Temporal Forecasting Models (Chapter 4.1)

June 2, 2023

1 Structure of the notebook

This notebook utilizes the pre-processed taxi trip record data.

The notebook sets the basis for **Chapter 4.1 Temporal Forecasting Models** and **Chapter 5.4 Analysis of Feature Importance:**

Linear Regression (Chapter 4.1.1)

Random Forest Regression (Chapter 4.1.2)

Recurrent Neural Network (LSTM) (Chapter 4.1.3)

Analysis of Feature Importance (Chapter 5.4)

2 Libraries required to run this notebook

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
! pip install -q openpyxl
import warnings
warnings.filterwarnings("ignore")
import joblib
from joblib import dump
from joblib import load
import cloudpickle

from sklearn.preprocessing import RobustScaler, MinMaxScaler,␣
↪FunctionTransformer, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline

from sklearn.model_selection import RandomizedSearchCV

from sklearn.linear_model import LinearRegression
from tensorflow.keras.optimizers import Adam
from sklearn.ensemble import RandomForestRegressor
```

```python
import tensorflow as tf
from tensorflow.keras.models import load_model
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import Dense, Dropout
from kerastuner.tuners import RandomSearch
import keras_tuner as kt

from sklearn.metrics import mean_squared_error, mean_absolute_error
from tensorflow.keras.metrics import RootMeanSquaredError

! pip install -q shap
import shap
```

```
2023-06-02 08:36:23.867645: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  AVX2 AVX512F FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
2023-06-02 08:36:29.390283: E tensorflow/stream_executor/cuda/cuda_blas.cc:2981]
Unable to register cuBLAS factory: Attempting to register factory for plugin
cuBLAS when one has already been registered
2023-06-02 08:36:41.827794: W
tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load
dynamic library 'libnvinfer.so.7'; dlerror: libnvinfer.so.7: cannot open shared
object file: No such file or directory; LD_LIBRARY_PATH:
/usr/local/cuda/lib64:/usr/local/cuda/lib:/usr/local/lib/x86_64-linux-gnu:/usr/l
ocal/nvidia/lib:/usr/local/nvidia/lib64:/usr/local/nvidia/lib:/usr/local/nvidia/
lib64
2023-06-02 08:36:41.828031: W
tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load
dynamic library 'libnvinfer_plugin.so.7'; dlerror: libnvinfer_plugin.so.7:
cannot open shared object file: No such file or directory; LD_LIBRARY_PATH:
/usr/local/cuda/lib64:/usr/local/cuda/lib:/usr/local/lib/x86_64-linux-gnu:/usr/l
ocal/nvidia/lib:/usr/local/nvidia/lib64:/usr/local/nvidia/lib:/usr/local/nvidia/
lib64
2023-06-02 08:36:41.828048: W
tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Cannot
dlopen some TensorRT libraries. If you would like to use Nvidia GPU with
TensorRT, please make sure the missing libraries mentioned above are installed
properly.
```

3 Data reading and initial exploration

[3]:
```
# Read the data
global_feat_data = pd.read_csv("gs://final_prep_data/global_temporal_features.
 ↪csv")
```

[4]:
```
# Info on the dataset
global_feat_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4344 entries, 0 to 4343
Data columns (total 16 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   tpep_pickup_datetime  4344 non-null   object
 1   PU_count              4344 non-null   int64
 2   PU_month              4344 non-null   int64
 3   PU_day_of_month       4344 non-null   int64
 4   PU_day_of_week        4344 non-null   int64
 5   PU_hour               4344 non-null   int64
 6   trip_distance         4343 non-null   float64
 7   total_amount          4343 non-null   float64
 8   lag_1h                4344 non-null   float64
 9   lag_2h                4344 non-null   float64
 10  lag_1d                4344 non-null   float64
 11  lag_2d                4344 non-null   float64
 12  ewma_3h               4344 non-null   float64
 13  ewma_6h               4344 non-null   float64
 14  ewma_12h              4344 non-null   float64
 15  ewma_24h              4344 non-null   float64
dtypes: float64(10), int64(5), object(1)
memory usage: 543.1+ KB
```

[6]:
```
global_feat_data.head()
```

[6]:
```
  tpep_pickup_datetime  PU_count  PU_month  PU_day_of_month  PU_day_of_week  \
0  2022-01-01 00:00:00      3507         1                1               5
1  2022-01-01 01:00:00      4051         1                1               5
2  2022-01-01 02:00:00      3100         1                1               5
3  2022-01-01 03:00:00      2211         1                1               5
4  2022-01-01 04:00:00      1321         1                1               5

   PU_hour  trip_distance  total_amount  lag_1h  lag_2h  lag_1d  lag_2d  \
0        0       2.757311     18.051933     0.0     0.0     0.0     0.0
1        1       2.851516     18.022978  3507.0     0.0     0.0     0.0
2        2       3.046068     18.365532  4051.0  3507.0     0.0     0.0
3        3       3.256635     18.679724  3100.0  4051.0     0.0     0.0
```

```
4         4       3.652210     19.909424  2211.0  3100.0     0.0     0.0

       ewma_3h      ewma_6h     ewma_12h     ewma_24h
0  3507.000000  3507.000000  3507.000000  3507.000000
1  3869.666667  3824.333333  3801.666667  3790.333333
2  3429.857143  3498.715596  3527.806005  3540.791209
3  2779.800000  3001.320946  3112.141810  3165.683113
4  2026.870968  2411.575208  2625.494982  2732.809394
```

[8]:
```
global_feat_data.tail(len(global_feat_data)-1)[:-1]
```

[8]:
```
     tpep_pickup_datetime  PU_count  PU_month  PU_day_of_month  \
1     2022-01-01 01:00:00      4051         1                1
2     2022-01-01 02:00:00      3100         1                1
3     2022-01-01 03:00:00      2211         1                1
4     2022-01-01 04:00:00      1321         1                1
5     2022-01-01 05:00:00       601         1                1
…                      …        …        …              …
4338  2022-06-30 18:00:00      6645         6               30
4339  2022-06-30 19:00:00      6095         6               30
4340  2022-06-30 20:00:00      4972         6               30
4341  2022-06-30 21:00:00      5177         6               30
4342  2022-06-30 22:00:00      4839         6               30

      PU_day_of_week  PU_hour  trip_distance  total_amount  lag_1h  lag_2h  \
1                  5        1       2.851516     18.022978  3507.0     0.0
2                  5        2       3.046068     18.365532  4051.0  3507.0
3                  5        3       3.256635     18.679724  3100.0  4051.0
4                  5        4       3.652210     19.909424  2211.0  3100.0
5                  5        5       4.515624     22.438236  1321.0  2211.0
…                …      …             …            …     …     …
4338               3       18       2.355977     18.268290  5928.0  5308.0
4339               3       19       2.446198     17.807930  6645.0  5928.0
4340               3       20       2.489914     17.327742  6095.0  6645.0
4341               3       21       2.577813     17.464085  4972.0  6095.0
4342               3       22       2.819064     18.180460  5177.0  4972.0

      lag_1d  lag_2d      ewma_3h      ewma_6h     ewma_12h     ewma_24h
1        0.0     0.0  3869.666667  3824.333333  3801.666667  3790.333333
2        0.0     0.0  3429.857143  3498.715596  3527.806005  3540.791209
3        0.0     0.0  2779.800000  3001.320946  3112.141810  3165.683113
4        0.0     0.0  2026.870968  2411.575208  2625.494982  2732.809394
5        0.0     0.0  1302.619048  1815.042284  2133.436193  2299.564333
…        …     …            …            …            …            …
4338  6886.0  7428.0  6143.583066  5724.549282  5058.373203  4477.559102
4339  6414.0  6315.0  6119.291533  5830.392345  5217.854249  4606.954374
4340  5513.0  5346.0  5545.645766  5585.137389  5180.030518  4636.158024
```

```
4341   5470.0   5209.0   5361.322883   5468.526706   5179.564285   4679.425382
4342   4883.0   4577.0   5100.161442   5288.661933   5127.169779   4692.191352

[4342 rows x 16 columns]
```

[4]:
```
# Drop the column 'tpep_pickup_datetime'
# Datetime information is now available in seperate columns (PU_month,␣
↪PU_day_of_month, PU_hour)
global_feat_data = global_feat_data.drop(['tpep_pickup_datetime'], axis = 1)
```

[5]:
```
# Experiment on multicorrelated feature removal
global_feat_data = global_feat_data.drop(['total_amount','ewma_24h', 'lag_2d'],␣
↪axis = 1)
# global_feat_data = global_feat_data.drop(['tpep_pickup_datetime','PU_month',␣
↪'total_amount', 'frost', 'ewma_12h', 'ewma_24h'], axis = 1)
# global_feat_data = global_feat_data.drop(['tpep_pickup_datetime','PU_month',␣
↪'total_amount', 'frost', 'ewma_6h','ewma_12h', 'ewma_24h'], axis = 1)
# global_feat_data = global_feat_data.drop(['tpep_pickup_datetime','PU_month',␣
↪'total_amount', 'frost', 'lag_2_days'], axis = 1)
# global_feat_data = global_feat_data.drop(['tpep_pickup_datetime','PU_month',␣
↪'total_amount', 'frost', 'lad_2_hours', 'lag_2_days'], axis = 1)
```

It was observed that removing multicorrelated features such as *total_amount*, *ewma_24h*, and *lag_2d* led to the best predictive results for the linear regression model. Consequently, these columns will be excluded from the dataset and will not be utilized for the temporal forecasting models.

[6]:
```
# Final check for missing values
global_feat_data.isna().sum()
global_feat_data.fillna(0, inplace = True)
```

4 Split the data in training and test set

[7]:
```
# Seperate explanatory features and target variable
# Definition of explanatory features
X = ['PU_month', 'PU_day_of_month', 'PU_day_of_week',␣
↪'PU_hour','trip_distance', 'lag_1h', 'lag_2h', 'lag_1d', 'ewma_3h',␣
↪'ewma_6h', 'ewma_12h']

# Definition of the target variable
y = 'PU_count'
```

[8]:
```
# Initialize split ratio: 80% train and 20% test
train_pct = 0.8
test_pct = 0.2
```

[9]:
```python
# Split the data into training and test set
n = len(global_feat_data)
train_idx = int(train_pct * n)
train_data = global_feat_data.iloc[:train_idx]
test_data = global_feat_data.iloc[train_idx:]

# Training and test sets for the explanatory variables and response variable
X_train = train_data[X]
y_train = train_data[y]
X_test  = test_data[X]
y_test = test_data[y]

