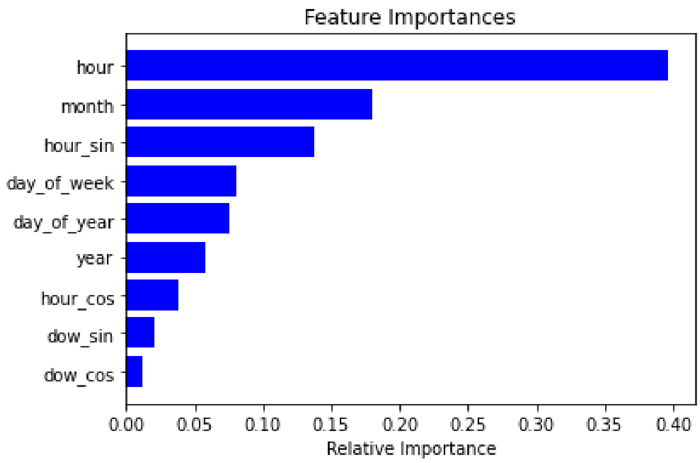
```
labels = y_train
features = X_train

# Fit the RF model with features and labels.
xgb=XGB_Model1.fit(X_train, y_train)

# Now that we've run our models and fit it, let's create
# dataframes to look at the results
predictions_XGB=xgb.predict(X_test)

# plot of predictions and actual values
fig = go.Figure()
fig.add_trace(go.Scatter(x=test_dates, y=y_test_RF, line_shape='linear',
              name = 'Ground Truth'))
fig.add_trace(go.Scatter(x=test_dates, y=predictions_XGB, line_shape='linear',
              name = 'Prediction'))
fig.show()

# calculating RMSE metrics
error = np.sqrt(mean_squared_error(y_test_RF[:-1], y_test_RF[1:]))
print('Baseline RMSE: %.3f' % error)
error = np.sqrt(mean_squared_error(predictions_XGB, y_test_RF))
print('Test RMSE: %.3f' % error)
print(error / np.mean(y_test_RF))
```

```
[04:14:01] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in fa
vor of reg:squarederror.
```

```
Baseline RMSE: 79.584
Test RMSE: 71.062
0.1379658527786796
```

In [ ]:

```
features = df_mt3.columns[df_mt3.columns != 'MT_3']
importances = xgb.feature_importances_
indices = np.argsort(importances)

plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='b', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



Evaluation

In [ ]:

```
len(test_dates), len(y_test_RF), len(predictions_RF), len(predictions_GBR), len(predictions_XGB), len(
```

Out[ ]: (3160, 3160, 3160, 3160, 3160, 3160, 3160)

In [ ]:

```
test_dates = test_dates.reset_index(drop='True')
test_dates.index
```

```
Out[ ]: RangeIndex(start=0, stop=3160, step=1)
```

In [ ]:

```
pd.concat([pd.DataFrame(list(test_dates), columns=['Timestamp']),
           pd.DataFrame(y_test_RF, columns=['Ground Truth']),
           pd.DataFrame(predictions_GBR, columns=['GBR']),
           pd.DataFrame(predictions_RF, columns=['RF']),
           pd.DataFrame(predictions_XGB, columns=['XGB']),
           pd.DataFrame(pred_Inverse_LSTM, columns=['LSTM']),
           pd.DataFrame(pred_Inverse_GRU, columns=['GRU'])], axis=1).to_csv('/content/drive/MyDrive/Co
```

In [ ]:

```
def calc_metrics(y_true, y_pred):
    mae = mean_absolute_error(y_true, y_pred)
    rmse = mean_squared_error(y_true, y_pred, squared=False)
    nrmse = rmse / (np.mean(y_true))
    mape = mean_absolute_percentage_error(y_true, y_pred)
    return mae, mape, rmse, nrmse

def return_metrics(Mape, Mae, Rmse, Nrmse):
  mape = str(round(np.mean(Mape), 2))+'%'+' +- '+str(round(np.std(Mape),2))
  mae = str(round(np.mean(Mae), 2)) + ' +- ' + str(round(np.std(Mae),2))
  rmse = str(round(np.mean(Rmse), 2)) + ' +- ' + str(round(np.std(Rmse),2))
  nrmse = str(round(np.mean(Nrmse), 2)) + ' +- ' + str(round(np.std(Nrmse),2))
  return mape, mae, rmse, nrmse

def generateValSet(test_size, sample_size):
  val_set = []
  i = 0
  while i < test_size:
    i += sample_size
    if i > test_size:
      i = test_size
      val_set.append(i)
      break
    val_set.append(i)
  return val_set
```

In [ ]:

```
df_res = pd.DataFrame(columns=['model', 'hours', 'mape', 'mae', 'rmse', 'nrmse'])
df_res = df_res.astype(dtype= {"model":"string",
        "hours":"int","mape":"string", "mae":"string", "rmse":"string", "nrmse":"string"})
pred_hours = [1,6,12,24,48]

for hours in pred_hours:
  for model_name in ['RF', 'GBR', 'XGB', 'LSTM', 'GRU']:
    Mape = []
    Mae = []
    Rmse = []
    Nrmse = []

    val_set = None

    if model_name == 'RF':
      val_set = generateValSet(len(y_test_RF), hours)
      holdout = predictions_RF
      ground_truth = y_test_RF
    elif model_name == 'GBR':
      val_set = generateValSet(len(y_test_RF), hours)
      holdout = predictions_GBR
      ground_truth = y_test_RF
    elif model_name == 'XGB':
      val_set = generateValSet(len(y_test_RF), hours)
      holdout = predictions_XGB
      ground_truth = y_test_RF
    elif model_name=='LSTM':
      val_set = generateValSet(len(y_test_LSTM), hours)
      holdout = pred_Inverse_LSTM
      ground_truth = y_test_inverse_LSTM
    else:
      val_set = generateValSet(len(y_test_LSTM), hours)
      holdout = pred_Inverse_GRU
      ground_truth = y_test_inverse_GRU
```

```
    for val in val_set:
      forecast = holdout[:val]
      pred = forecast[-hours:]
      true = ground_truth[:val]
      actual = true[-hours:]
      mae, mape, rmse, nrmse = calc_metrics(actual, pred)
      Mape.append(mape)
      Mae.append(mae)
      Rmse.append(rmse)
      Nrmse.append(nrmse)

    metrics = return_metrics(Mape, Mae, Rmse, Nrmse)
    df_res = df_res.append({'model':model_name, 'hours': hours, 'mape': metrics[0], 'mae': metrics[1],
```

In [ ]:

