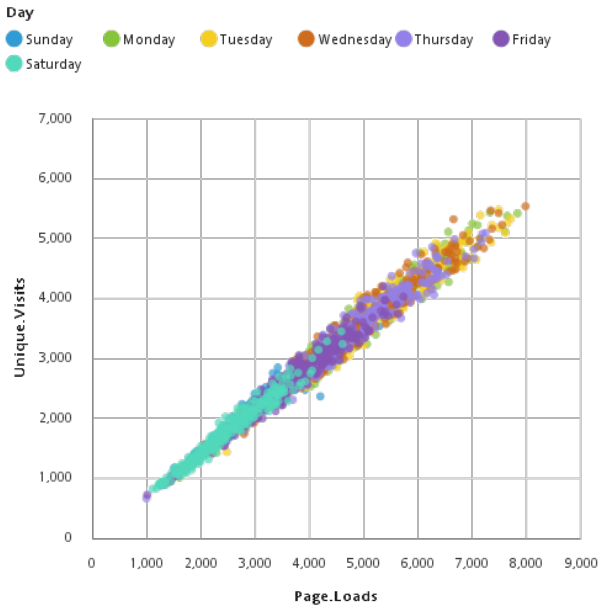
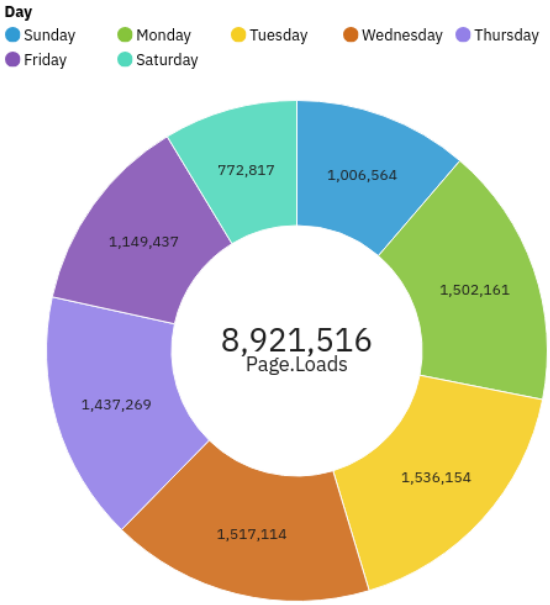
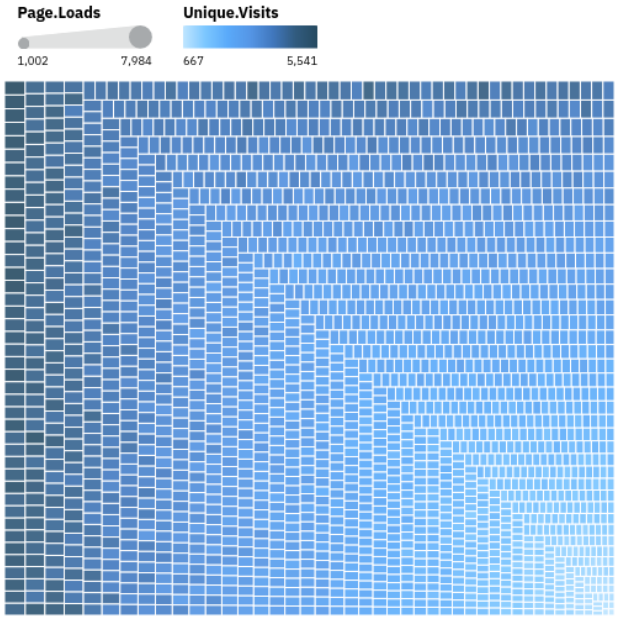
page loads in each day of week

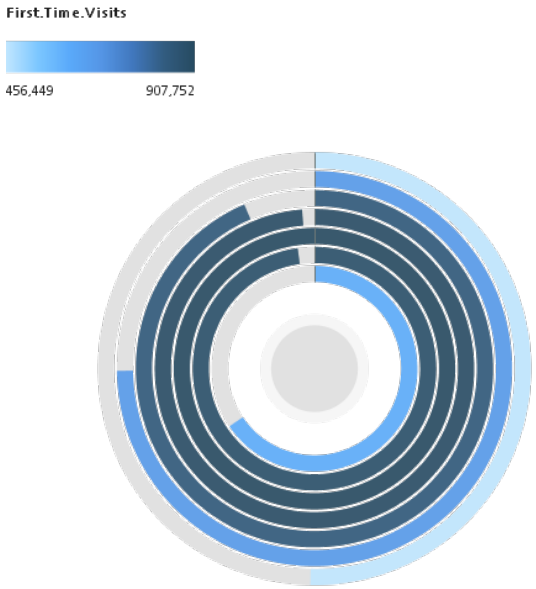


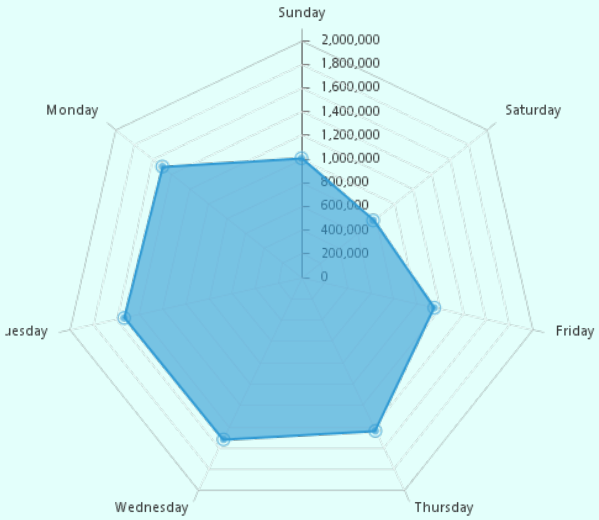


unique visits



visualizing the first time visits in overall page loads




Sunday
2,000,000
1,800,000
1,600,000
1,400,000
1,200,000
1,000,000
800,000
600,000
400,000
200,000
0
Saturday
Friday
Thursday
Wednesday
uesday
Monday

website-visitors-analysis

November 5, 2023

[3]:
```
import pandas as pd
file_loc = '/daily-website-visitors.csv'
dataset = pd.read_csv(file_loc,
                      index_col = 'Date',
                      thousands=',')
dataset.index = pd.to_datetime(dataset.index)
dataset
```