# Print the shapes of the train and test set
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(3475, 11) (3475,) (869, 11) (869,)
```

5 Temporal forecasting models

5.1 Linear regression

[10]:
```python
# Create a copy of the 'X_train' and 'X_test' set because different␣
↪pre-processing methods will be applied to the explanatory features in each␣
↪temporal forecasting model
X_train_lr = X_train.copy()
X_test_lr = X_test.copy()
y_train_lr = y_train.copy()
y_test_lr = y_test.copy()
```

[11]:
```python
# Definition of transformer functions for sine and cosine transformation on␣
↪categorical/cyclic data
def sin_transformer(period):
    return FunctionTransformer(lambda x: np.sin(x / period * 2 * np.pi))
def cos_transformer(period):
    return FunctionTransformer(lambda x: np.cos(x / period * 2 * np.pi))
```

[12]:
```python
# Definition of the column transformer
# Categorical/cyclic features are transformed using sine and cosine transformers
# Numerical features are scaled using RobustScaler()
cyclic_cossin_transformer = ColumnTransformer(
    transformers=[
        ("PU_month_sin", sin_transformer(6), ["PU_month"]),
        ("PU_month_cos", cos_transformer(6), ["PU_month"]),
        ("PU_day_of_month_sin", sin_transformer(31), ["PU_day_of_month"]),
        ("PU_day_of_month_cos", cos_transformer(31), ["PU_day_of_month"]),
        ("PU_day_of_week_sin", sin_transformer(7), ["PU_day_of_week"]),
        ("PU_day_of_week_cos", cos_transformer(7), ["PU_day_of_week"]),
```

```
        ("PU_hour_sin", sin_transformer(24), ["PU_hour"]),
        ("PU_hour_cos", cos_transformer(24), ["PU_hour"]),
    ],
    remainder= RobustScaler(),
)

# Definition of column pipeline to pre-process the input data and define a␣
 ↪linear regression component for modeling and prediction
cyclic_cossin_linear_pipeline = make_pipeline(
cyclic_cossin_transformer,
LinearRegression(),
)
```

5.1.1 Model training and performance evaluation

[13]:
```
# Fit the pipeline on the train set
cyclic_cossin_linear_pipeline.fit(X_train_lr, y_train_lr)

# Predictions for the train set
y_pred_train_lr = cyclic_cossin_linear_pipeline.predict(X_train_lr)
mae_train_lr = mean_absolute_error(y_train_lr, y_pred_train_lr)
rmse_train_lr = np.sqrt(mean_squared_error(y_train_lr, y_pred_train_lr))

# Predictions for the test set
y_pred_test_lr = cyclic_cossin_linear_pipeline.predict(X_test_lr)
mae_test_lr = mean_absolute_error(y_test_lr, y_pred_test_lr)
rmse_test_lr = np.sqrt(mean_squared_error(y_test_lr, y_pred_test_lr))

# Print the RMSE and MAE for the train set
print("Train set:")
print(f"RMSE: {rmse_train_lr:.2f}")
print(f"MAE: {mae_train_lr:.2f}")

# Print the RMSE and MAE for the test set
print("Test set:")
print(f"RMSE: {rmse_test_lr:.2f}")
print(f"MAE: {mae_test_lr:.2f}")#
```

```
Train set:
RMSE: 53.51
MAE: 28.79
Test set:
RMSE: 38.04
MAE: 29.09
```

5.1.2 Visualization of performance results

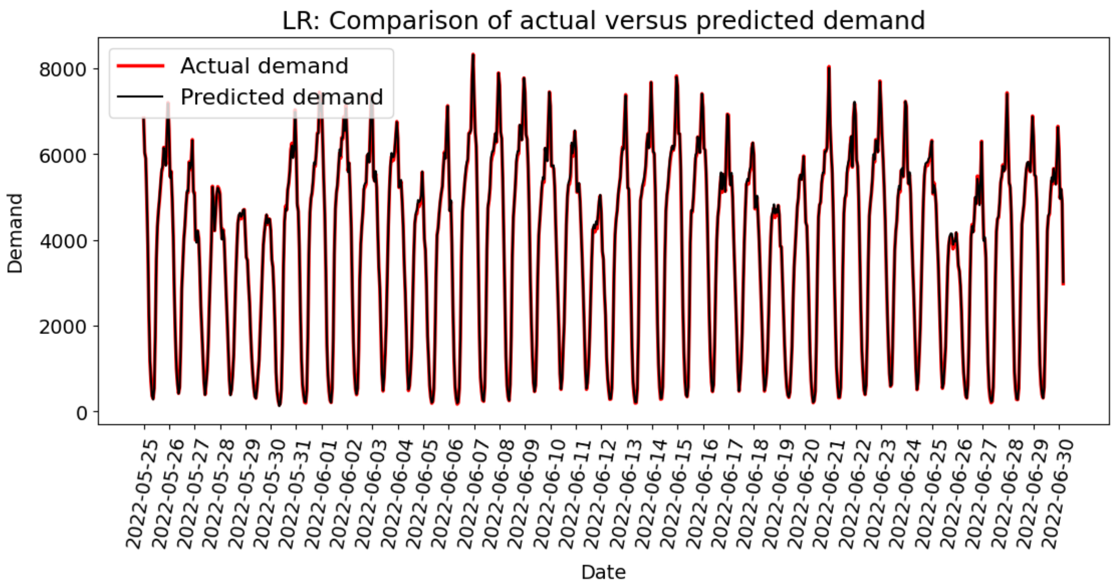
[14]:
```python
# A dataframe of the actual versus predicted values for the test set is created

# Copy of the X_test_lr data
X_test_lr_datetime = X_test_lr.copy()

# Combine the month, day of month, and hour columns to create a new datetime␣
↪column
X_test_lr_datetime['datetime'] = pd.to_datetime(dict(year=2022,␣
↪month=X_test_lr['PU_month'], day=X_test_lr['PU_day_of_month'],␣
↪hour=X_test_lr['PU_hour']))

# Set the datetime column as the index
X_test_lr_datetime.set_index('datetime', inplace=True)

# Drop the original  'PU_month','PU_day_of_month', and 'PU_hour' columns␣
↪because this information is now available in the 'datetime' column
X_test_lr_datetime.drop(['PU_month', 'PU_day_of_month', 'PU_hour'], axis=1,␣
↪inplace=True)

# Convert the response variable of the test data to a numpy array
y_test_array = y_test.to_numpy()

# Round predicted values to integers
y_pred_test_lr_rounded = y_pred_test_lr.round().astype(int)

# Create a dataframe of the actual and predicted values
results_lr = pd.DataFrame({'Actual': y_test_array, 'Predicted':␣
↪y_pred_test_lr_rounded}, index=X_test_lr_datetime.index)

# Calculate the difference between actual and predicted values and store them␣
↪in a new column
results_lr['Difference'] = results_lr['Actual'] - results_lr['Predicted']
results_lr
```

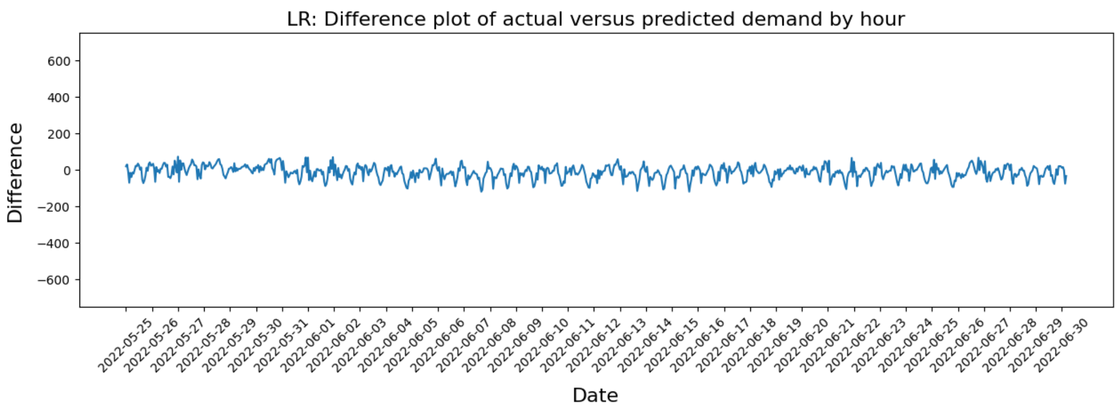
[14]:

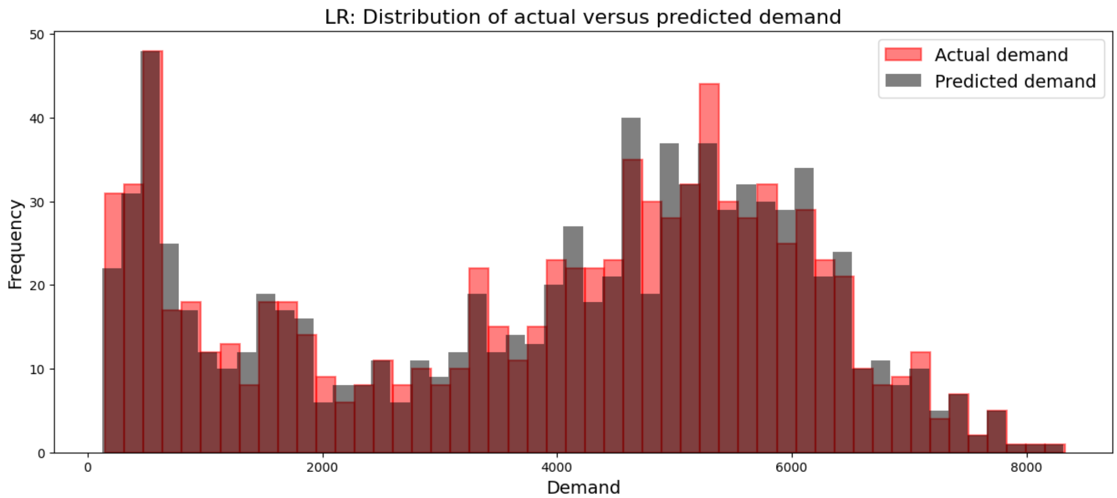
datetime	Actual	Predicted	Difference
2022-05-25 19:00:00	6837	6819	18
2022-05-25 20:00:00	6046	6018	28
2022-05-25 21:00:00	5893	5904	-11
2022-05-25 22:00:00	4929	5001	-72
2022-05-25 23:00:00	3829	3846	-17
…	…	…	…
2022-06-30 19:00:00	6095	6085	10
2022-06-30 20:00:00	4972	4958	14
2022-06-30 21:00:00	5177	5181	-4

```
2022-06-30 22:00:00    4839      4916        -77
2022-06-30 23:00:00    2979      3014        -35

[869 rows x 3 columns]
```

[16]:
```
# Time series plot of the actual versus predicted values for the test set
plt.figure(figsize=(13,5))
plt.plot(results_lr.index, results_lr['Actual'], label='Actual demand', color =␣
↪'red', linewidth = 2.5)
plt.plot(results_lr.index, results_lr['Predicted'], label='Predicted demand',␣
↪color = 'black')
plt.xlabel('Date', fontsize = 14, labelpad = 10)
plt.xticks(results_lr.index[::24], results_lr.index.date[::24], rotation= 80,␣
↪fontsize = 14)
plt.yticks(fontsize = 14)
plt.ylabel('Demand', fontsize = 14, labelpad = 10)
plt.title('LR: Comparison of actual versus predicted demand', fontsize = 18)
plt.legend(fontsize = 16)
plt.savefig('LR_actual_predicted.png', bbox_inches = 'tight')
plt.show()