```
df_res
```

Out[ ]:

	model	hours	mape	mae	rmse	nrmse
0	RF	1	0.13% +- 0.08	68.05 +- 51.24	68.05 +- 51.24	0.13 +- 0.08
1	GBR	1	0.11% +- 0.08	53.64 +- 42.0	53.64 +- 42.0	0.11 +- 0.08
2	XGB	1	0.11% +- 0.08	56.34 +- 43.31	56.34 +- 43.31	0.11 +- 0.08
3	LSTM	1	0.14% +- 0.12	66.57 +- 53.2	66.57 +- 53.2	0.14 +- 0.12
4	GRU	1	0.13% +- 0.09	66.99 +- 59.73	66.99 +- 59.73	0.13 +- 0.09
5	RF	6	0.13% +- 0.06	68.05 +- 37.31	75.95 +- 38.54	0.15 +- 0.06
6	GBR	6	0.11% +- 0.05	53.61 +- 28.85	60.91 +- 30.46	0.12 +- 0.05
7	XGB	6	0.11% +- 0.05	56.31 +- 28.22	64.32 +- 30.16	0.12 +- 0.05
8	LSTM	6	0.14% +- 0.08	66.55 +- 35.43	76.02 +- 38.44	0.15 +- 0.08
9	GRU	6	0.13% +- 0.06	66.96 +- 42.72	76.96 +- 46.13	0.15 +- 0.07
10	RF	12	0.13% +- 0.05	67.99 +- 32.08	78.15 +- 33.74	0.15 +- 0.05
11	GBR	12	0.11% +- 0.04	53.55 +- 23.09	63.2 +- 25.23	0.12 +- 0.04
12	XGB	12	0.11% +- 0.03	56.24 +- 23.21	66.23 +- 25.54	0.13 +- 0.04
13	LSTM	12	0.14% +- 0.06	66.46 +- 26.39	79.55 +- 30.28	0.16 +- 0.07
14	GRU	12	0.13% +- 0.05	66.87 +- 31.13	80.75 +- 38.93	0.16 +- 0.07
15	RF	24	0.13% +- 0.04	67.97 +- 28.21	79.67 +- 29.92	0.15 +- 0.04
16	GBR	24	0.11% +- 0.03	53.56 +- 19.31	64.57 +- 21.5	0.12 +- 0.04
17	XGB	24	0.11% +- 0.03	56.25 +- 19.55	67.51 +- 21.95	0.13 +- 0.03
18	LSTM	24	0.14% +- 0.05	66.52 +- 21.57	81.44 +- 24.88	0.16 +- 0.06
19	GRU	24	0.13% +- 0.04	66.92 +- 28.11	82.15 +- 35.94	0.16 +- 0.05
20	RF	48	0.13% +- 0.04	68.01 +- 25.83	80.4 +- 27.94	0.15 +- 0.04
21	GBR	48	0.11% +- 0.03	53.57 +- 16.73	65.36 +- 18.97	0.13 +- 0.03
22	XGB	48	0.11% +- 0.03	56.25 +- 17.52	68.14 +- 19.89	0.13 +- 0.03
23	LSTM	48	0.14% +- 0.04	66.82 +- 16.09	83.29 +- 19.94	0.16 +- 0.05
24	GRU	48	0.13% +- 0.03	67.03 +- 24.25	83.98 +- 31.71	0.16 +- 0.05

In [ ]:

```
df_res.to_csv('/content/drive/MyDrive/Colab Notebooks/Research/no_lag_results_metrics.csv', index=Fals
```

In [ ]:

```
def plot_forecast(interval:int, hours:int, y_test, predictions_RF, predictions_GBR, predictions_XGB, p

  val_set = generateValSet(len(y_test), hours)
  if interval < 0 or interval > len(val_set):
    print(f"Please select between 1 and {len(val_set)}")

  low, high = val_set[interval-1]-hours, val_set[interval-1]
```

```
    forecast_rf = predictions_RF[low:high]
    forecast_gbr = predictions_GBR[low:high]
    forecast_xgb = predictions_XGB[low:high]
    forecast_lstm = [i[0] for i in pred_Inverse_LSTM[low:high]]
    forecast_gru = [i[0] for i in pred_Inverse_GRU[low:high]]
    true = y_test[low:high]

    fig = go.Figure()
    fig.add_trace(go.Scatter(x=[i for i in range(1, hours+1)], y=true, mode='lines', line=dict(color='gr
                  name = 'Ground Truth'))
    fig.add_trace(go.Scatter(x=[i for i in range(1, hours+1)], y=forecast_rf, mode='lines', line=dict(co
                  name = 'RF'))
    fig.add_trace(go.Scatter(x=[i for i in range(1, hours+1)], y=forecast_gbr, mode='lines', line=dict(c
                  name = 'GBR'))
    fig.add_trace(go.Scatter(x=[i for i in range(1, hours+1)], y=forecast_xgb, mode='lines', line=dict(c
                  name = 'XGB'))
    fig.add_trace(go.Scatter(x=[i for i in range(1, hours+1)], y=forecast_lstm, mode='lines', line=dict(
                  name = 'LSTM'))
    fig.add_trace(go.Scatter(x=[i for i in range(1, hours+1)], y=forecast_gru, mode='lines', line=dict(c
                  name = 'GRU'))

    fig.show()
    # pio.write_image(fig, "Images/RFx_Prediction.pdf", width=1000)
```

6 Hour Window

In [ ]:

```
plot_forecast(11,6, y_test_RF, predictions_RF, predictions_GBR, predictions_XGB, pred_Inverse_LSTM, pr
```

12 Hour Window

In [ ]:

```
plot_forecast(24,12, y_test_RF, predictions_RF, predictions_GBR, predictions_XGB, pred_Inverse_LSTM, p
```

24 Hour Window

In [ ]:
```
plot_forecast(11,24, y_test_RF, predictions_RF, predictions_GBR, predictions_XGB, pred_Inverse_LSTM, p
```

48 Hour Window

In [ ]:
```
plot_forecast(10,48, y_test_RF, predictions_RF, predictions_GBR, predictions_XGB, pred_Inverse_LSTM, p
```

Tree SHAP - GBR

In [ ]:

```
explainer = shap.TreeExplainer(model=gbr,
                               data=None,
                               model_output='raw',
                               feature_perturbation='tree_path_dependent')
```

In [ ]:

```
shap_values = explainer.shap_values(X_test)
```

In [ ]:

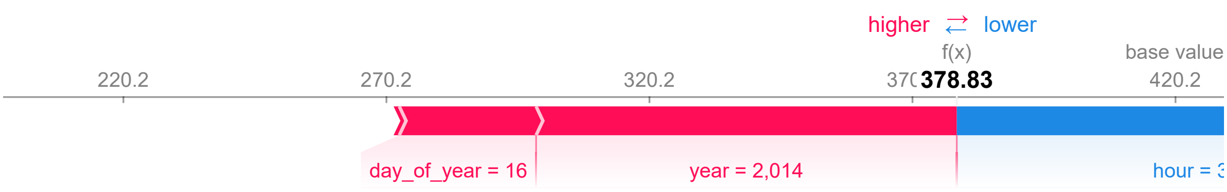
```
print(f'Shape of test dataset: {X_test.shape}')
print(f'Type of shap_values: {type(shap_values)}. Length of the list: {len(shap_values)}')
print(f'Shape of shap_values: {np.array(shap_values).shape}')
```

```
Shape of test dataset: (3160, 9)
Type of shap_values: <class 'numpy.ndarray'>. Length of the list: 3160
Shape of shap_values: (3160, 9)
```

In [ ]:

```
shap.initjs()
shap.force_plot(explainer.expected_value, shap_values[0], features=X_test[0,:], feature_names=df_mt3.c
```

Out[ ]:

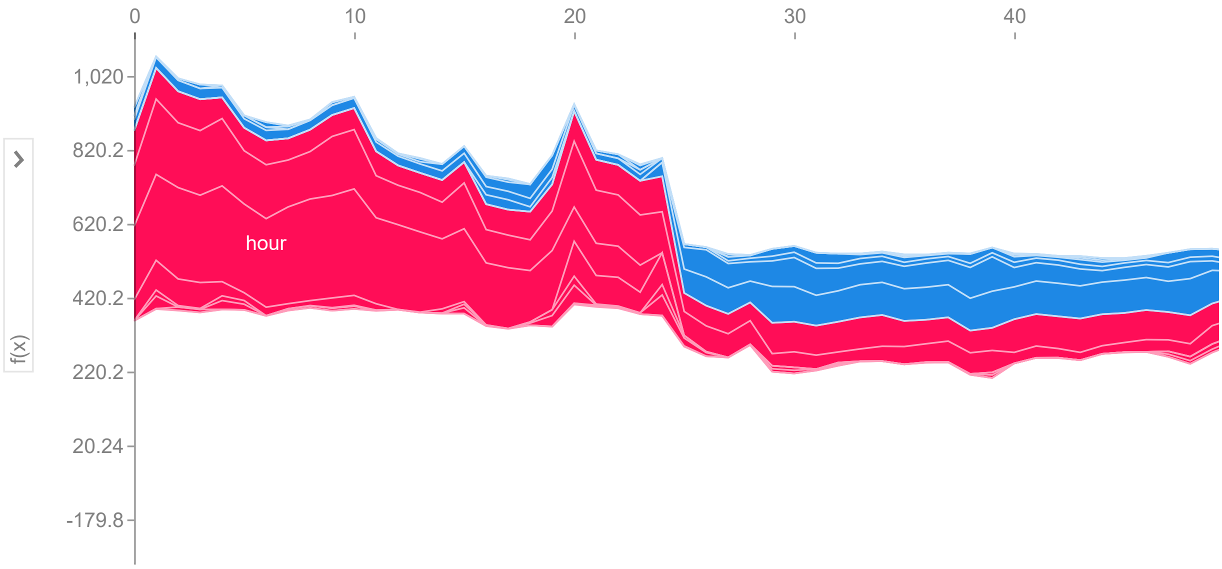


In [ ]:

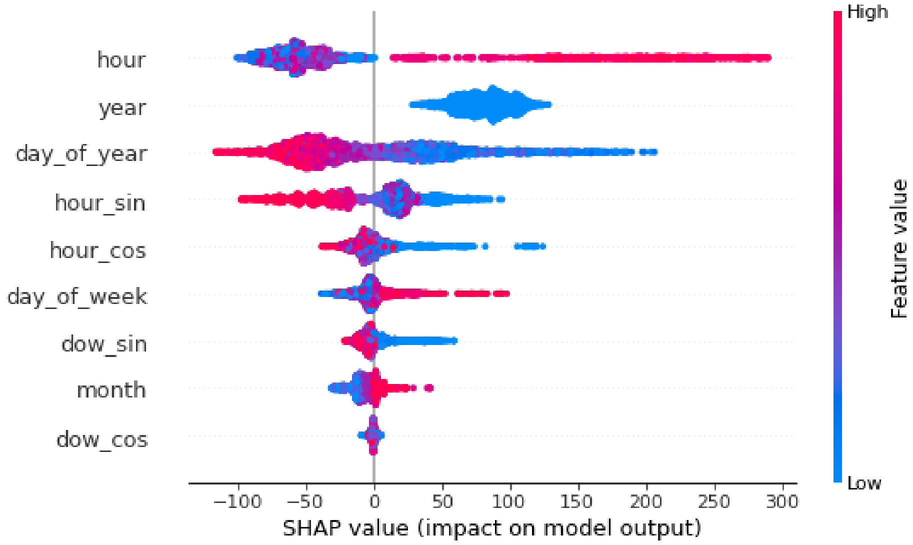
```
shap.initjs()
shap.force_plot(explainer.expected_value, shap_values[:100], features=X_test[:100,:], feature_names=df
```

Out[ ]:

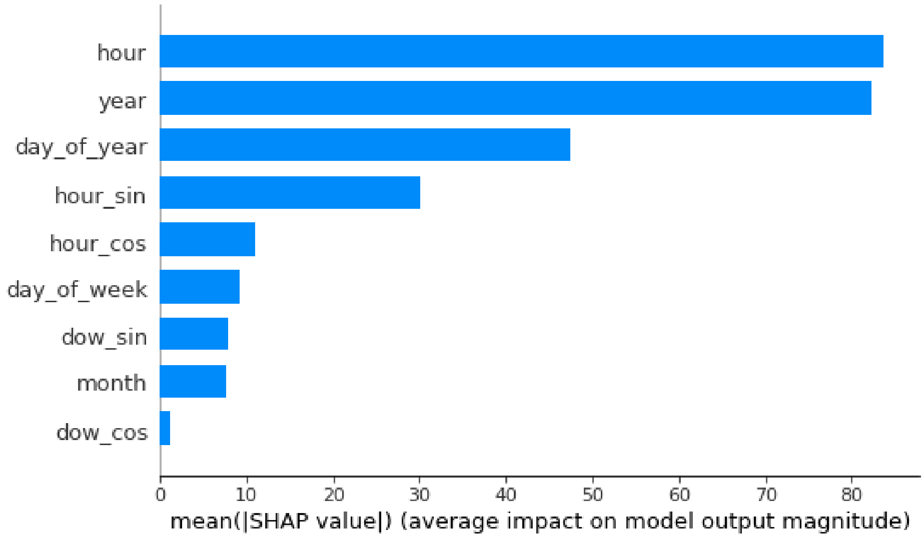
sample order by similarity



In [ ]:
```
shap.summary_plot(shap_values, features=X_test, feature_names=df_mt3.columns[df_mt3.columns != 'MT_3']
```



In [ ]:
```
shap.summary_plot(shap_values, features=X_test, feature_names=df_mt3.columns[df_mt3.columns != 'MT_3']
```



24h Lag

Dataset

In [ ]:
```
df_mt3_lag = Dataset.copy()

lag = 24

for l in range(1,lag+1):
  df_mt3_lag['lag_'+str(l)] = df_mt3_lag['MT_3'].shift(l)

df_mt3_lag.dropna(inplace=True)