[3]:

Date	Row	Day	Day.Of.Week	Page.Loads	Unique.Visits	First.Time.Visits	Returning.Visits
2014-09-14	1	Sunday	1	2146	1582	1430	152
2014-09-15	2	Monday	2	3621	2528	2297	231
2014-09-16	3	Tuesday	3	3698	2630	2352	278
2014-09-17	4	Wednesday	4	3667	2614	2327	287
2014-09-18	5	Thursday	5	3316	2366	2130	236
…	…	…	…	…	…	…	…
2020-08-15	2163	Saturday	7	2221	1696	1373	323
2020-08-16	2164	Sunday	1	2724	2037	1686	351
2020-08-17	2165	Monday	2	3456	2638	2181	457
2020-08-18	2166	Tuesday	3	3581	2683	2184	499
2020-08-19	2167	Wednesday	4	2064	1564	1297	267

[2167 rows x 7 columns]

[4]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2167 entries, 2014-09-14 to 2020-08-19
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   Row                2167 non-null   int64 
 1   Day                2167 non-null   object
 2   Day.Of.Week        2167 non-null   int64 
 3   Page.Loads         2167 non-null   int64 
 4   Unique.Visits      2167 non-null   int64 
 5   First.Time.Visits  2167 non-null   int64 
 6   Returning.Visits   2167 non-null   int64 
dtypes: int64(6), object(1)
memory usage: 135.4+ KB
```

[5]:
```
dataset.describe()
```

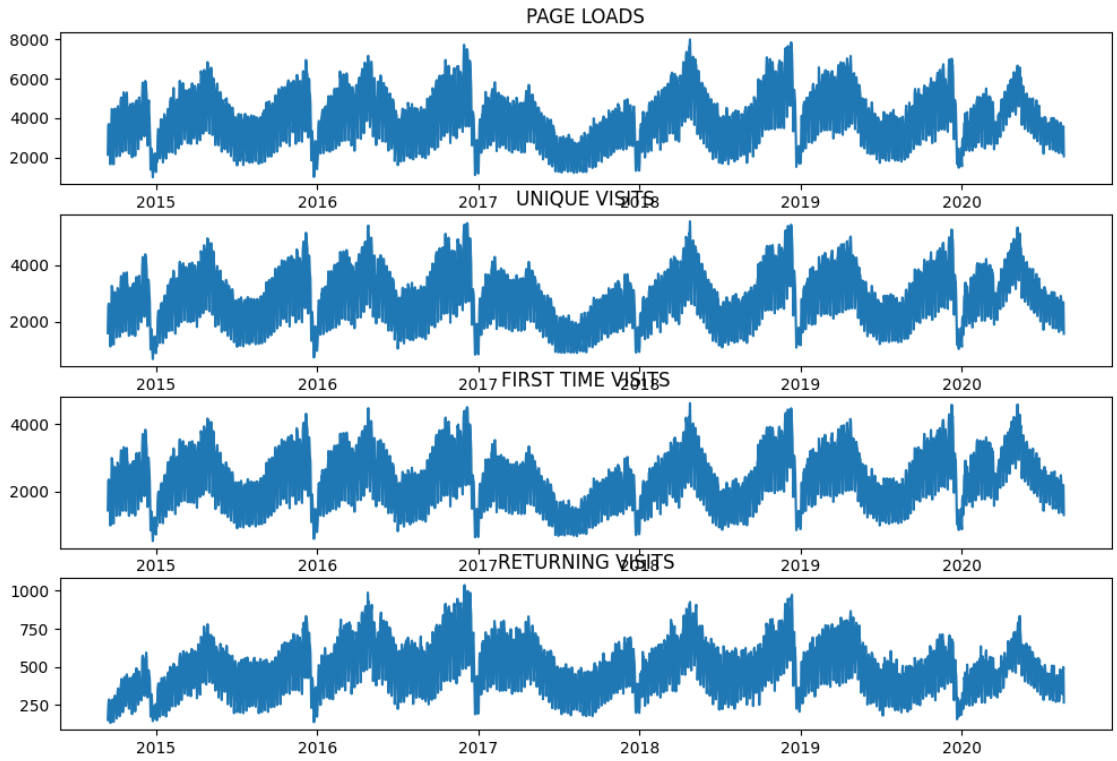
[5]:

	Row	Day.Of.Week	Page.Loads	Unique.Visits	First.Time.Visits	Returning.Visits
count	2167.000000	2167.000000	2167.000000	2167.000000	2167.000000	2167.000000
mean	1084.000000	3.997231	4116.989386	2943.646516	2431.824181	511.822335
std	625.703338	2.000229	1350.977843	977.886472	828.704688	168.736370
min	1.000000	1.000000	1002.000000	667.000000	522.000000	133.000000
25%	542.500000	2.000000	3114.500000	2226.000000	1830.000000	388.500000
50%	1084.000000	4.000000	4106.000000	2914.000000	2400.000000	509.000000
75%	1625.500000	6.000000	5020.500000	3667.500000	3038.000000	626.500000
max	2167.000000	7.000000	7984.000000	5541.000000	4616.000000	1036.000000

#LET'S make a little visual about the visits.

[13]:
```
import matplotlib.pyplot as plt

fig, ax =plt.subplots(4, figsize=(12, 8))
ax[0].plot(dataset['Page.Loads'])
ax[1].plot(dataset['Unique.Visits'])
ax[2].plot(dataset['First.Time.Visits'])
ax[3].plot(dataset['Returning.Visits'])
```