# Difference plot of actual and predicted values for the test set
plt.figure(figsize=(15,4))
plt.plot(results_lr.index, results_lr['Difference'])
plt.xlabel('Date', fontsize = 16, labelpad = 10)
plt.xticks(results_lr.index[::24], results_lr.index.date[::24], rotation=45)
plt.ylim([-750, 750])  # Set y-axis limits
plt.ylabel('Difference', fontsize = 16, labelpad = 10)
plt.title('LR: Difference plot of actual versus predicted demand by hour',␣
↪fontsize = 16)
plt.show()

# Distribution plot of actual and predicted values for the test set
plt.figure(figsize=(15,6))
plt.hist(results_lr['Actual'], bins=50, alpha=0.5, label='Actual demand', color␣
↪= 'red', edgecolor='red', linewidth=1.5)
plt.hist(results_lr['Predicted'], bins=50, alpha=0.5, label='Predicted demand',␣
↪color = 'black')
plt.xlabel('Demand', fontsize = 14)
plt.ylabel('Frequency', fontsize = 14)
plt.title('LR: Distribution of actual versus predicted demand', fontsize = 16)
plt.legend(fontsize = 14)
plt.savefig('LR_distribution_actual_predicted.png', bbox_inches = 'tight')
plt.show()
```


LR: Comparison of actual versus predicted demand
Actual demand
Predicted demand
Demand
Date


LR: Difference plot of actual versus predicted demand by hour
Difference
Date



5.1.3 Analysis of Feature Importance using SHAP values

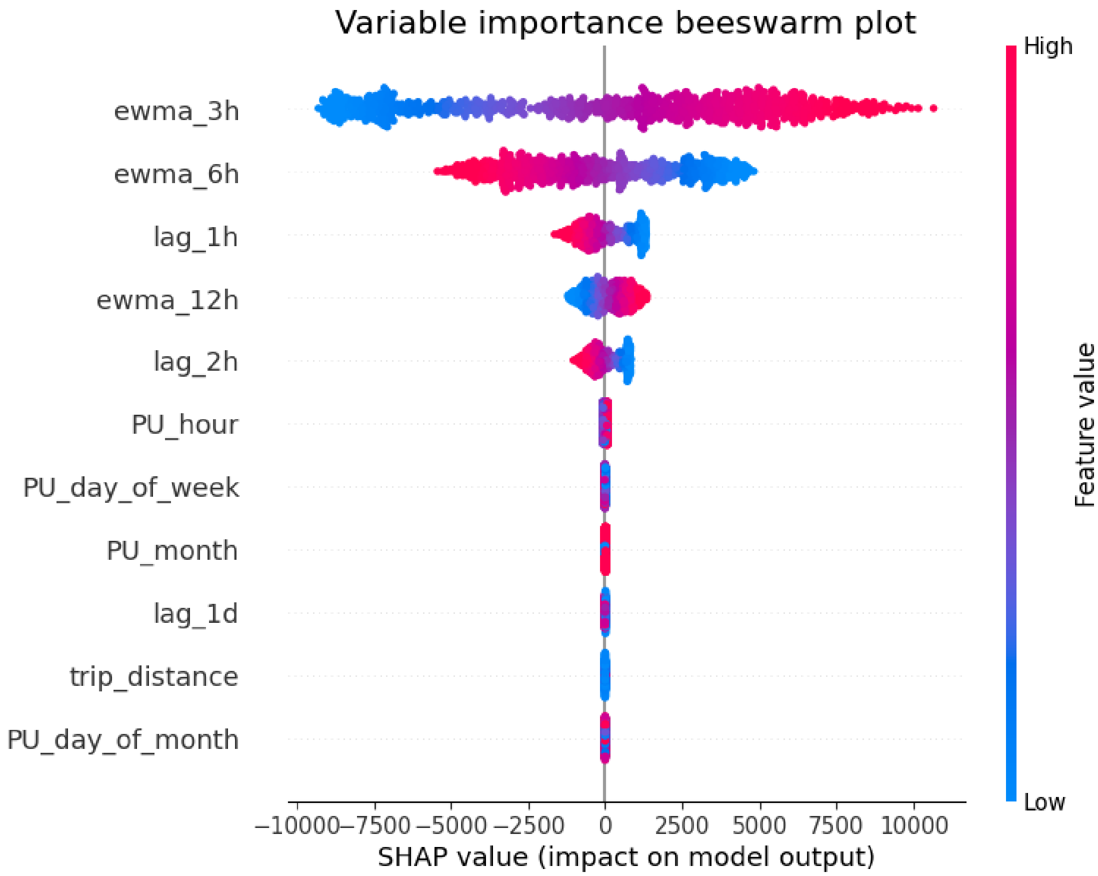
Note: The SHAP values have been saved and can be loaded in the subsequent code section due to significant runtime.

[17]:
```
# Create a function that takes a set of inputs and returns the model predictions
model_func = lambda x: cyclic_cossin_linear_pipeline.predict(x)

# Create an explainer object
explainer_lr = shap.Explainer(model_func, X_train, n_jobs = -1)

# Compute SHAP values for the test data
shap_values = explainer_lr(X_test)

# Save the SHAP values
with open("shap_values_lr.joblib", "wb") as f:
    cloudpickle.dump(shap_values, f)
```

```
Permutation explainer: 870it [06:22,  2.21it/s]
```

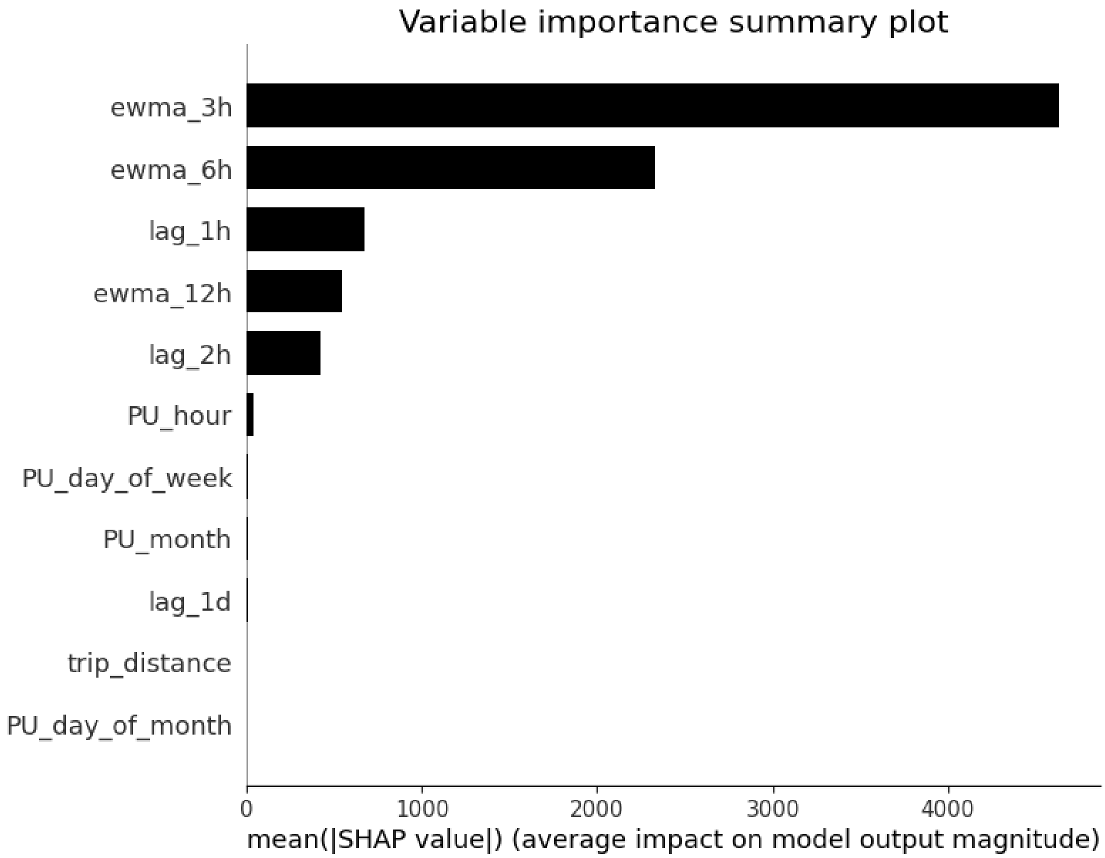
[14]:
```
# Load the SHAP values
with open("shap_values_lr.joblib", "rb") as f:
    shap_values = joblib.load(f)
```

[15]:
```
# Visualize the SHAP values using a swarm plot
shap.summary_plot(shap_values, X_test, plot_size=(8, 6), show = False)
plt.title('Variable importance beeswarm plot', fontsize = 16)
plt.savefig('Swarmplot_LR', bbox_inches = 'tight')
```



[16]:

```
# Visualize the SHAP values using a summary plot
shap.summary_plot(shap_values, X_test, plot_type = "bar", color = 'black',␣
 ↪plot_size = (8,6), show = False)
plt.title('Variable importance summary plot', fontsize = 16)
plt.savefig('Summaryplot_LR', bbox_inches = 'tight')
```



5.2 Random forest

[17]:
```
# Specification of categorical features
categorical_features = ['PU_hour']

# Option 2 tested: categorical_features = ['PU_day_of_month', 'PU_day_of_week',␣
↪'PU_hour']
```

[18]:
```
# Initialize an instance of the One-Hot-Encoder to pre-process the categorical␣
↪features
one_hot_encoder = OneHotEncoder(handle_unknown="ignore", sparse = False)
```

[19]:
```
# Create copies of the train and test data
X_train_rf = X_train.copy()
X_test_rf = X_test.copy()
```

[20]:
```
# Create a pipeline for random forest regression
# Column Transformer is used to one-hot-encode 'PU_hour'
rf_pipeline = make_pipeline(
```

```
    # The ColumnTransformer component allows for different transformations to␣
 ↪be applied to different subsets of the input data
    ColumnTransformer(
        # Tuple specifying the name of the name of the transformation, and the␣
 ↪transformer object to be applied on the categorical features
        transformers=[
        ("categorical", one_hot_encoder, categorical_features),
        ],
        # The remaining columns are not further transformed
        remainder= "passthrough",
    ),
    # Initialize Random Forest Regression
    RandomForestRegressor(n_jobs = -1)
)
```

5.3 Build a tuned random forest model

Note: The code snippet below can be skipped, and the model along with the tuned hyperparameter results can be loaded in the subsequent section "Performance evaluation of the tuned random forest model".

[54]:
```
# Define hyperparameter search space
param_distributions = {
    "randomforestregressor__n_estimators":  [int (x) for x in np.linspace(start␣
 ↪= 100, stop = 1000, num= 10)] , # Determine the number of trees (list of␣
 ↪integer values ranging from 100 to 1000, with 10 evenly spaced values)
    "randomforestregressor__max_depth": [3,4,5,10,30,50,80,100], # Determine␣
 ↪the maximum depth of each tree from the list of pre-defined values
    "randomforestregressor__min_samples_split": [2,4,6,8,10], # Determine the␣
 ↪number of samples required to split an internal node from a list of␣
 ↪pre-defined values
    "randomforestregressor__min_samples_leaf": [1,2,4,5,8,10], # Determine the␣
 ↪number of samples required to be at a leaf node from a list of pre-defined␣
 ↪values
    "randomforestregressor__max_features": ["auto", "sqrt", "log2"], #␣
 ↪Determine the number of features to consider when looking for the best split
}