df_mt3_lag.shape
```

Out[ ]: (21041, 35)

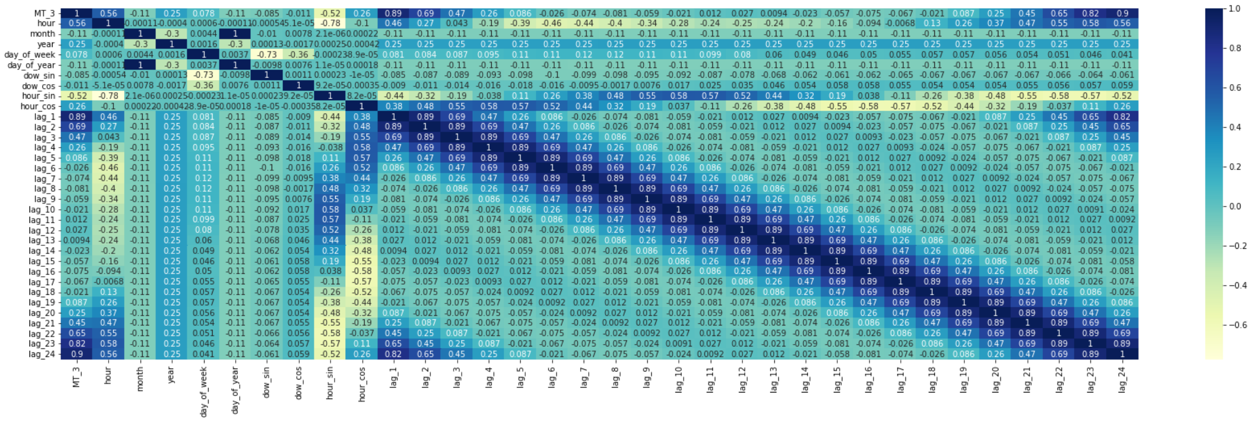
In [ ]:
```
Dataset_time = df_mt3_lag['timestamp']
df_mt3_lag.drop('timestamp', axis=1, inplace=True)
df_mt3_lag.head()
```

Out[ ]:

	MT_3	hour	month	year	day_of_week	day_of_year	dow_sin	dow_cos	hour_sin	hour_cos	...	lag_15	lag_16	la
24	462.0	0	1	2012	0	2	0.0	1.0	0.000000	1.000000	...	402.0	259.0	3
25	402.0	1	1	2012	0	2	0.0	1.0	0.258819	0.965926	...	446.0	402.0	2
26	376.0	2	1	2012	0	2	0.0	1.0	0.500000	0.866025	...	551.0	446.0	4
27	298.0	3	1	2012	0	2	0.0	1.0	0.707107	0.707107	...	532.0	551.0	4
28	253.0	4	1	2012	0	2	0.0	1.0	0.866025	0.500000	...	364.0	532.0	5

5 rows × 34 columns

In [ ]:
```
plt.figure(figsize=(30,8))
sns.heatmap(df_mt3_lag.corr(), cmap="YlGnBu", annot=True)
plt.show()
```



LSTM

In [ ]:
```
X_scaler = MinMaxScaler()
Y_scaler = MinMaxScaler()
X_data = X_scaler.fit_transform(df_mt3_lag.iloc[:,1:])
Y_data = Y_scaler.fit_transform(df_mt3_lag['MT_3'].to_numpy().reshape(-1,1))

n_train = int(len(df_mt3_lag) * data_split)
n_test = (len(df_mt3_lag) - n_train)
print(n_train, n_test)

X_train = X_data[:-n_test]
y_train = Y_data[:-n_test]
train_dates_lstm = Dataset_time[:-n_test]
```

```
X_test = X_data[-n_test:]
y_test_LSTM = Y_data[-n_test:]
test_dates_lstm = Dataset_time[-n_test:]

X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)

print(X_train.shape, y_train.shape, X_test.shape, y_test_LSTM.shape)
```

```
17884 3157
(17884, 33, 1) (17884, 1) (3157, 33, 1) (3157, 1)
```

In [ ]:

```
model = Sequential()
model.add(LSTM(200, activation='relu', return_sequences=True, input_shape=(X_train.shape[1],X_train.sh
model.add(LSTM(100, activation='relu', return_sequences=True))
model.add(LSTM(50, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mae')
model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_5 (LSTM)               (None, 33, 200)           161600

 lstm_6 (LSTM)               (None, 33, 100)           120400

 lstm_7 (LSTM)               (None, 50)                30200

 dense_4 (Dense)             (None, 1)                 51

=================================================================
Total params: 312,251
Trainable params: 312,251
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
batch_size = 256
buffer_size = 150
train_data = tf.data.Dataset.from_tensor_slices((X_train, y_train))
train_data = train_data.cache().shuffle(buffer_size).batch(batch_size).repeat()
val_data = tf.data.Dataset.from_tensor_slices((X_test, y_test_LSTM))
val_data = val_data.batch(batch_size).repeat()
```

In [ ]:

```
model_path = 'LSTM_Multivariate_With_Lag.h5'
early_stopings = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0, patience=10, verbos
checkpoint =  tf.keras.callbacks.ModelCheckpoint(model_path, monitor='val_loss', save_best_only=True,
callbacks=[early_stopings,checkpoint]
history = model.fit(train_data,epochs=100,steps_per_epoch=100,validation_data=val_data,validation_step
```

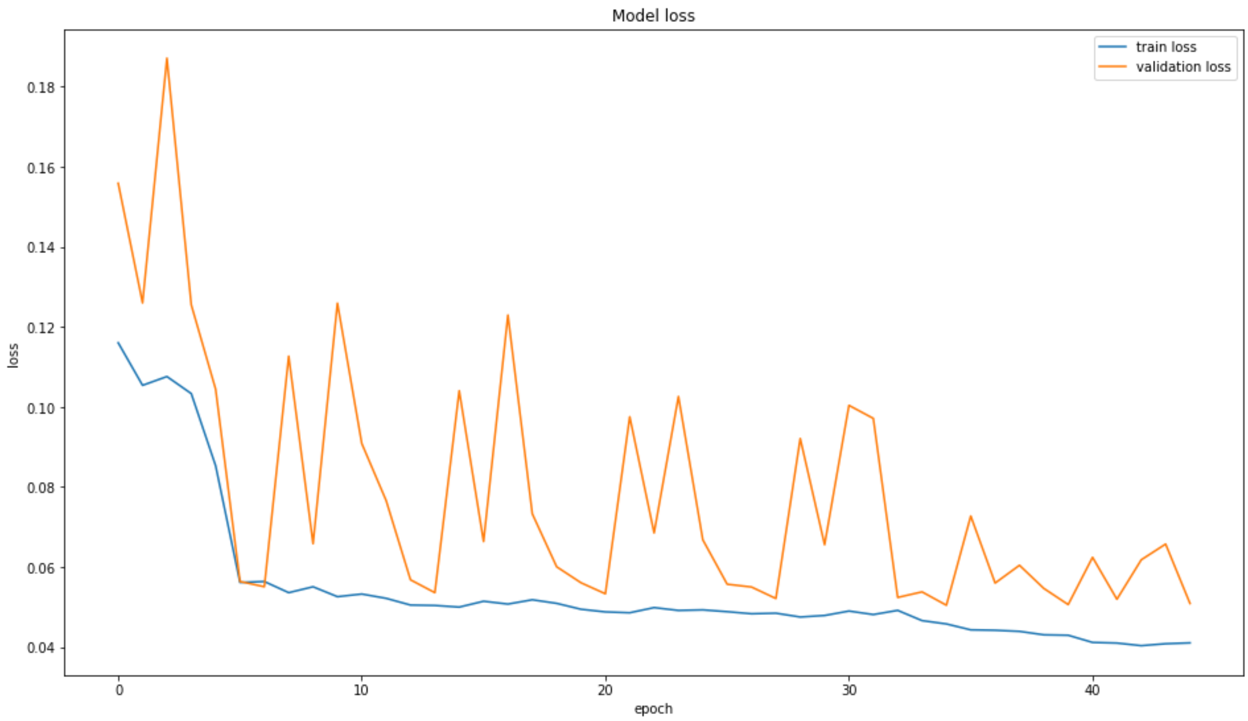
```
Train on 100 steps, validate on 50 steps
Epoch 1/100
100/100 [==============================] - ETA: 0s - batch: 49.5000 - size: 1.0000 - loss: 0.1160
`Model.state_updates` will be removed in a future version. This property should not be used in TensorF
low 2.0, as `updates` are applied automatically.
100/100 [==============================] - 17s 163ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.11
60 - val_loss: 0.1559
Epoch 2/100
100/100 [==============================] - 16s 164ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.10
54 - val_loss: 0.1260
Epoch 3/100
100/100 [==============================] - 15s 146ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.10
76 - val_loss: 0.1871
Epoch 4/100
100/100 [==============================] - 10s 96ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.103
3 - val_loss: 0.1255
Epoch 5/100
100/100 [==============================] - 10s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.085
3 - val_loss: 0.1044
Epoch 6/100
100/100 [==============================] - 10s 96ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.056
2 - val_loss: 0.0564
Epoch 7/100
100/100 [==============================] - 9s 92ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0564
```