```
ax[0].set_title("PAGE LOADS")
ax[1].set_title("UNIQUE VISITS")
ax[2].set_title("FIRST TIME VISITS")
ax[3].set_title("RETURNING VISITS")

plt.show()
```



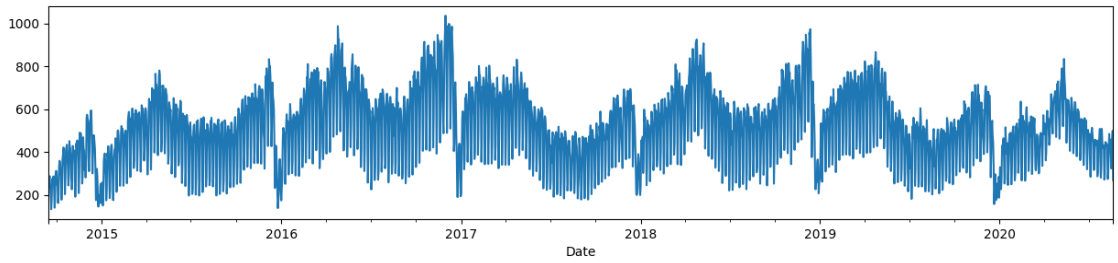
#LET'S PREPROCESS THE DATA.#

[57]:
```
target_col = dataset['Returning.Visits']
target_col
```

[57]:
```
Date
2014-09-14    152
2014-09-15    231
2014-09-16    278
2014-09-17    287
2014-09-18    236
              ...
2020-08-15    323
2020-08-16    351
2020-08-17    457
2020-08-18    499
```

```
2020-08-19    267
Name: Returning.Visits, Length: 2167, dtype: int64
```

[23]:
```
target_col.plot(figsize=(15, 3))
plt.show()
```



[26]:
```
len(target_col)
```

[26]: 2167

[25]:
```
TEST_DATA_PERCENTAGE = 0.1
boundary_indx = int((1 - TEST_DATA_PERCENTAGE) * len(target_col))

train_data = target_col[:boundary_indx]
test_data = target_col[boundary_indx:]

print(f"Train data:\tReturning Visits [:{boundary_indx}] ({boundary_indx})")
print(f"Test data:\tReturning Visits [{boundary_indx}:] ({len(target_col) -␣
  ↪boundary_indx})")
print(f"\nLast target on train data: {train_data[-1]}")
```

```
Train data:     Returning Visits [:1950] (1950)
Test data:      Returning Visits [1950:] (217)

Last target on train data: 394
```

[33]:
```
print(f"Train data ending values:{target_col[TEST_DATA_BOUNDARY_INDEX - 10:␣
  ↪TEST_DATA_BOUNDARY_INDEX].values}")
print(f"Test datset starting valuesL {target_col[TEST_DATA_BOUNDARY_INDEX:␣
  ↪TEST_DATA_BOUNDARY_INDEX + 10].values}")
```

```
Train data ending values:[429 423 442 464 372 253 277 515 434 394]
Test datset starting valuesL [441 413 246 314 443 484 473 490 353 249]
```

#WINDOW_IZE THE DATASET

[58]:
```
import numpy as np
import pandas as pd

if isinstance(target_col, pd.DataFrame) or isinstance(target_col, pd.Series):
    target_array = target_col.values
else:
    target_array = np.array(target_col)
WINDOW_SIZE = 3
# Now, you can use target_array in your code
train_dataset = timeseries_dataset_from_array(target_array[:-WINDOW_SIZE],
                                              target_array[WINDOW_SIZE:],
                                              sequence_length=WINDOW_SIZE,
                                             ␣
 ↪end_index=TEST_DATA_BOUNDARY_INDEX - 1)
```

[60]:
```
from keras.utils import timeseries_dataset_from_array
import numpy as np