# Number of parameter settings that are sampled
n_iter = 100

# Perform random search with cross-validation
random_search = RandomizedSearchCV(
    rf_pipeline, param_distributions, n_iter=n_iter, verbose=1, n_jobs=-1, cv =␣
 ↪2
)
random_search.fit(X_train_rf, y_train)
```

```
# Print the best hyparameters and score
print("Best Parameters: ", random_search.best_params_)
print("Best Score: ", random_search.best_score_)

# Save the best model
best_random_forest = random_search.best_estimator_
dump(best_random_forest, 'best_random_forest.joblib')
```

```
Fitting 2 folds for each of 100 candidates, totalling 200 fits
Best Parameters:  {'randomforestregressor__n_estimators': 900,
'randomforestregressor__min_samples_split': 2,
'randomforestregressor__min_samples_leaf': 1,
'randomforestregressor__max_features': 'auto',
'randomforestregressor__max_depth': 100}
Best Score:  0.977855049369899
```

[54]:
```
['best_random_forest.joblib']
```

5.3.1 Performance evaluation of the tuned random forest model

[21]:
```
# Load the saved model
best_random_forest = load('best_random_forest.joblib')
```

[22]:
```
# Create predictions for the train set
y_pred_train_rf = best_random_forest.predict(X_train_rf)

# Calculate RMSE and MAE for the train set
rmse_train_rf = np.sqrt(mean_squared_error(y_train, y_pred_train_rf))
mae_train_rf = mean_absolute_error(y_train, y_pred_train_rf)

# Print the RMSE and MAE for the train set
print("Train set:")
print(f"RMSE: {rmse_train_rf:.2f}")
print(f"MAE: {mae_train_rf:.2f}")

# Create predictions for the test set
y_pred_test_rf = best_random_forest.predict(X_test_rf)

# Calculate metrics for the test set
mae_test_rf = mean_absolute_error(y_test, y_pred_test_rf)
rmse_test_rf = np.sqrt(mean_squared_error(y_test, y_pred_test_rf))

# Print the RMSE and MAE for the test set
print("Test set:")
print(f"RMSE: {rmse_test_rf:.2f}")
print(f"MAE: {mae_test_rf:.2f}")
```

```
Train set:
RMSE: 43.07
MAE: 28.97
Test set:
RMSE: 123.27
MAE: 82.99
```

5.3.2 Visualizations of performance results

[23]:
```
# A dataframe of the actual versus predicted values for the test set is created:
↪

# Round predicted values to integers
y_pred_test_rf_rounded = y_pred_test_rf.round().astype(int)

# Create a dataframe of the actual and rounded predicted values
results_rf = pd.DataFrame({'Actual': y_test_array, 'Predicted':␣
↪y_pred_test_rf_rounded}, index=X_test_lr_datetime.index)

# Calculate the difference between actual and predicted values and store the␣
↪difference in a new column
results_rf['Difference'] = results_rf['Actual'] - results_rf['Predicted']

# Print the dataframe
results_rf
```

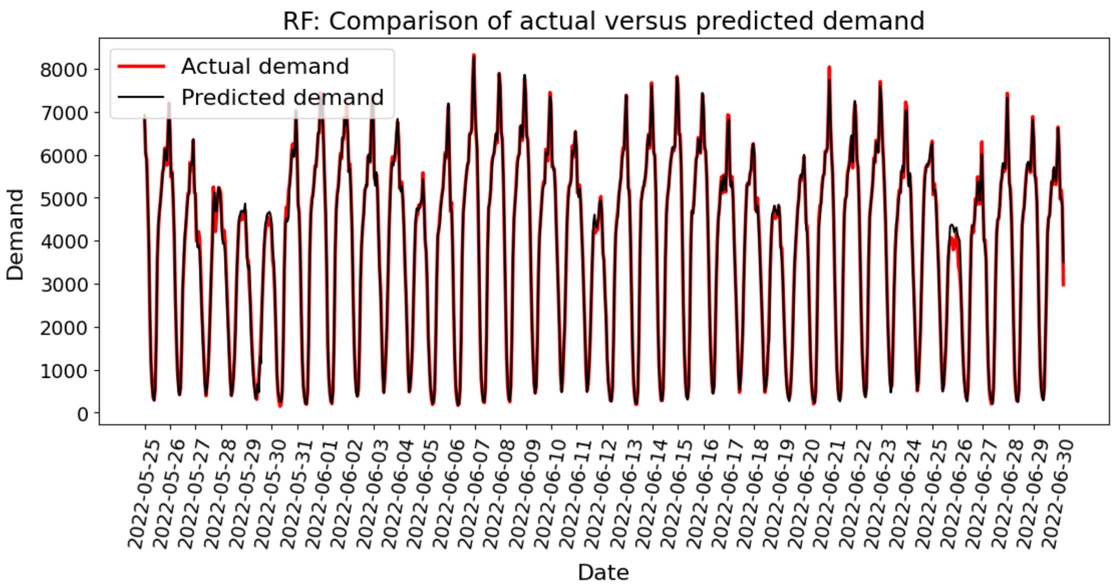
[23]:

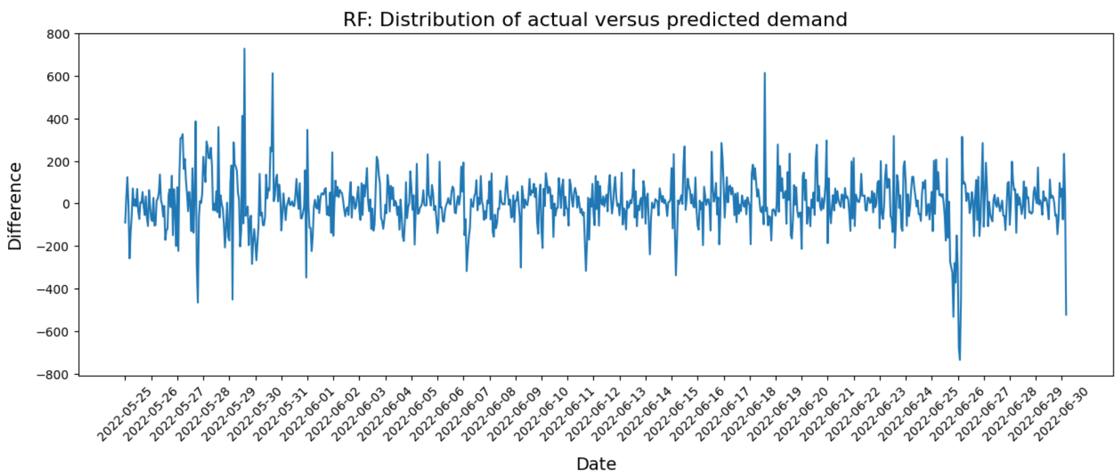
	Actual	Predicted	Difference
datetime			
2022-05-25 19:00:00	6837	6927	-90
2022-05-25 20:00:00	6046	6013	33
2022-05-25 21:00:00	5893	5769	124
2022-05-25 22:00:00	4929	4937	-8
2022-05-25 23:00:00	3829	4087	-258
…	…	…	…
2022-06-30 19:00:00	6095	6025	70
2022-06-30 20:00:00	4972	5047	-75
2022-06-30 21:00:00	5177	4943	234
2022-06-30 22:00:00	4839	4800	39
2022-06-30 23:00:00	2979	3502	-523

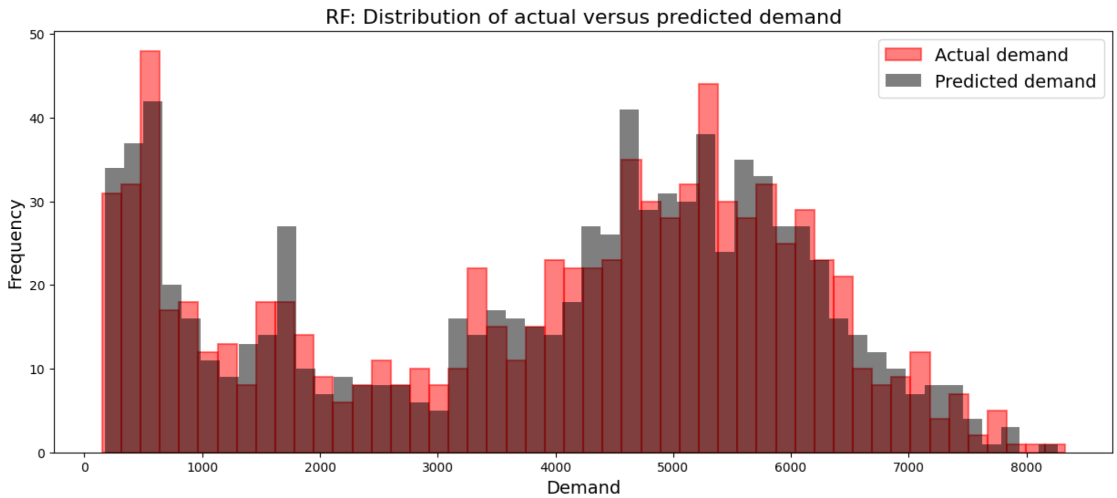
[869 rows x 3 columns]

[24]:
```
# Time series plot of actual versus predicted results

plt.figure(figsize=(13,5))
plt.plot(results_rf.index, results_rf['Actual'], label='Actual demand', color =␣
↪'red', linewidth = 2.5)
```

```python
plt.plot(results_rf.index, results_rf['Predicted'], label='Predicted demand', color = 'black')
plt.xlabel('Date', fontsize = 16, labelpad = 10)
plt.xticks(results_rf.index[::24], results_rf.index.date[::24], rotation=80, fontsize = 14)
plt.yticks(fontsize = 14)
plt.ylabel('Demand', fontsize = 16, labelpad = 10)
plt.title('RF: Comparison of actual versus predicted demand', fontsize = 18)
plt.legend(fontsize = 16)
plt.savefig('RF_actual_predicted.png', bbox_inches = 'tight')
plt.show()

# Difference plot of actual versus predicted values

plt.figure(figsize=(15,5))
plt.plot(results_rf.index, results_rf['Difference'])
plt.xlabel('Date', fontsize = 14, labelpad = 10)
plt.xticks(results_rf.index[::24], results_rf.index.date[::24], rotation=45)
plt.ylabel('Difference', fontsize = 14, labelpad = 10)
plt.title('RF: Distribution of actual versus predicted demand', fontsize = 16)
plt.show()