```
- val_loss: 0.0551
Epoch 8/100
100/100 [==============================] - 9s 91ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0536
- val_loss: 0.1127
Epoch 9/100
100/100 [==============================] - 10s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.055
1 - val_loss: 0.0658
Epoch 10/100
100/100 [==============================] - 9s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0526
- val_loss: 0.1259
Epoch 11/100
100/100 [==============================] - 9s 94ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0533
- val_loss: 0.0909
Epoch 12/100
100/100 [==============================] - 9s 94ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0522
- val_loss: 0.0766
Epoch 13/100
100/100 [==============================] - 9s 94ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0505
- val_loss: 0.0568
Epoch 14/100
100/100 [==============================] - 10s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.050
4 - val_loss: 0.0536
Epoch 15/100
100/100 [==============================] - 9s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0500
- val_loss: 0.1041
Epoch 16/100
100/100 [==============================] - 10s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.051
5 - val_loss: 0.0664
Epoch 17/100
100/100 [==============================] - 10s 96ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.050
8 - val_loss: 0.1230
Epoch 18/100
100/100 [==============================] - 9s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0518
- val_loss: 0.0733
Epoch 19/100
100/100 [==============================] - 9s 93ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0509
- val_loss: 0.0601
Epoch 20/100
100/100 [==============================] - 9s 94ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0495
- val_loss: 0.0561
Epoch 21/100
100/100 [==============================] - 9s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0488
- val_loss: 0.0533
Epoch 22/100
100/100 [==============================] - 10s 96ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.048
6 - val_loss: 0.0976
Epoch 23/100
100/100 [==============================] - 10s 96ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.049
9 - val_loss: 0.0685
Epoch 24/100
100/100 [==============================] - 9s 92ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0492
- val_loss: 0.1026
Epoch 25/100
100/100 [==============================] - 9s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0493
- val_loss: 0.0668
Epoch 26/100
100/100 [==============================] - 9s 92ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0489
- val_loss: 0.0557
Epoch 27/100
100/100 [==============================] - 14s 136ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
83 - val_loss: 0.0550
Epoch 28/100
100/100 [==============================] - 16s 159ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
85 - val_loss: 0.0521
Epoch 29/100
100/100 [==============================] - 10s 102ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
75 - val_loss: 0.0921
Epoch 30/100
100/100 [==============================] - 9s 93ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0479
- val_loss: 0.0656
Epoch 31/100
100/100 [==============================] - 9s 93ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0490
- val_loss: 0.1004
Epoch 32/100
100/100 [==============================] - 9s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0481
- val_loss: 0.0971
Epoch 33/100
100/100 [==============================] - 9s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0492
- val_loss: 0.0524
Epoch 34/100
100/100 [==============================] - 9s 93ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0466
- val_loss: 0.0538
```

```
Epoch 35/100
100/100 [==============================] - 10s 97ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.045
8 - val_loss: 0.0505
Epoch 36/100
100/100 [==============================] - 9s 92ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0443
- val_loss: 0.0728
Epoch 37/100
100/100 [==============================] - 9s 93ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0442
- val_loss: 0.0560
Epoch 38/100
100/100 [==============================] - 10s 96ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.043
9 - val_loss: 0.0605
Epoch 39/100
100/100 [==============================] - 10s 96ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.043
1 - val_loss: 0.0547
Epoch 40/100
100/100 [==============================] - 10s 97ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.043
0 - val_loss: 0.0506
Epoch 41/100
100/100 [==============================] - 10s 96ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.041
2 - val_loss: 0.0624
Epoch 42/100
100/100 [==============================] - 9s 95ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0410
- val_loss: 0.0520
Epoch 43/100
100/100 [==============================] - 9s 94ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0404
- val_loss: 0.0618
Epoch 44/100
100/100 [==============================] - 9s 94ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0409
- val_loss: 0.0658
Epoch 45/100
100/100 [==============================] - 9s 94ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.0411
- val_loss: 0.0509
Epoch 45: early stopping
```

In [ ]:

```
plt.figure(figsize=(16,9))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train loss', 'validation loss'])
plt.show()
```



In [ ]:

```
model = load_model('/content/drive/MyDrive/Colab Notebooks/Research/LSTM_Multivariate_With_Lag.h5')
model.evaluate(X_test, y_test_LSTM)
```

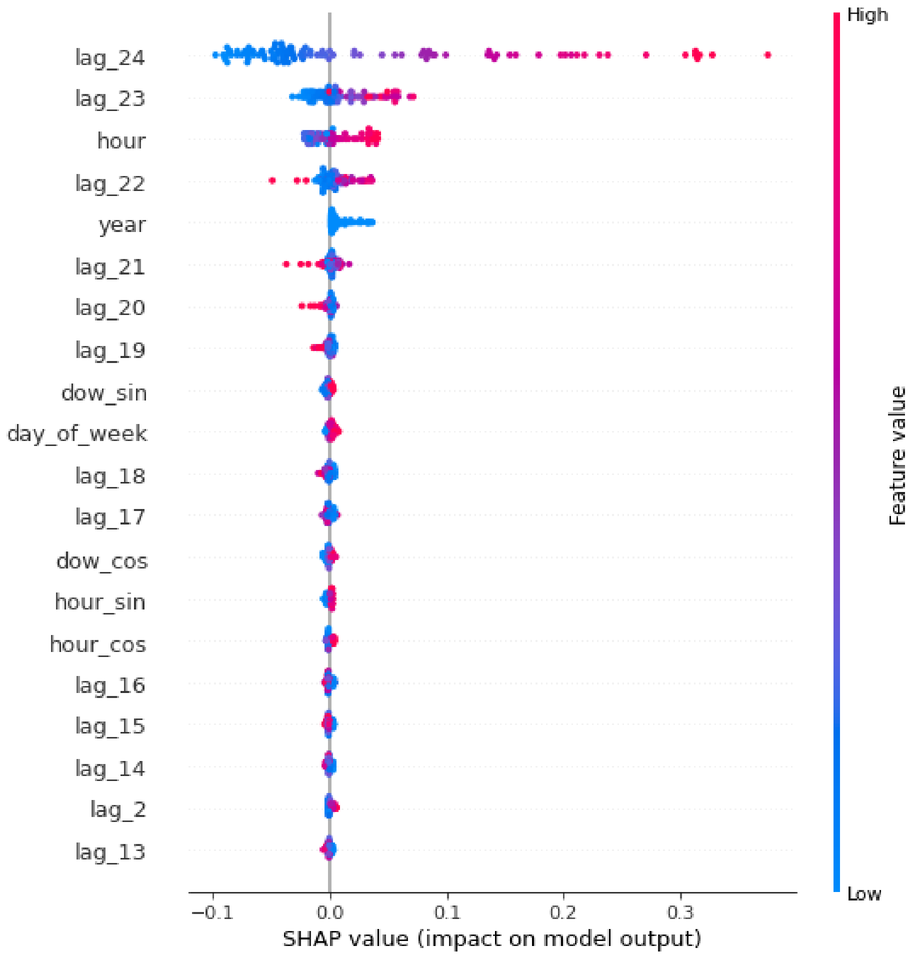
Out[ ]: 0.05019617347370645