WINDOW_SIZE = 3

# Ensure target_col is a NumPy array
target_col1 = np.array(target_col)

# Create the train_set
train_set = timeseries_dataset_from_array(
    data=target_col1[:-WINDOW_SIZE],
    targets=target_col1[WINDOW_SIZE:],
    sequence_length=WINDOW_SIZE,
    end_index=TEST_DATA_BOUNDARY_INDEX - WINDOW_SIZE)
```

[59]:
```
target_col[TEST_DATA_BOUNDARY_INDEX-10:TEST_DATA_BOUNDARY_INDEX+10].values,␣
 ↪(list(train_dataset)[-1][0][-1].numpy(), list(train_dataset)[-1][1][-1].
 ↪numpy())
```

[59]:
```
(array([429, 423, 442, 464, 372, 253, 277, 515, 434, 394, 441, 413, 246,
        314, 443, 484, 473, 490, 353, 249]),
 (array([277, 515, 434]), 394))
```

[62]:
```
test_dataset =␣
 ↪timeseries_dataset_from_array(target_col[TEST_DATA_BOUNDARY_INDEX -␣
 ↪WINDOW_SIZE:],
                                                ␣
 ↪target_col[TEST_DATA_BOUNDARY_INDEX:],
                                                  sequence_length=WINDOW_SIZE
                                               )
len(test_dataset), len(list(test_dataset.unbatch()))
(2, 217)
```

[62]: (2, 217)

[64]:
```
target_col[TEST_DATA_BOUNDARY_INDEX-10:TEST_DATA_BOUNDARY_INDEX+10].values,␣
↪list(test_dataset)[0][0][0].numpy(), list(test_dataset)[0][1][0].numpy()
```

[64]:
```
(array([429, 423, 442, 464, 372, 253, 277, 515, 434, 394, 441, 413, 246,
        314, 443, 484, 473, 490, 353, 249]),
 array([515, 434, 394]),
 441)
```

first point in test dataset

[65]:
```
list(test_dataset)[0][0][0].numpy(), list(test_dataset)[0][1][0].numpy()
```

[65]:
```
(array([515, 434, 394]), 441)
```

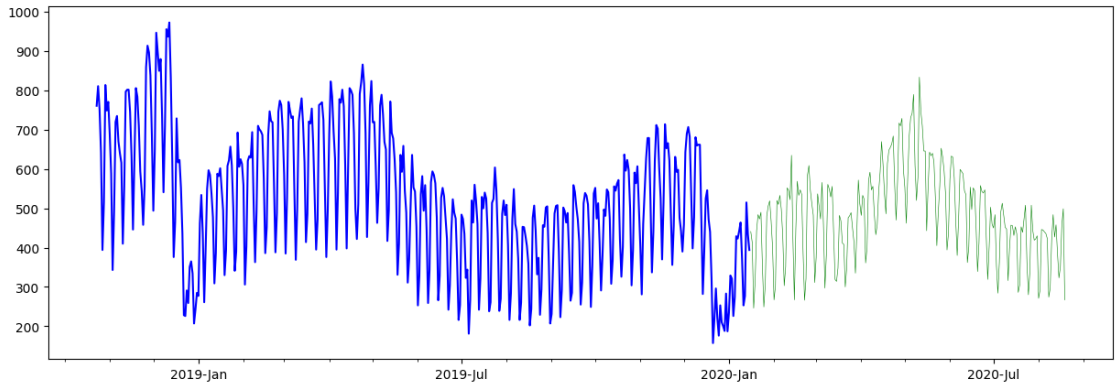
last point in test dataset

[66]:
```
list(test_dataset)[-1][0][-1].numpy(), list(test_dataset)[-1][1][-1].numpy()
```

[66]:
```
(array([351, 457, 499]), 267)
```

LET'S PLOT THE TRAIN AND TEST DATA

[68]:
```
import matplotlib.dates as mdates

def plot_time_series(predictions = None, start_index=1500):
    timesteps = pd.to_datetime(target_col.index)

    fig,ax = plt.subplots(1,figsize=(15,5))
    ax.xaxis.set_major_locator(mdates.MonthLocator(bymonth=(1, 7)))
    ax.xaxis.set_minor_locator(mdates.MonthLocator())
    ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%b'))
    #plot train data
    plt.plot(timesteps[start_index:TEST_DATA_BOUNDARY_INDEX],␣
 ↪target_col[start_index:TEST_DATA_BOUNDARY_INDEX],
             color='blue')
    #plot test dataset
    plt.plot(timesteps[TEST_DATA_BOUNDARY_INDEX:],␣
 ↪target_col[TEST_DATA_BOUNDARY_INDEX:],
              color='green', linewidth=0.4)
    if predictions is not None:
        pred_timesteps = timesteps[TEST_DATA_BOUNDARY_INDEX:]
        plt.plot(pred_timesteps, predictions, linewidth=0.4, color='red')
        plt.scatter(pred_timesteps, predictions, s=0.4, color='red')

plot_time_series()
```



#BASELINE MODEL

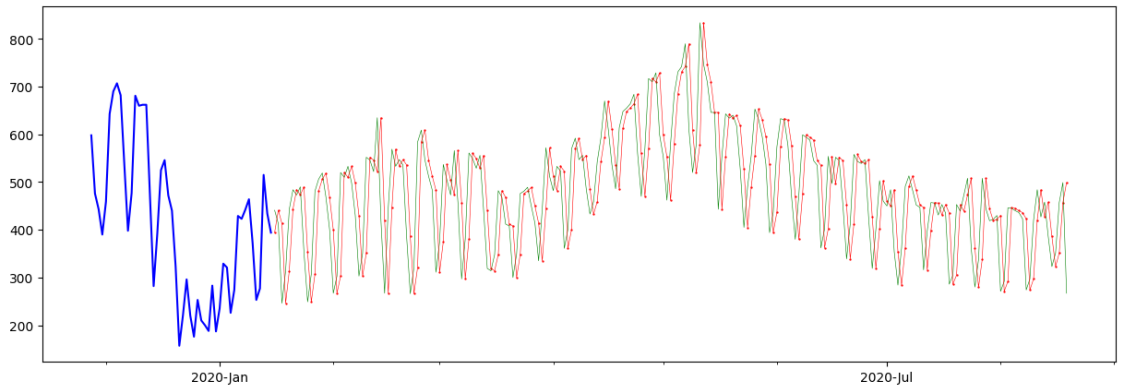
[70]:
```
import tensorflow as tf
from keras.layers import Layer
from keras import Model

class NaiveForecastLayer(Model):
    def __init__(self):
        super().__init__()

    def call(self, inputs):
        result = inputs[:, -1]
        return result[:, tf.newaxis]
```

[71]:
```
baseline_model = NaiveForecastLayer()
baseline_model._name = 'model_0'

baseline_model.compile(metrics=[tf.keras.metrics.MeanAbsoluteError()])
```

[72]:
```
baseline_predictions = baseline_model.predict(test_dataset)
```

```
2/2 [==============================] - 0s 20ms/step
```

[75]:
```
plot_time_series(baseline_predictions.ravel(), start_index=1900)
```



[77]:
```
y_true = target_col[TEST_DATA_BOUNDARY_INDEX : ]

len(y_true), y_true
```

[77]:
```
(217,
 Date
 2020-01-16    441
 2020-01-17    413
 2020-01-18    246
 2020-01-19    314
 2020-01-20    443
               …
 2020-08-15    323
 2020-08-16    351
 2020-08-17    457
 2020-08-18    499
 2020-08-19    267
 Name: Returning.Visits, Length: 217, dtype: int64)
```

[78]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
 ↪mean_absolute_percentage_error

def evaluate_predictions(y_true, y_preds):
    mae = mean_absolute_error(y_true, y_preds)
    mse = mean_squared_error(y_true, y_preds)
    rmse = np.sqrt(mse)
    mape = mean_absolute_percentage_error(y_true, y_preds)

    return {
        'mae': mae,
        'mse': mse,
        "rmse": rmse,
        "mape": mape
```