# Distribution plot of actual and predicted values

plt.figure(figsize=(15,6))
plt.hist(results_rf['Actual'], bins=50, alpha=0.5, label='Actual demand', color = 'red', edgecolor = 'red', linewidth = 1.5)
plt.hist(results_rf['Predicted'], bins=50, alpha=0.5, label='Predicted demand', color = 'black')
plt.xlabel('Demand', fontsize = 14)
plt.ylabel('Frequency', fontsize = 14)
plt.title('RF: Distribution of actual versus predicted demand', fontsize = 16)
plt.legend(fontsize = 14)
plt.savefig('RF_distribution_actual_predicted.png', bbox_inches = 'tight')
plt.show()
```


RF: Comparison of actual versus predicted demand
Actual demand
Predicted demand
Demand
8000
7000
6000
5000
4000
3000
2000
1000
0
2022-05-25
2022-05-26
2022-05-27
2022-05-28
2022-05-29
2022-05-30
2022-05-31
2022-06-01
2022-06-02
2022-06-03
2022-06-04
2022-06-05
2022-06-06
2022-06-07
2022-06-08
2022-06-09
2022-06-10
2022-06-11
2022-06-12
2022-06-13
2022-06-14
2022-06-15
2022-06-16
2022-06-17
2022-06-18
2022-06-19
2022-06-20
2022-06-21
2022-06-22
2022-06-23
2022-06-24
2022-06-25
2022-06-26
2022-06-27
2022-06-28
2022-06-29
2022-06-30
Date


RF: Distribution of actual versus predicted demand
Difference
800
600
400
200
0
−200
−400
−600
−800
2022-05-25
2022-05-26
2022-05-27
2022-05-28
2022-05-29
2022-05-30
2022-05-31
2022-06-01
2022-06-02
2022-06-03
2022-06-04
2022-06-05
2022-06-06
2022-06-07
2022-06-08
2022-06-09
2022-06-10
2022-06-11
2022-06-12
2022-06-13
2022-06-14
2022-06-15
2022-06-16
2022-06-17
2022-06-18
2022-06-19
2022-06-20
2022-06-21
2022-06-22
2022-06-23
2022-06-24
2022-06-25
2022-06-26
2022-06-27
2022-06-28
2022-06-29
2022-06-30
Date



5.4 Long Short-Term Memory (LSTM)

5.4.1 Set-up the data for the univariate LSTM

The deployed LSTM differs from the Linear Regression and Random Forest model because it does not utilize explanatory variables. Initially, it was attempted to create a multivariate LSTM. However, the results displayed an array of NaNs. This is likely because the features represent autoregressive and rolling statistics features of the dependent variable. This information may be already captured from the memory of the LSTM.

[2]:
```
# Read the data for a fresh start
global_feat_data_lstm = pd.read_csv("gs://final_prep_data/
↪global_temporal_features.csv")

# Convert the 'tpep_pickup_datetime' column to datetime format
global_feat_data_lstm['tpep_pickup_datetime'] = pd.
↪to_datetime(global_feat_data_lstm['tpep_pickup_datetime'])

# Drop all explanatory features from the dataframe
global_feat_data_lstm.drop(['PU_month', 'PU_day_of_month','PU_day_of_week',␣
↪'PU_hour', 'trip_distance', 'total_amount','lag_1h', 'lag_2h', 'lag_1d',␣
↪'lag_2d', 'ewma_3h','ewma_6h', 'ewma_12h', 'ewma_24h'], axis = 1, inplace =␣
↪True)

# Set the column 'tpep_pickup_datetime' as index of the dataframe
data = global_feat_data_lstm.set_index('tpep_pickup_datetime')

# Display the first five rows of the dataframe
data.head()
```

[2]:

```
                     PU_count
tpep_pickup_datetime
2022-01-01 00:00:00      3507
2022-01-01 01:00:00      4051
2022-01-01 02:00:00      3100
2022-01-01 03:00:00      2211
2022-01-01 04:00:00      1321
```

5.4.2 Split the data into training and test set

[3]:

```python
# Split the data in 80 % train and 20 % test data
train_size = int(len(data) * 0.8)
train_data, test_data = data[:train_size], data[train_size:]

# Print the shape of the train and test dataset
print(train_data.shape, test_data.shape)
```

```
(3475, 1) (869, 1)
```

5.4.3 Scale the data and seperate explanatory features and target variable

[4]:

```python
# The 'PU_count' column is scaled using RobustScaler
# Initialize the RobustScaler instance
scaler = RobustScaler()

# Fit the RobustScaler instance to the training data using the fit() method
train_scaled = scaler.fit_transform(train_data)

# Use the trained instance to transform the test data
test_scaled = scaler.transform(test_data)

# Split the data into input (X) and output (y) variables
def create_dataset(X, y, time_steps=1):
    Xs, ys = [], []
    for i in range(len(X) - time_steps):
        v = X[i:i + time_steps, :]
        Xs.append(v)
        ys.append(y[i + time_steps])
    return np.array(Xs), np.array(ys)

# Define the number of time steps to consider for each input sequence
time_steps = 24

# Create input-output pairs for the training data
X_train, y_train = create_dataset(train_scaled, train_scaled[:, 0], time_steps)

# Create input-output pairs for the test data
```

```
X_test, y_test = create_dataset(test_scaled, test_scaled[:, 0], time_steps)

# Print the shape of the created input-output pairs
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(3451, 24, 1) (3451,) (845, 24, 1) (845,)
```

5.5 Build a tuned LSTM model using keras

Note: The code snippet below can be skipped and the model along with the tuned hyperparameter results can be loaded in the subsequent section "Performance evaluation of the tuned LSTM model".

[32]:
```
# Define a function named 'build_model' that constructs a LSTM
def build_model(hp):
    # Build the sequential LSTM model, which allows us to build the model by␣
 ↪adding layers one after another
    model = Sequential()

    # Loop to add LSTM layers with different configurations
    for i in range(hp.Int('num_layers', 1, 4)):
        model.add(LSTM(units=hp.Int('units_' + str(i), 10, 300, step=10), #␣
 ↪Determine the number of units in each LSTM (chosen from a range of integers␣
 ↪between 10 and 300, with a step size of 10)
                       activation=hp.Choice('activation_' + str(i),␣
 ↪values=['tanh', 'relu', 'elu', 'softplus']), # Determine the activation␣
 ↪function used in each layer (tanh, relu, elu and softplus)
                       return_sequences=(i < hp.Int('num_layers', 1, 4) - 1), #␣
 ↪Determine the number of layers (integer between 1 and 4)
                       input_shape=(X_train.shape[1], X_train.shape[2])))
        model.add(Dropout(hp.Float('dropout_' + str(i), 0.0, 0.5, step=0.1))) #␣
 ↪Determine the dropout rate applied after each LSTM to prevent overfitting␣
 ↪(chosen from a range of floats between 0.0 and 0.5, with a step size of 0.1)

    # Add dense layer for the output
    model.add(Dense(units=1))

    # Compile the model using the Adam optimizer, loss function and evaluation␣
 ↪metrics
    model.compile(optimizer=Adam(hp.Choice('learning_rate', values=[1e-2, 1e-3,␣
 ↪1e-4])), # Determine the learning rate of the Adam optimizer (chosen from a␣
 ↪set of pre-defined values)
                  loss='mean_squared_error', metrics=['mean_squared_error']) #␣
 ↪Determine the loss function and metrics for the model

    # Determine the batch size used during training (chosen from a set of␣
 ↪pre-defined values)
```

```
    batch_size = hp.Choice('batch_size', values=[16, 18, 20, 22, 24, 26, 28])
    return model
```

[33]:
```
# Set the tuner object using an instance of the RandomSearch class

tuner = RandomSearch(
    build_model, # function that defines the model architecture and␣
 ↪hyperparameter space (previously specified)
    objective='val_mean_squared_error', # Metric to optimize during the␣
 ↪hyperparameter search
    max_trials=10, # Maximum number of hyperparameter combination to try
    executions_per_trial=3, # Number of times to train and evaluate each model␣
 ↪configuration
    directory='tuned_lstm_dir', # Directory with search results and checkpoints
    project_name='tuned_lstm_proj') # Name of the project
```

```
INFO:tensorflow:Reloading Tuner from tuned_lstm_dir/tuned_lstm_proj/tuner0.json
```

[33]:
```
# Start the hyperparameter search process

tuner.search(X_train,
             y_train,
             epochs=25, # Number of epochs to train each model configuration
             validation_split=0.1, # Fraction of training data to be used for␣
 ↪validation
             shuffle=False) # The data is not shuffled because it is a time␣
 ↪series
```

```
Trial 10 Complete [00h 07m 44s]
val_mean_squared_error: 0.006213583673040072

Best val_mean_squared_error So Far: 0.005567961217214663
Total elapsed time: 01h 14m 58s
INFO:tensorflow:Oracle triggered exit
```

[34]:
```
# Retrieve the best hyperparameters found during hyperparameter search
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

# Print the best hyperparameters
print("Number of LSTM layers: ", best_hps.get('num_layers'))
for i in range(best_hps.get('num_layers')):
    print("Units in LSTM layer", i+1, ": ", best_hps.get('units_'+str(i)))
    print("Activation function in LSTM layer", i+1, ": ", best_hps.
 ↪get('activation_'+str(i)))
    print("Dropout in LSTM layer", i+1, ": ", best_hps.get('dropout_'+str(i)))
print("Learning rate: ", best_hps.get('learning_rate'))
print("Batch size: ", best_hps.get('batch_size'))
```

```
Number of LSTM layers:  1
Units in LSTM layer 1 :  60
Activation function in LSTM layer 1 :  elu
Dropout in LSTM layer 1 :  0.30000000000000004
Learning rate:  0.01
Batch size:  24
```

[35]:
```
# Create the model using the best hyperparameters obtained from the␣
↪hyperparameter search
model_lstm_tuned = build_model(best_hps)

# Train the model
# The training history is stored in 'history_lstm_tuned'
history_lstm_tuned = model_lstm_tuned.fit(X_train, y_train,epochs = 25,␣
↪validation_split=0.1, shuffle=False)
```

```
Epoch 1/25
98/98 [==============================] - 3s 16ms/step - loss: 0.0474 -
mean_squared_error: 0.0474 - val_loss: 0.0215 - val_mean_squared_error: 0.0215
Epoch 2/25
98/98 [==============================] - 1s 14ms/step - loss: 0.0225 -
mean_squared_error: 0.0225 - val_loss: 0.0134 - val_mean_squared_error: 0.0134
Epoch 3/25
98/98 [==============================] - 1s 14ms/step - loss: 0.0188 -
mean_squared_error: 0.0188 - val_loss: 0.0117 - val_mean_squared_error: 0.0117
Epoch 4/25
98/98 [==============================] - 2s 19ms/step - loss: 0.0166 -
mean_squared_error: 0.0166 - val_loss: 0.0102 - val_mean_squared_error: 0.0102
Epoch 5/25
98/98 [==============================] - 2s 16ms/step - loss: 0.0152 -
mean_squared_error: 0.0152 - val_loss: 0.0082 - val_mean_squared_error: 0.0082
Epoch 6/25
98/98 [==============================] - 1s 14ms/step - loss: 0.0131 -
mean_squared_error: 0.0131 - val_loss: 0.0074 - val_mean_squared_error: 0.0074
Epoch 7/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0130 -
mean_squared_error: 0.0130 - val_loss: 0.0072 - val_mean_squared_error: 0.0072
Epoch 8/25
98/98 [==============================] - 1s 14ms/step - loss: 0.0139 -
mean_squared_error: 0.0139 - val_loss: 0.0069 - val_mean_squared_error: 0.0069
Epoch 9/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0120 -
mean_squared_error: 0.0120 - val_loss: 0.0067 - val_mean_squared_error: 0.0067
Epoch 10/25
98/98 [==============================] - 1s 14ms/step - loss: 0.0122 -
mean_squared_error: 0.0122 - val_loss: 0.0062 - val_mean_squared_error: 0.0062
Epoch 11/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0118 -
```