```
In [ ]: y_pred_LSTM = model.predict(X_test)
        pred_Inverse_LSTM = Y_scaler.inverse_transform(np.reshape(y_pred_LSTM, (y_pred_LSTM.shape[0], y_pred_L
        y_test_inverse_LSTM = df_mt3_lag.iloc[-n_test:,0]
```

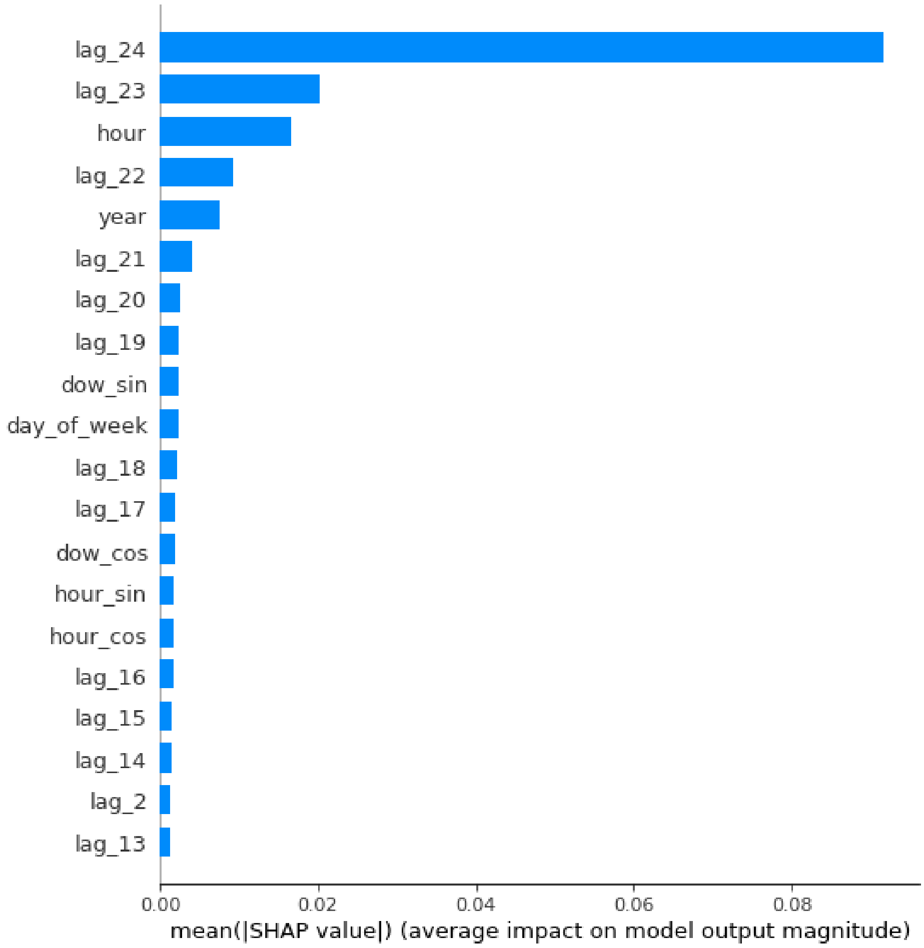
Deep SHAP

```
In [ ]: explainer = shap.DeepExplainer(model, X_train[:1000])
        shap_values = explainer.shap_values(X_test[:100], check_additivity=False)
```

```
In [ ]: shap.summary_plot(np.array(shap_values[0]).reshape(100,33), features=np.array(X_test[:100]).reshape(10
```




```
In [ ]: shap.summary_plot(np.array(shap_values[0]).reshape(100,33), features=np.array(X_test[:100]).reshape(10
```



GRU

In [ ]:

```
model = Sequential()
model.add(GRU(200, activation='relu', return_sequences=True, input_shape=(X_train.shape[1],X_train.sha
model.add(GRU(100, activation='relu', return_sequences=True))
model.add(GRU(50, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mae')
model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 gru_5 (GRU)                 (None, 33, 200)           121800

 gru_6 (GRU)                 (None, 33, 100)           90600

 gru_7 (GRU)                 (None, 50)                22800

 dense_5 (Dense)             (None, 1)                 51

=================================================================
Total params: 235,251
Trainable params: 235,251
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
model_path = 'GRU_Multivariate_With_Lag.h5'
early_stopings = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0, patience=10, verbos
checkpoint =  tf.keras.callbacks.ModelCheckpoint(model_path, monitor='val_loss', save_best_only=True,
callbacks=[early_stopings,checkpoint]
history = model.fit(train_data,epochs=100,steps_per_epoch=100,validation_data=val_data,validation_step
```

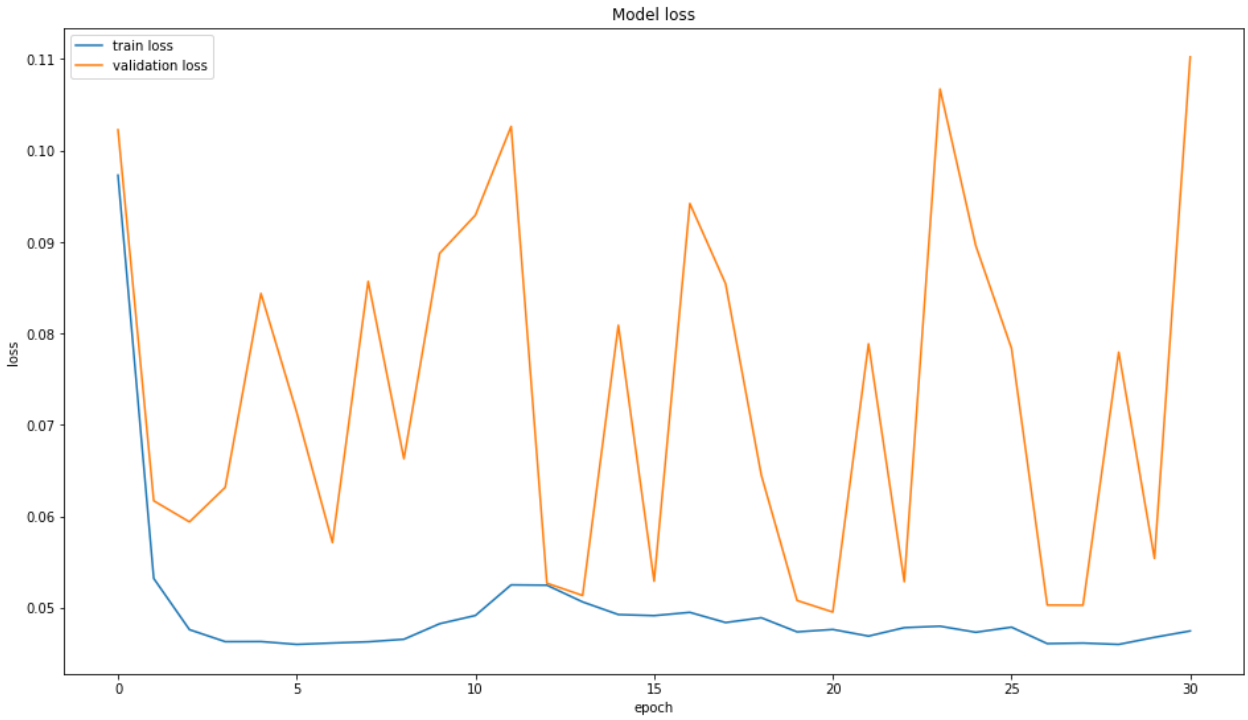
```
Train on 100 steps, validate on 50 steps
Epoch 1/100
100/100 [==============================] - 48s 468ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.09
73 - val_loss: 0.1023
Epoch 2/100
```