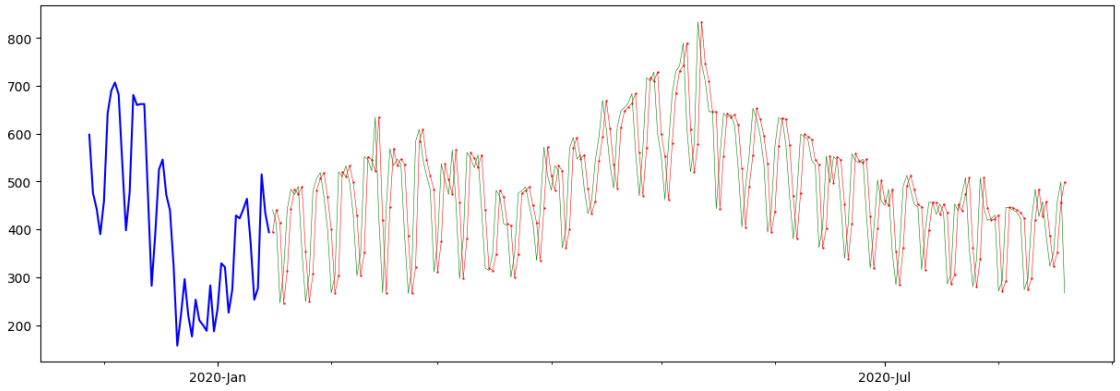
```
    }

evaluate_predictions(y_true, baseline_predictions)
```

[78]:
```
{'mae': 72.19815668202764,
 'mse': 8508.622119815669,
 'rmse': 92.24219273096054,
 'mape': 0.16713927858326993}
```

[80]:
```
MODEL_METRICS = pd.DataFrame(columns=['mae', 'mse', 'rmse', 'mape'])

def evaluate_model(model):
    predictions = model.predict(test_dataset, verbose=0)
    metrics = evaluate_predictions(y_true, predictions)

    MODEL_METRICS.loc[model.name] = metrics
    plot_time_series(predictions.ravel(), start_index=1900)
    return metrics
```

[81]:
```
evaluate_model(baseline_model)
```

[81]:
```
{'mae': 72.19815668202764,
 'mse': 8508.622119815669,
 'rmse': 92.24219273096054,
 'mape': 0.16713927858326993}
```



[82]:
```
MODEL_METRICS
```

[82]:

	mae	mse	rmse	mape
model_0	72.198157	8508.62212	92.242193	0.167139

#Recurrent Network Model

[83]:
```
from keras.layers import GRU, Dense, Input, Lambda
from keras import Sequential

tf.random.set_seed(42)
model_1 = Sequential([
    Input(shape=(WINDOW_SIZE,)),
    Lambda(lambda x: tf.expand_dims(x, axis=1)),
    GRU(128, activation="relu"),
    Dense(1)
], name='model_1')

model_1.compile(
    loss=tf.keras.losses.MeanAbsoluteError(),
    optimizer=tf.keras.optimizers.Adam()
)

model_1.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lambda (Lambda)             (None, 1, 3)              0

 gru (GRU)                   (None, 128)               51072

 dense (Dense)               (None, 1)                 129

=================================================================
Total params: 51201 (200.00 KB)
Trainable params: 51201 (200.00 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[84]:
```
from keras.callbacks import ModelCheckpoint
import os

def create_checkpoint_callback(model):
    filepath = os.path.join('models', model.name)
    return ModelCheckpoint(filepath, monitor='loss', save_weights_only=True,␣
 ↪save_best_only=True)

model_1.fit(train_dataset, epochs=5, callbacks=[␣
 ↪create_checkpoint_callback(model_1) ])
```

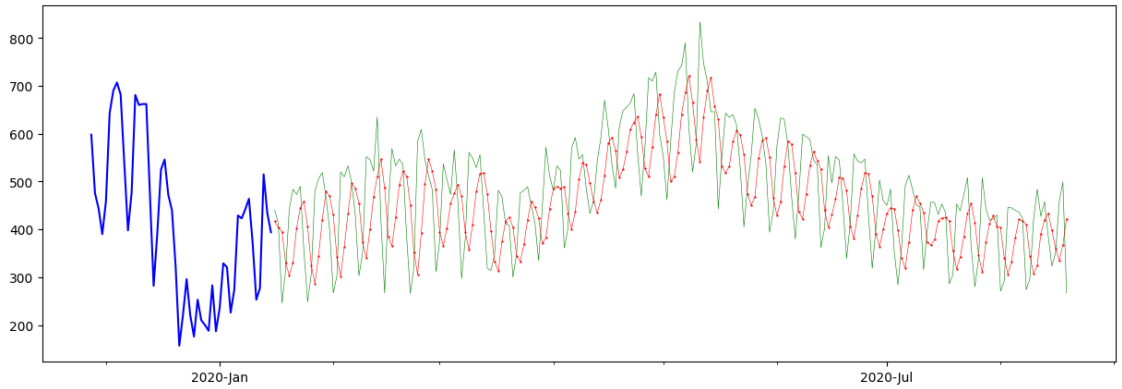
```
Epoch 1/5
16/16 [==============================] - 3s 32ms/step - loss: 478.9003
```