```
mean_squared_error: 0.0118 - val_loss: 0.0064 - val_mean_squared_error: 0.0064
Epoch 12/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0113 -
mean_squared_error: 0.0113 - val_loss: 0.0062 - val_mean_squared_error: 0.0062
Epoch 13/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0113 -
mean_squared_error: 0.0113 - val_loss: 0.0071 - val_mean_squared_error: 0.0071
Epoch 14/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0108 -
mean_squared_error: 0.0108 - val_loss: 0.0072 - val_mean_squared_error: 0.0072
Epoch 15/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0116 -
mean_squared_error: 0.0116 - val_loss: 0.0067 - val_mean_squared_error: 0.0067
Epoch 16/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0107 -
mean_squared_error: 0.0107 - val_loss: 0.0062 - val_mean_squared_error: 0.0062
Epoch 17/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0105 -
mean_squared_error: 0.0105 - val_loss: 0.0055 - val_mean_squared_error: 0.0055
Epoch 18/25
98/98 [==============================] - 1s 14ms/step - loss: 0.0106 -
mean_squared_error: 0.0106 - val_loss: 0.0061 - val_mean_squared_error: 0.0061
Epoch 19/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0104 -
mean_squared_error: 0.0104 - val_loss: 0.0055 - val_mean_squared_error: 0.0055
Epoch 20/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0105 -
mean_squared_error: 0.0105 - val_loss: 0.0054 - val_mean_squared_error: 0.0054
Epoch 21/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0094 -
mean_squared_error: 0.0094 - val_loss: 0.0052 - val_mean_squared_error: 0.0052
Epoch 22/25
98/98 [==============================] - 1s 12ms/step - loss: 0.0096 -
mean_squared_error: 0.0096 - val_loss: 0.0078 - val_mean_squared_error: 0.0078
Epoch 23/25
98/98 [==============================] - 1s 13ms/step - loss: 0.0097 -
mean_squared_error: 0.0097 - val_loss: 0.0058 - val_mean_squared_error: 0.0058
Epoch 24/25
98/98 [==============================] - 1s 15ms/step - loss: 0.0095 -
mean_squared_error: 0.0095 - val_loss: 0.0065 - val_mean_squared_error: 0.0065
Epoch 25/25
98/98 [==============================] - 1s 14ms/step - loss: 0.0097 -
mean_squared_error: 0.0097 - val_loss: 0.0059 - val_mean_squared_error: 0.0059
```

[36]:
```
# Overview of the model's architecture, layer types, output shapes, and number
↪of parameters
model_lstm_tuned.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_3 (LSTM)               (None, 60)                14880

 dropout_3 (Dropout)         (None, 60)                0

 dense_1 (Dense)             (None, 1)                 61

=================================================================
Total params: 14,941
Trainable params: 14,941
Non-trainable params: 0
_________________________________________________________________
```

[37]:
```python
# Save the model
model_lstm_tuned.save('model_lstm_tuned_final.h5')
```

5.5.1 Performance evaluation of the tuned LSTM model

[5]:
```python
# Load the model
model_lstm_tuned_loaded = load_model('model_lstm_tuned_final.h5')
```

```
2023-06-02 08:37:36.598676: W
tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load
dynamic library 'libcuda.so.1'; dlerror: libcuda.so.1: cannot open shared object
file: No such file or directory; LD_LIBRARY_PATH:
/usr/local/cuda/lib64:/usr/local/cuda/lib:/usr/local/lib/x86_64-linux-gnu:/usr/l
ocal/nvidia/lib:/usr/local/nvidia/lib64:/usr/local/nvidia/lib:/usr/local/nvidia/
lib64
2023-06-02 08:37:36.618796: W
tensorflow/stream_executor/cuda/cuda_driver.cc:263] failed call to cuInit:
UNKNOWN ERROR (303)
2023-06-02 08:37:36.618834: I
tensorflow/stream_executor/cuda/cuda_diagnostics.cc:156] kernel driver does not
appear to be running on this host (85f97a510381): /proc/driver/nvidia/version
does not exist
2023-06-02 08:37:36.620132: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  AVX2 AVX512F FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
```

[6]:
```python
model_lstm_tuned_loaded.summary()
```

```
Model: "sequential_1"
```

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_3 (LSTM)               (None, 60)                14880

 dropout_3 (Dropout)         (None, 60)                0

 dense_1 (Dense)             (None, 1)                 61

=================================================================
Total params: 14,941
Trainable params: 14,941
Non-trainable params: 0
_________________________________________________________________
```

[7]:
```
# Make predictions on training and test data
train_pred_lstm_tuned = model_lstm_tuned_loaded.predict(X_train)
test_pred_lstm_tuned = model_lstm_tuned_loaded.predict(X_test)
```

```
108/108 [==============================] - 3s 4ms/step
27/27 [==============================] - 0s 4ms/step
```

[8]:
```
# Inverse scaling of the predictions and the actual values
# This is required as the dependent variable 'PU_count' was previously scaled␣
↪using RobustScaler()
train_pred_lstm_tuned_inv = scaler.inverse_transform(np.
↪concatenate((train_pred_lstm_tuned, X_train[:, -1, 0].reshape(-1, 1)),␣
↪axis=1))[:, 0]
test_pred_lstm_tuned_inv = scaler.inverse_transform(np.
↪concatenate((test_pred_lstm_tuned, X_test[:, -1, 0].reshape(-1, 1)),␣
↪axis=1))[:, 0]
y_train_inv = scaler.inverse_transform(np.concatenate((y_train.reshape(-1, 1),␣
↪X_train[:, -1, 0].reshape(-1, 1)), axis=1))[:, 0]
y_test_inv = scaler.inverse_transform(np.concatenate((y_test.reshape(-1, 1),␣
↪X_test[:, -1, 0].reshape(-1, 1)), axis=1))[:, 0]

# Calculate MAE and RMSE on the train data
train_mae_lstm_tuned_inv = mean_absolute_error(y_train_inv,␣
↪train_pred_lstm_tuned_inv)
train_rmse_lstm_tuned_inv = np.sqrt(mean_squared_error(y_train_inv,␣
↪train_pred_lstm_tuned_inv))

# Print the RMSE and MAE for the train set
print("Train set:")
print(f"MAE (inverse scaled): {train_mae_lstm_tuned_inv:.2f}")
print(f"RMSE (inverse scaled): {train_rmse_lstm_tuned_inv:.2f}")
```

```
# Calculate MAE and RMSE on the test data
test_mae_lstm_tuned_inv = mean_absolute_error(y_test_inv,␣
 ↪test_pred_lstm_tuned_inv)
test_rmse_lstm_tuned_inv = np.sqrt(mean_squared_error(y_test_inv,␣
 ↪test_pred_lstm_tuned_inv))

# Print the RMSE and MAE for the test set
print("Test set:")
print(f"MAE (inverse scaled): {test_mae_lstm_tuned_inv:.2f}")
print(f"RMSE (inverse scaled): {test_rmse_lstm_tuned_inv:.2f}")
```

```
Train set:
MAE (inverse scaled): 244.97
RMSE (inverse scaled): 317.28
Test set:
MAE (inverse scaled): 239.83
RMSE (inverse scaled): 309.83
```

5.5.2 Visualization of performance results

[9]:
```
# Round predicted values to integers
test_pred_lstm_tuned_inv= test_pred_lstm_tuned_inv.round().astype(int)

# Create a dataframe of the actual and predicted values for the test set
results_lstm = pd.DataFrame({'Actual': y_test_inv, 'Predicted':␣
 ↪test_pred_lstm_tuned_inv}, index=test_data.index[time_steps:])



# Calculate the difference between actual and predicted values
results_lstm['Difference'] = results_lstm['Actual'] - results_lstm['Predicted']

# Print the results
results_lstm
```

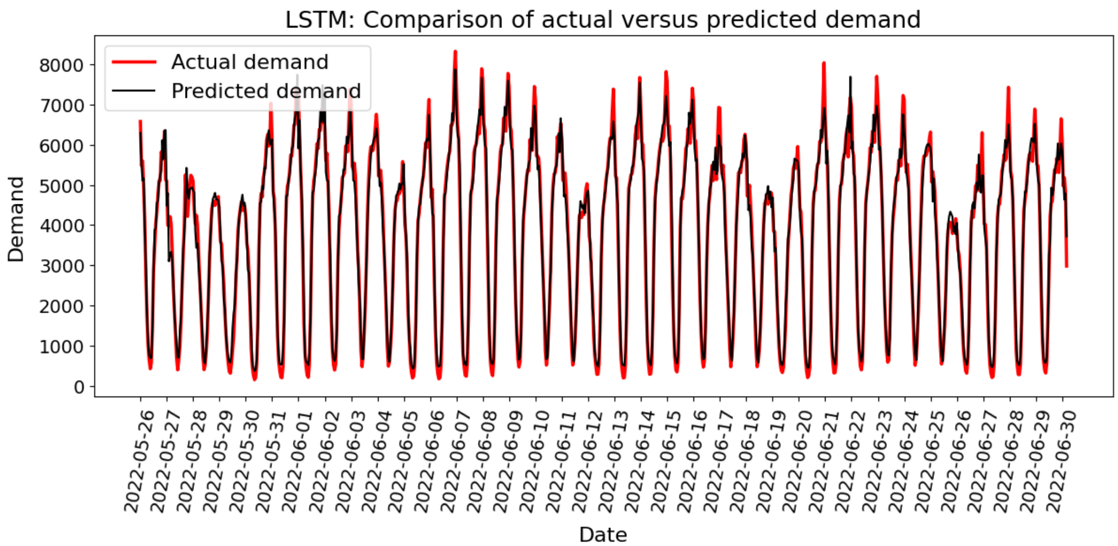
[9]:

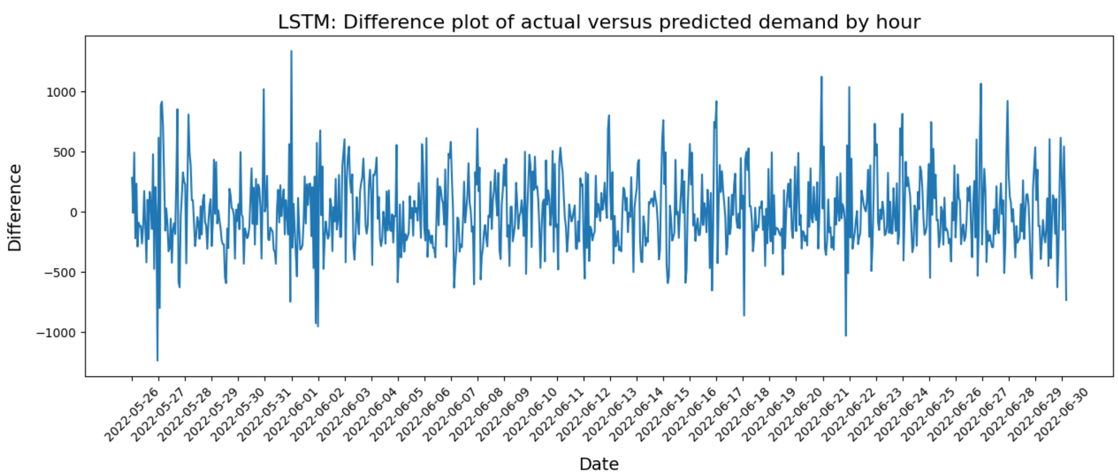
tpep_pickup_datetime	Actual	Predicted	Difference
2022-05-26 19:00:00	6577.0	6294	283.0
2022-05-26 20:00:00	5480.0	5489	-9.0
2022-05-26 21:00:00	5598.0	5105	493.0
2022-05-26 22:00:00	4944.0	5165	-221.0
2022-05-26 23:00:00	4091.0	3857	234.0
…	…	…	…
2022-06-30 19:00:00	6095.0	5837	258.0
2022-06-30 20:00:00	4972.0	5124	-152.0
2022-06-30 21:00:00	5177.0	4633	544.0
2022-06-30 22:00:00	4839.0	4787	52.0
2022-06-30 23:00:00	2979.0	3714	-735.0