```
100/100 [==============================] - 41s 411ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.05
32 - val_loss: 0.0617
Epoch 3/100
100/100 [==============================] - 41s 413ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
76 - val_loss: 0.0594
Epoch 4/100
100/100 [==============================] - 41s 411ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
63 - val_loss: 0.0632
Epoch 5/100
100/100 [==============================] - 41s 411ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
63 - val_loss: 0.0844
Epoch 6/100
100/100 [==============================] - 41s 412ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
60 - val_loss: 0.0714
Epoch 7/100
100/100 [==============================] - 41s 411ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
62 - val_loss: 0.0571
Epoch 8/100
100/100 [==============================] - 41s 411ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
63 - val_loss: 0.0857
Epoch 9/100
100/100 [==============================] - 41s 411ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
66 - val_loss: 0.0663
Epoch 10/100
100/100 [==============================] - 41s 412ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
83 - val_loss: 0.0888
Epoch 11/100
100/100 [==============================] - 49s 493ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
92 - val_loss: 0.0929
Epoch 12/100
100/100 [==============================] - 41s 413ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.05
25 - val_loss: 0.1026
Epoch 13/100
100/100 [==============================] - 47s 469ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.05
25 - val_loss: 0.0527
Epoch 14/100
100/100 [==============================] - 45s 454ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.05
06 - val_loss: 0.0513
Epoch 15/100
100/100 [==============================] - 45s 454ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
93 - val_loss: 0.0809
Epoch 16/100
100/100 [==============================] - 47s 462ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
91 - val_loss: 0.0529
Epoch 17/100
100/100 [==============================] - 45s 454ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
95 - val_loss: 0.0942
Epoch 18/100
100/100 [==============================] - 47s 471ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
84 - val_loss: 0.0854
Epoch 19/100
100/100 [==============================] - 45s 455ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
89 - val_loss: 0.0645
Epoch 20/100
100/100 [==============================] - 45s 456ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
74 - val_loss: 0.0508
Epoch 21/100
100/100 [==============================] - 46s 459ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
76 - val_loss: 0.0495
Epoch 22/100
100/100 [==============================] - 45s 455ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
69 - val_loss: 0.0789
Epoch 23/100
100/100 [==============================] - 41s 410ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
78 - val_loss: 0.0529
Epoch 24/100
100/100 [==============================] - 41s 410ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
80 - val_loss: 0.1067
Epoch 25/100
100/100 [==============================] - 45s 456ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
73 - val_loss: 0.0896
Epoch 26/100
100/100 [==============================] - 45s 456ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
79 - val_loss: 0.0784
Epoch 27/100
100/100 [==============================] - 45s 454ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
61 - val_loss: 0.0503
Epoch 28/100
100/100 [==============================] - 45s 454ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
61 - val_loss: 0.0503
Epoch 29/100
100/100 [==============================] - 41s 408ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
```

```
60 - val_loss: 0.0780
Epoch 30/100
100/100 [==============================] - 45s 455ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
68 - val_loss: 0.0554
Epoch 31/100
100/100 [==============================] - 41s 409ms/step - batch: 49.5000 - size: 1.0000 - loss: 0.04
75 - val_loss: 0.1102
Epoch 31: early stopping
```

In [ ]:

```
plt.figure(figsize=(16,9))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train loss', 'validation loss'])
plt.show()
```



In [ ]:

```
model = load_model('/content/drive/MyDrive/Colab Notebooks/Research/GRU_Multivariate_With_Lag.h5')
model.evaluate(X_test, y_test_LSTM)
```

Out[ ]: 0.04924493924132585

In [ ]:

```
y_pred_GRU = model.predict(X_test)
pred_Inverse_GRU = Y_scaler.inverse_transform(np.reshape(y_pred_GRU, (y_pred_GRU.shape[0], y_pred_GRU.
y_test_inverse_GRU = df_mt3_lag.iloc[-n_test:,0]
```

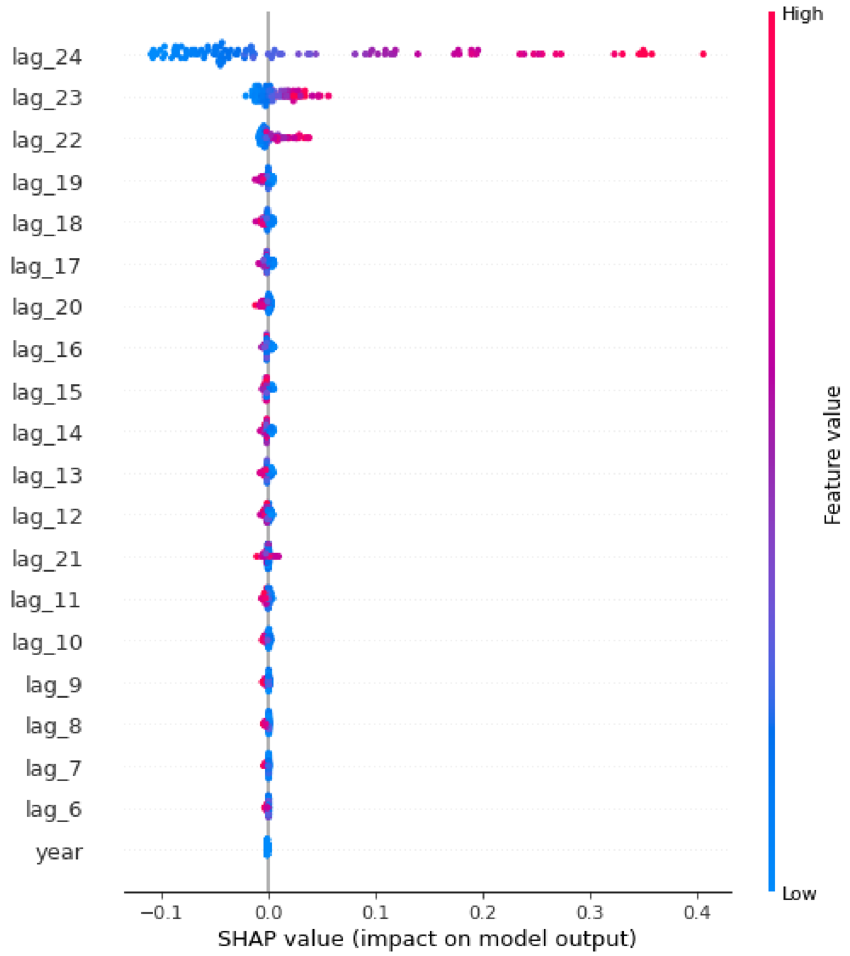
Deep SHAP

In [ ]:

```
explainer = shap.DeepExplainer(model, X_train[:1000])
shap_values = explainer.shap_values(X_test[:100], check_additivity=False)
```

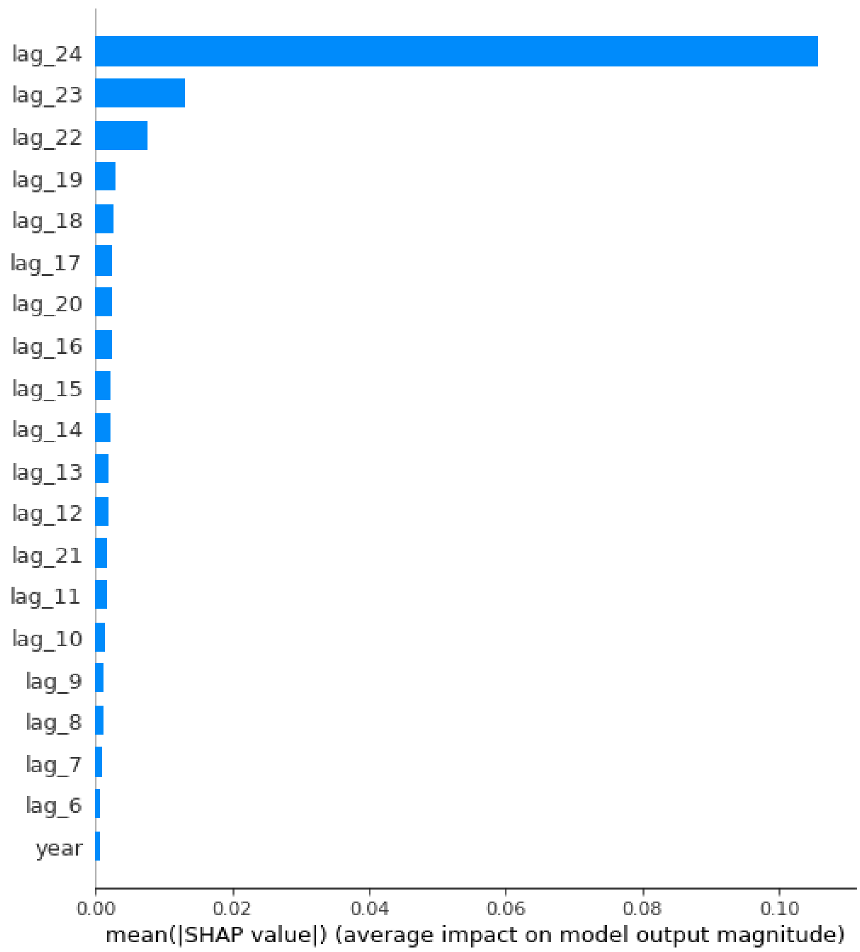
In [ ]:

```
shap.summary_plot(np.array(shap_values[0]).reshape(100,33), features=np.array(X_test[:100]).reshape(10
```



In [ ]:

```
shap.summary_plot(np.array(shap_values[0]).reshape(100,33), features=np.array(X_test[:100]).reshape(10
```



Evaluation

In [ ]:

```
df_res = pd.DataFrame(columns=['model', 'hours', 'mape', 'mae', 'rmse', 'nrmse'])
df_res = df_res.astype(dtype= {"model":"string",
        "hours":"int","mape":"string", "mae":"string", "rmse":"string", "nrmse":"string"})
pred_hours = [1,6,12,24,48]

for hours in pred_hours:
  for model_name in ['LSTM', 'GRU']:
    Mape = []
    Mae = []
    Rmse = []
    Nrmse = []

    val_set = None

    if model_name == 'LSTM':
      val_set = generateValSet(len(y_test_LSTM), hours)
      holdout = pred_Inverse_LSTM
      ground_truth = y_test_inverse_LSTM
    else:
      val_set = generateValSet(len(y_test_LSTM), hours)
      holdout = pred_Inverse_GRU
      ground_truth = y_test_inverse_GRU

    for val in val_set:
      forecast = holdout[:val]
      pred = forecast[-hours:]
      true = ground_truth[:val]
      actual = true[-hours:]
      mae, mape, rmse, nrmse = calc_metrics(actual, pred)
      Mape.append(mape)
      Mae.append(mae)
      Rmse.append(rmse)
      Nrmse.append(nrmse)

    metrics = return_metrics(Mape, Mae, Rmse, Nrmse)
    df_res = df_res.append({'model':model_name, 'hours': hours, 'mape': metrics[0], 'mae': metrics[1],
```

In [ ]:

```
df_res
```

Out[ ]:

	model	hours	mape	mae	rmse	nrmse
0	LSTM	1	0.1% +- 0.1	51.0 +- 48.94	51.0 +- 48.94	0.1 +- 0.1
1	GRU	1	0.1% +- 0.1	50.03 +- 49.71	50.03 +- 49.71	0.1 +- 0.1
2	LSTM	6	0.1% +- 0.07	50.97 +- 34.36	59.67 +- 37.81	0.12 +- 0.08
3	GRU	6	0.1% +- 0.07	49.97 +- 35.78	58.62 +- 39.11	0.12 +- 0.07
4	LSTM	12	0.1% +- 0.06	50.92 +- 28.45	62.34 +- 33.12	0.12 +- 0.07
5	GRU	12	0.1% +- 0.06	49.93 +- 29.95	61.39 +- 34.5	0.12 +- 0.07
6	LSTM	24	0.1% +- 0.04	50.92 +- 21.27	64.78 +- 28.04	0.13 +- 0.05
7	GRU	24	0.1% +- 0.04	49.95 +- 22.83	63.91 +- 29.6	0.12 +- 0.05
8	LSTM	48	0.1% +- 0.03	50.91 +- 15.39	66.96 +- 22.31	0.13 +- 0.04
9	GRU	48	0.1% +- 0.03	49.99 +- 16.06	66.44 +- 23.41	0.13 +- 0.04

In [ ]:

```
df_res.to_csv('/content/drive/MyDrive/Colab Notebooks/Research/lag_results_metrics.csv', index=False)
```