```
Epoch 2/5
16/16 [==============================] - 1s 31ms/step - loss: 302.9468
Epoch 3/5
16/16 [==============================] - 0s 28ms/step - loss: 170.8370
Epoch 4/5
16/16 [==============================] - 0s 28ms/step - loss: 133.6493
Epoch 5/5
16/16 [==============================] - 0s 22ms/step - loss: 130.8549
```

[84]:
```
<keras.src.callbacks.History at 0x7be4abaff850>
```

[85]:
```
evaluate_model(model_1)
```

[85]:
```
{'mae': 88.47757000198013,
 'mse': 11614.890892560847,
 'rmse': 107.77240320490607,
 'mape': 0.1947460150386166}
```



[86]:
```
MODEL_METRICS
```

[86]:

	mae	mse	rmse	mape
model_0	72.198157	8508.622120	92.242193	0.167139
model_1	88.477570	11614.890893	107.772403	0.194746

[87]:
```
unbatched_train_dataset = dataset[:TEST_DATA_BOUNDARY_INDEX + 1].copy()
unbatched_train_dataset
```

[87]:

Date	Row	Day	Day.Of.Week	Page.Loads	Unique.Visits	\
2014-09-14	1	Sunday	1	2146	1582	
2014-09-15	2	Monday	2	3621	2528	
2014-09-16	3	Tuesday	3	3698	2630	
2014-09-17	4	Wednesday	4	3667	2614	

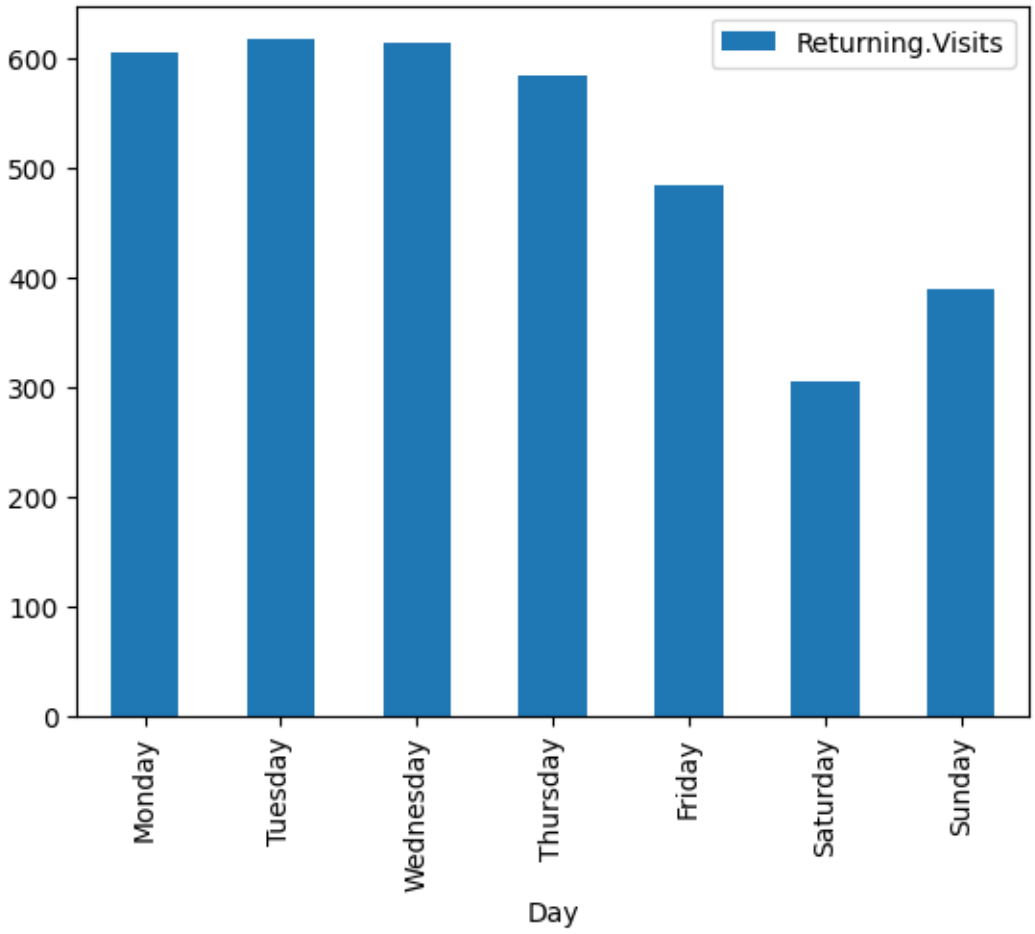
```
2014-09-18     5   Thursday            5        3316           2366
…            …        …          …          …             …
2020-01-12  1947     Sunday            1        2762           2238
2020-01-13  1948     Monday            2        4298           3242
2020-01-14  1949    Tuesday            3        3838           2884
2020-01-15  1950  Wednesday            4        3754           2864
2020-01-16  1951   Thursday            5        3817           2951

            First.Time.Visits  Returning.Visits
Date
2014-09-14               1430               152
2014-09-15               2297               231
2014-09-16               2352               278
2014-09-17               2327               287
2014-09-18               2130               236
…                         …                 …
2020-01-12               1961               277
2020-01-13               2727               515
2020-01-14               2450               434
2020-01-15               2470               394
2020-01-16               2510               441