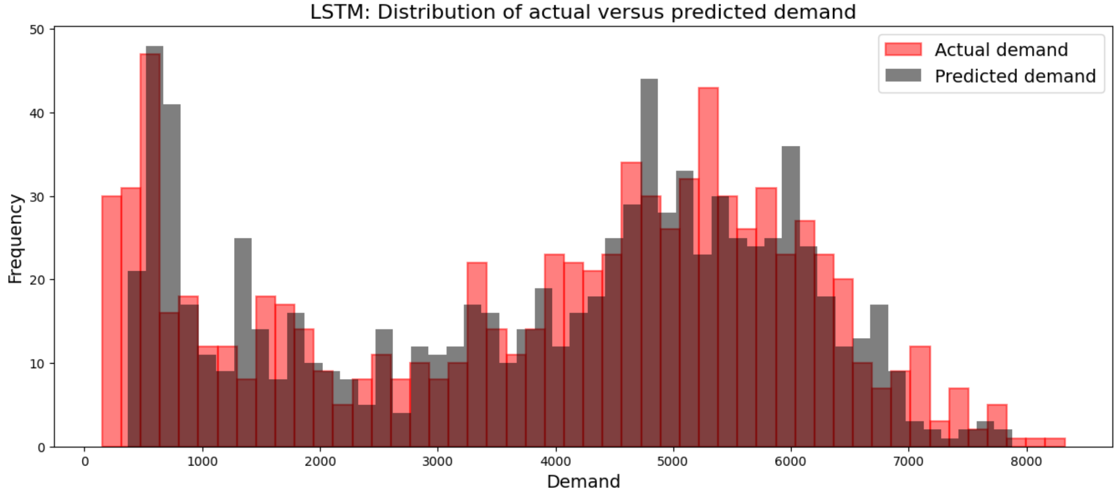
[845 rows x 3 columns]

[10]:

```
# Time series plot of actual versus predicted values
plt.figure(figsize=(14,5))
plt.plot(results_lstm.index, results_lstm['Actual'], label='Actual demand',␣
 ↪color = 'red', linewidth = 2.5 )
plt.plot(results_lstm.index, results_lstm['Predicted'], label='Predicted␣
 ↪demand', color = 'black')
plt.xlabel('Date', fontsize = 16, labelpad = 10)
plt.xticks(results_lstm.index[::24], results_lstm.index.date[::24], rotation=␣
 ↪80, fontsize = 14) # Set xticks for every 24 hours (1 day) with  .date
plt.yticks(fontsize = 14)
plt.ylabel('Demand', fontsize = 16, labelpad = 10)
plt.title('LSTM: Comparison of actual versus predicted demand', fontsize = 18)
plt.legend(fontsize = 16, loc='upper left')
plt.savefig('LSTM_actual_predicted.png', bbox_inches = 'tight')
plt.show()

# Difference plot of actual and predicted values
plt.figure(figsize=(15,5))
plt.plot(results_lstm.index, results_lstm['Difference'])
plt.xlabel('Date', fontsize = 14, labelpad = 10)
plt.xticks(results_lstm.index[::24], results_lstm.index.date[::24], rotation=45)
plt.ylabel('Difference', fontsize = 14, labelpad = 10)
plt.title('LSTM: Difference plot of actual versus predicted demand by hour',␣
 ↪fontsize = 16)
plt.show()

# Distribution plot of actual and predicted values
plt.figure(figsize=(15,6))
plt.hist(results_lstm['Actual'], bins=50, alpha=0.5, label='Actual demand',␣
 ↪color = 'red', edgecolor = 'red', linewidth = 1.5)
plt.hist(results_lstm['Predicted'], bins=50, alpha=0.5, label='Predicted␣
 ↪demand', color = 'black')
plt.xlabel('Demand', fontsize = 14)
plt.ylabel('Frequency', fontsize = 14)
plt.title('LSTM: Distribution of actual versus predicted demand', fontsize = 16)
plt.legend(fontsize = 14)
plt.savefig('LSTM_distribution_actual_predicted.png', bbox_inches = 'tight')
plt.show()
```


LSTM: Comparison of actual versus predicted demand
Actual demand
Predicted demand
Demand
Date


LSTM: Difference plot of actual versus predicted demand by hour
Difference
Date



6 Comparison of the temporal forecasting models

6.1 Create a dataframe for the temporal forecasting model results

[47]:
```
# Rename columns to get a better overview ob the individual model's results␣
↪when combined in one dataframe
results_lr.rename(columns = {'Predicted': 'Predicted_LR',
                             'Difference': 'Difference_LR'}, inplace = True)
results_rf.rename(columns = {'Predicted' : 'Predicted_RF',
                             'Difference' : 'Difference_RF'}, inplace = True)
results_lstm.rename(columns = {'Predicted': 'Predicted_LSTM',
                               'Difference': 'Difference_LSTM'}, inplace = True)
```

[48]:
```
# Merge the dataframes results_lr, results_rf, and results_lstm based on their␣
↪datetime indices
results_all_models = pd.merge(pd.merge(results_lr,results_rf,left_index = True,␣
↪right_index = True),results_lstm,left_index = True, right_index = True)

# Drop unnecessary columns and rename the column that displays the actual values
results_all_models.drop(['Actual_y', 'Actual'], inplace = True, axis = 1)
results_all_models.rename(columns = {'Actual_x': 'Actual'}, inplace = True)

# Print the merged dataframe
print(results_all_models)
```

```
                     Actual  Predicted_LR  Difference_LR  Predicted_RF  \
2022-05-26 19:00:00    6577          6551             26          6651
2022-05-26 20:00:00    5480          5448             32          5563
2022-05-26 21:00:00    5598          5592              6          5571
2022-05-26 22:00:00    4944          5011            -67          5048
```

```
2022-05-26 23:00:00    4091          4077             14          4192
…                         …             …              …             …
2022-06-30 19:00:00    6095          6085             10          6025
2022-06-30 20:00:00    4972          4958             14          5047
2022-06-30 21:00:00    5177          5181             -4          4943
2022-06-30 22:00:00    4839          4916            -77          4800
2022-06-30 23:00:00    2979          3014            -35          3502

                     Difference_RF  Predicted_LSTM  Difference_LSTM
2022-05-26 19:00:00            -74            6294            283.0
2022-05-26 20:00:00            -83            5489             -9.0
2022-05-26 21:00:00             27            5105            493.0
2022-05-26 22:00:00           -104            5165           -221.0
2022-05-26 23:00:00           -101            3857            234.0
…                                …               …                …
2022-06-30 19:00:00             70            5837            258.0
2022-06-30 20:00:00            -75            5124           -152.0
2022-06-30 21:00:00            234            4633            544.0
2022-06-30 22:00:00             39            4787             52.0
2022-06-30 23:00:00           -523            3714           -735.0

[845 rows x 7 columns]
```

The comparison of predictive results will only be displayed for the last 24 hours of the test data.

[49]:
```python
# Set the end datetime as the last predicted datetime in the test set
end_datetime = results_all_models.index[-2]

# Set the start datetime as 24 hours before the end datetime
start_datetime = end_datetime - pd.Timedelta(hours=24)

# Filter the results for the desired time span
results_24h_all_models = results_all_models[(results_all_models.index >=
 ↪start_datetime) & (results_all_models.index <= end_datetime)]
results_24h_all_models
```

[49]:
```
                     Actual  Predicted_LR  Difference_LR  Predicted_RF  \
2022-06-29 22:00:00    4883          4963            -80          4888
2022-06-29 23:00:00    3681          3716            -35          3665
2022-06-30 00:00:00    2164          2197            -33          2166
2022-06-30 01:00:00    1086          1126            -40          1139
2022-06-30 02:00:00     617           655            -38           559
2022-06-30 03:00:00     388           405            -17           375
2022-06-30 04:00:00     314           309              5           286
2022-06-30 05:00:00     566           555             11           548
2022-06-30 06:00:00    1644          1625             19          1668
2022-06-30 07:00:00    2811          2812             -1          2885
2022-06-30 08:00:00    4215          4193             22          4102
```

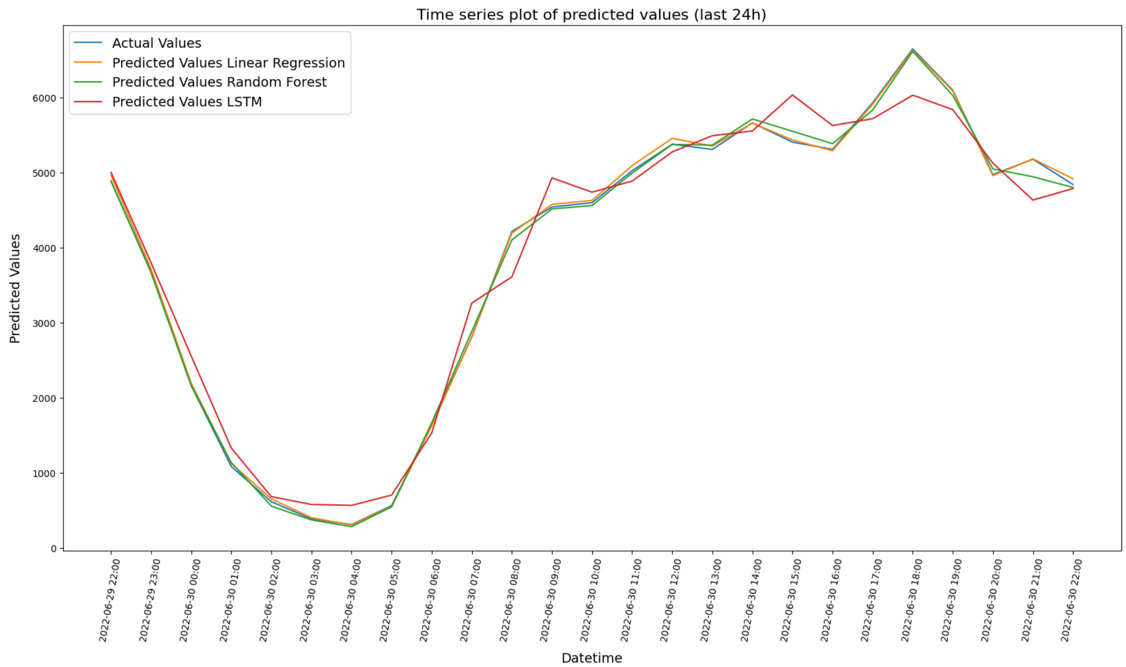
2022-06-30 09:00:00	4540	4575	-35	4514
2022-06-30 10:00:00	4598	4628	-30	4560
2022-06-30 11:00:00	5023	5091	-68	4992
2022-06-30 12:00:00	5376	5455	-79	5373
2022-06-30 13:00:00	5306	5351	-45	5364
2022-06-30 14:00:00	5660	5658	2	5712
2022-06-30 15:00:00	5404	5433	-29	5549
2022-06-30 16:00:00	5308	5290	18	5383
2022-06-30 17:00:00	5928	5909	19	5831
2022-06-30 18:00:00	6645	6627	18	6612
2022-06-30 19:00:00	6095	6085	10	6025
2022-06-30 20:00:00	4972	4958	14	5047
2022-06-30 21:00:00	5177	5181	-4	4943
2022-06-30 22:00:00	4839	4916	-77	4800

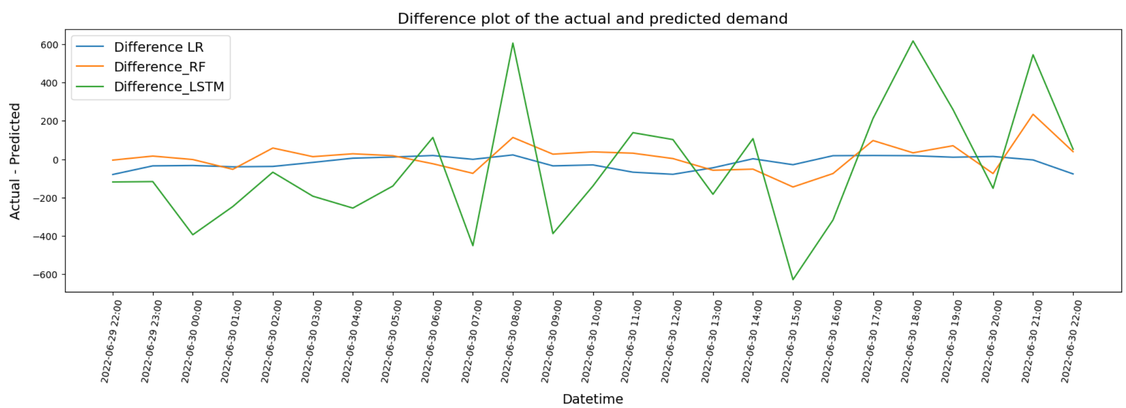
	Difference_RF	Predicted_LSTM	Difference_LSTM
2022-06-29 22:00:00	-5	5002	-119.0
2022-06-29 23:00:00	16	3798	-117.0
2022-06-30 00:00:00	-2	2558	-394.0
2022-06-30 01:00:00	-53	1333	-247.0
2022-06-30 02:00:00	58	685	-68.0
2022-06-30 03:00:00	13	581	-193.0
2022-06-30 04:00:00	28	569	-255.0
2022-06-30 05:00:00	18	706	-140.0
2022-06-30 06:00:00	-24	1531	113.0
2022-06-30 07:00:00	-74	3262	-451.0
2022-06-30 08:00:00	113	3610	605.0
2022-06-30 09:00:00	26	4928	-388.0
2022-06-30 10:00:00	38	4738	-140.0
2022-06-30 11:00:00	31	4885	138.0
2022-06-30 12:00:00	3	5274	102.0
2022-06-30 13:00:00	-58	5489	-183.0
2022-06-30 14:00:00	-52	5553	107.0
2022-06-30 15:00:00	-145	6032	-628.0
2022-06-30 16:00:00	-75	5625	-317.0
2022-06-30 17:00:00	97	5716	212.0
2022-06-30 18:00:00	33	6029	616.0
2022-06-30 19:00:00	70	5837	258.0
2022-06-30 20:00:00	-75	5124	-152.0
2022-06-30 21:00:00	234	4633	544.0
2022-06-30 22:00:00	39	4787	52.0

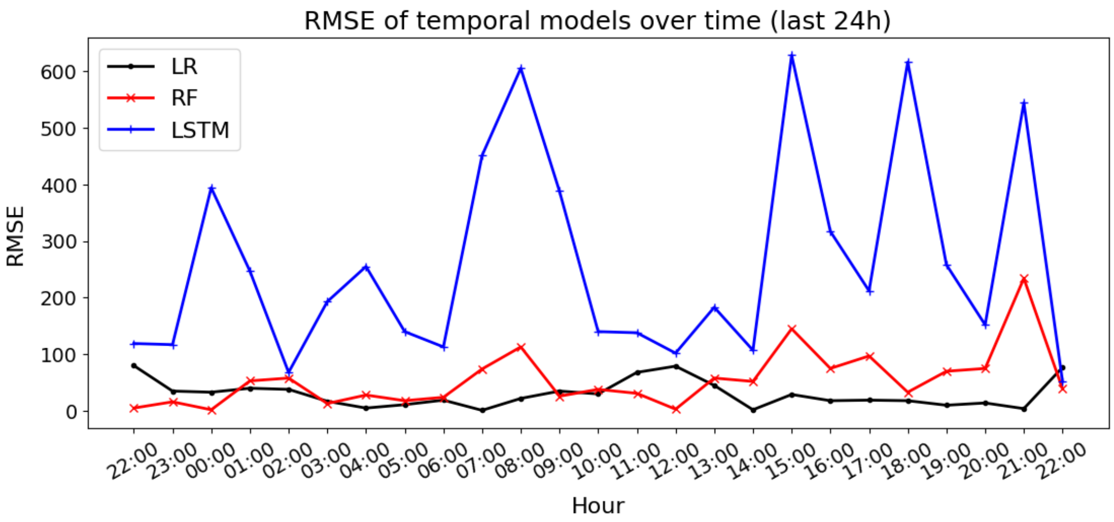
6.2 Visualization of the results of the temporal forecasting models

[50]:
```
# Time series plot of the actual versus predicted values on the last 24 hours␣
↪of the test set
fig, ax = plt.subplots(figsize=(20,10))
ax.plot(results_24h_all_models.index, results_24h_all_models['Actual'],␣
↪label='Actual Values')
ax.plot(results_24h_all_models.index, results_24h_all_models['Predicted_LR'],␣
↪label='Predicted Values Linear Regression')
ax.plot(results_24h_all_models.index, results_24h_all_models['Predicted_RF'],␣
↪label='Predicted Values Random Forest')
ax.plot(results_24h_all_models.index, results_24h_all_models['Predicted_LSTM'],␣
↪label='Predicted Values LSTM')
ax.set_xlabel('Datetime', fontsize = 14, labelpad = 10)
ax.set_ylabel('Predicted Values', fontsize = 14, labelpad = 10)
ax.set_title('Time series plot of predicted values (last 24h)', fontsize = 16)
plt.xticks(rotation=80)
ax.set_xticks(results_24h_all_models.index)
ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d %H:%M'))
ax.legend(fontsize = 14)
plt.show()

# Difference plot of actual versus predicted values on the last 24 hours of the␣
↪test set
fig, ax = plt.subplots(figsize=(20,5))
ax.plot(results_24h_all_models.index, results_24h_all_models['Difference_LR'],␣
↪label = 'Difference LR')
ax.plot(results_24h_all_models.index, results_24h_all_models['Difference_RF'],␣
↪label = 'Difference_RF')
ax.plot(results_24h_all_models.index,␣
↪results_24h_all_models['Difference_LSTM'], label = 'Difference_LSTM')
ax.set_xlabel('Datetime', fontsize = 14, labelpad = 10)
plt.xticks(rotation= 80)
ax.set_xticks(results_24h_all_models.index)
ax.set_ylabel('Actual - Predicted', fontsize = 14, labelpad = 10)
ax.set_title('Difference plot of the actual and predicted demand', fontsize =␣
↪16)
ax.legend(fontsize = 14)
# ax.xaxis.set_major_formatter(mdates.DateFormatter('%H:%M'))
ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d %H:%M'))
plt.show()

# Comparison plot of the RMSE of the temporal models on the last 24 hours of␣
↪the test set
# Calculate the squared error for each datetime
results_24h_all_models['Squared_Error_LR'] = (results_24h_all_models['Actual']␣
↪- results_24h_all_models['Predicted_LR'])**2
```

```
results_24h_all_models['Squared_Error_RF'] = (results_24h_all_models['Actual']␣
↪- results_24h_all_models['Predicted_RF'])**2
results_24h_all_models['Squared_Error_LSTM'] =␣
↪(results_24h_all_models['Actual'] -␣
↪results_24h_all_models['Predicted_LSTM'])**2
# Take the square root of the mean squared error to get the RMSE
results_24h_all_models['RMSE_LR'] = np.
↪sqrt(results_24h_all_models['Squared_Error_LR'])
results_24h_all_models['RMSE_RF'] = np.
↪sqrt(results_24h_all_models['Squared_Error_RF'])
results_24h_all_models['RMSE_LSTM'] = np.
↪sqrt(results_24h_all_models['Squared_Error_LSTM'])

# Plot the RMSE over time
fig, ax = plt.subplots(figsize=(13,5))
ax.plot(results_24h_all_models.index, results_24h_all_models['RMSE_LR'], label␣
↪= 'LR',  marker='.', color = 'black', linewidth = 2)
ax.plot(results_24h_all_models.index, results_24h_all_models['RMSE_RF'], label␣
↪= 'RF', marker = 'x', color = 'red', linewidth = 2)
ax.plot(results_24h_all_models.index, results_24h_all_models['RMSE_LSTM'],␣
↪label = 'LSTM', marker = '+', color = 'blue', linewidth = 2)
ax.set_xlabel('Hour', fontsize = 16, labelpad = 10)
ax.set_ylabel('RMSE', fontsize = 16, labelpad = 10)
ax.set_title('RMSE of temporal models over time (last 24h)', fontsize = 18)
plt.xticks(rotation = 30, fontsize = 14)
plt.yticks(fontsize = 14)
ax.set_xticks(results_24h_all_models.index)
ax.xaxis.set_major_formatter(mdates.DateFormatter('%H:%M'))
ax.legend(fontsize = 16)
plt.savefig('RMSE_temporal.png', bbox_inches = 'tight')
plt.show()
```


Time series plot of predicted values (last 24h)
Actual Values
Predicted Values Linear Regression
Predicted Values Random Forest
Predicted Values LSTM
Predicted Values
Datetime


Difference plot of the actual and predicted demand
Difference LR
Difference_RF
Difference_LSTM
Actual - Predicted
Datetime


RMSE of temporal models over time (last 24h)
LR
RF
LSTM
RMSE
Hour
0
100
200
300
400
500
600
22:00
23:00
00:00
01:00
02:00
03:00
04:00
05:00
06:00
07:00
08:00
09:00
10:00
11:00
12:00
13:00
14:00
15:00
16:00
17:00
18:00
19:00
20:00
21:00
22:00