[1951 rows x 7 columns]
```

[88]:
```
dataset_by_day = unbatched_train_dataset.groupby(by=['Day'])
dataset_by_day['Returning.Visits'].mean()
```

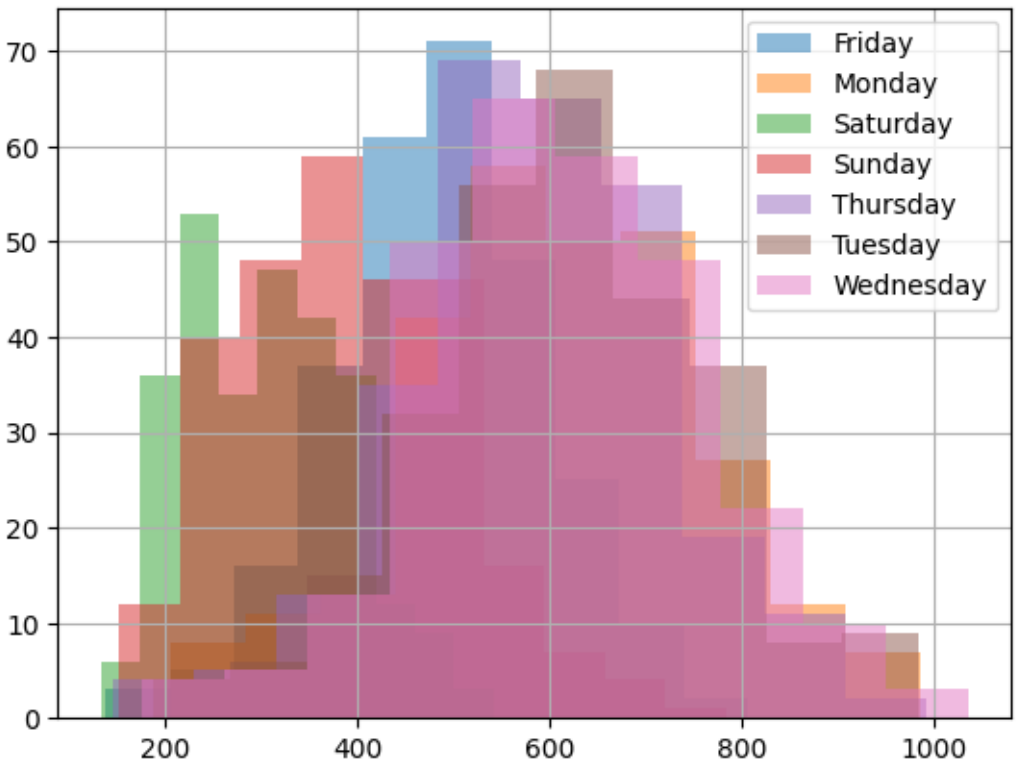
[88]:
```
Day
Friday       484.697842
Monday       606.512545
Saturday     306.071942
Sunday       390.573477
Thursday     584.627240
Tuesday      617.888889
Wednesday    614.369176
Name: Returning.Visits, dtype: float64
```

[89]:
```
DAYS_OF_WEEK = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
 ↪'Saturday', 'Sunday']
pd.DataFrame(dataset_by_day['Returning.Visits'].mean()).loc[DAYS_OF_WEEK].
 ↪plot(kind='bar')
```

[89]:
```
<Axes: xlabel='Day'>
```



[90]:
```
dataset_by_day['Returning.Visits'].hist(legend=True, alpha=0.5)
plt.show()
```



[91]:
```
import calendar

train_dataset_with_months = unbatched_train_dataset.copy()
train_dataset_with_months['Month.Name'] = pd.Series(train_dataset_with_months.
 ↪index,

 ↪index=train_dataset_with_months.index)\
                                                .apply(lambda x: calendar.
 ↪month_name[x.month])
train_dataset_with_months
```

[91]:

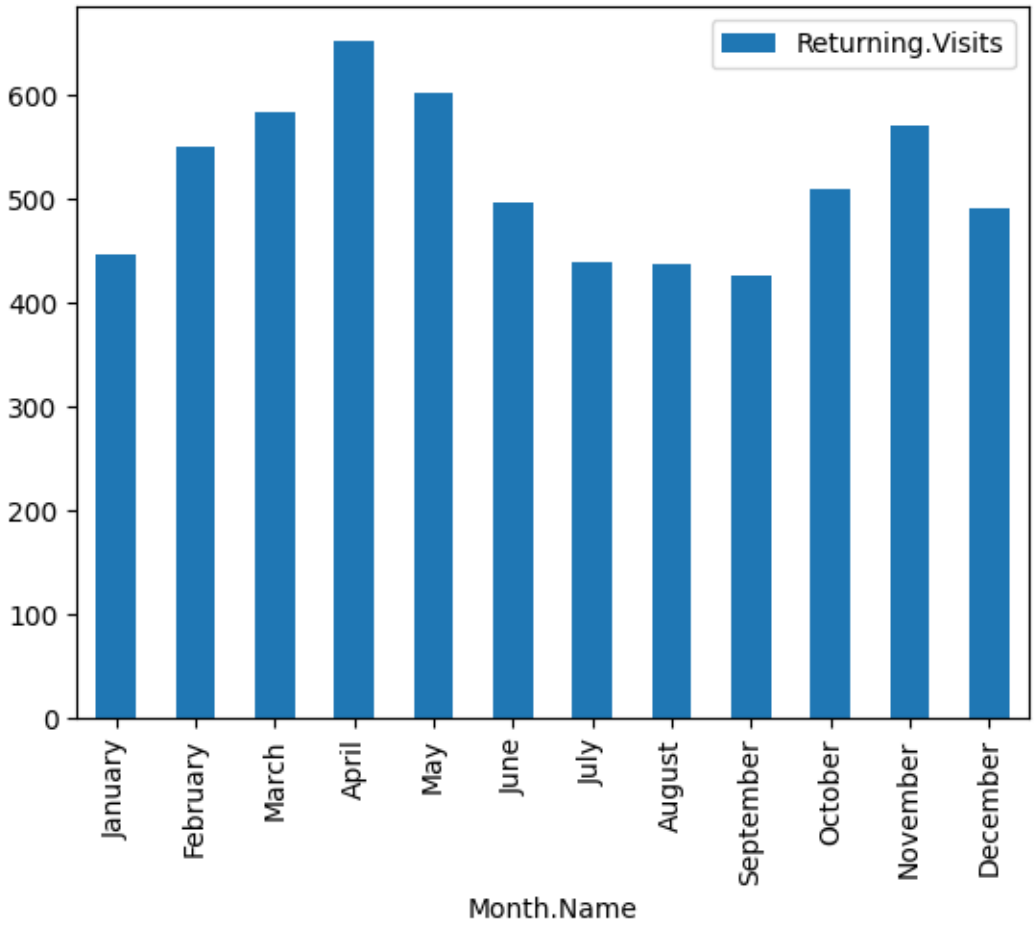
Date	Row	Day	Day.Of.Week	Page.Loads	Unique.Visits	\
2014-09-14	1	Sunday	1	2146	1582	
2014-09-15	2	Monday	2	3621	2528	
2014-09-16	3	Tuesday	3	3698	2630	
2014-09-17	4	Wednesday	4	3667	2614	
2014-09-18	5	Thursday	5	3316	2366	
…	…	…	…	…	…	
2020-01-12	1947	Sunday	1	2762	2238	
2020-01-13	1948	Monday	2	4298	3242	
2020-01-14	1949	Tuesday	3	3838	2884	

```
2020-01-15  1950  Wednesday            4        3754           2864
2020-01-16  1951   Thursday            5        3817           2951

            First.Time.Visits  Returning.Visits Month.Name
Date
2014-09-14               1430               152  September
2014-09-15               2297               231  September
2014-09-16               2352               278  September
2014-09-17               2327               287  September
2014-09-18               2130               236  September
…                           …                 …          …
2020-01-12               1961               277    January
2020-01-13               2727               515    January
2020-01-14               2450               434    January
2020-01-15               2470               394    January
2020-01-16               2510               441    January

[1951 rows x 8 columns]
```

[92]:
```
MONTH_NAMES = list(calendar.month_name)[1:]
dataset_group_by_month = train_dataset_with_months.groupby(by='Month.Name')
dataset_group_by_month['Returning.Visits'].mean().loc[MONTH_NAMES]
```

[92]:
```
Month.Name
January      445.976608
February     549.354610
March        583.470968
April        651.740000
May          601.135484
June         496.180000
July         438.509677
August       437.522581
September    426.173653
October      509.209677
November     569.716667
December     490.274194
Name: Returning.Visits, dtype: float64
```

[93]:
```
pd.DataFrame(dataset_group_by_month['Returning.Visits'].mean()).
  ↪loc[MONTH_NAMES].plot(kind='bar')
plt.show()
```



Prepare the dataset

[94]:
```
train_dataset_with_months
```

[94]:

Date	Row	Day	Day.Of.Week	Page.Loads	Unique.Visits
2014-09-14	1	Sunday	1	2146	1582
2014-09-15	2	Monday	2	3621	2528
2014-09-16	3	Tuesday	3	3698	2630
2014-09-17	4	Wednesday	4	3667	2614
2014-09-18	5	Thursday	5	3316	2366
…	…	…	…	…	…
2020-01-12	1947	Sunday	1	2762	2238
2020-01-13	1948	Monday	2	4298	3242
2020-01-14	1949	Tuesday	3	3838	2884
2020-01-15	1950	Wednesday	4	3754	2864
2020-01-16	1951	Thursday	5	3817	2951

```
            First.Time.Visits  Returning.Visits Month.Name
Date
2014-09-14               1430               152  September
2014-09-15               2297               231  September
2014-09-16               2352               278  September
2014-09-17               2327               287  September
2014-09-18               2130               236  September
…                         …                  …         …
2020-01-12               1961               277    January
2020-01-13               2727               515    January
2020-01-14               2450               434    January
2020-01-15               2470               394    January
2020-01-16               2510               441    January

[1951 rows x 8 columns]
```

[95]:
```
dataset2 = train_dataset_with_months.copy()[['Day', 'Month.Name', 'Returning.
 ↪Visits']]
dataset2
```

[95]:
```
                 Day Month.Name  Returning.Visits
Date
2014-09-14     Sunday  September               152
2014-09-15     Monday  September               231
2014-09-16    Tuesday  September               278
2014-09-17  Wednesday  September               287
2014-09-18   Thursday  September               236
…                 …          …                 …
2020-01-12     Sunday    January               277
2020-01-13     Monday    January               515
2020-01-14    Tuesday    January               434
2020-01-15  Wednesday    January               394
2020-01-16   Thursday    January               441

[1951 rows x 3 columns]
```

[96]:
```
def windowize_dataset(dataset):
    for i in range(WINDOW_SIZE):
        dataset[f'Returning.Visits[t-{i+1}]'] = dataset['Returning.Visits'].
 ↪shift(periods=i+1)
    return dataset

dataset2 = windowize_dataset(dataset2.copy())
dataset2
```

[96]:
```
                 Day Month.Name  Returning.Visits  Returning.Visits[t-1]  \
Date
```

```
2014-09-14     Sunday  September               152                    NaN
2014-09-15     Monday  September               231                  152.0
2014-09-16    Tuesday  September               278                  231.0
2014-09-17  Wednesday  September               287                  278.0
2014-09-18   Thursday  September               236                  287.0
…                …        …                   …                      …
2020-01-12     Sunday    January               277                  253.0
2020-01-13     Monday    January               515                  277.0
2020-01-14    Tuesday    January               434                  515.0
2020-01-15  Wednesday    January               394                  434.0
2020-01-16   Thursday    January               441                  394.0

            Returning.Visits[t-2]  Returning.Visits[t-3]
Date
2014-09-14                    NaN                    NaN
2014-09-15                    NaN                    NaN
2014-09-16                  152.0                    NaN
2014-09-17                  231.0                  152.0
2014-09-18                  278.0                  231.0
…                             …                      …
2020-01-12                  372.0                  464.0
2020-01-13                  253.0                  372.0
2020-01-14                  277.0                  253.0
2020-01-15                  515.0                  277.0
2020-01-16                  434.0                  515.0

[1951 rows x 6 columns]
```

[97]:
```
dataset2 = dataset2.dropna()
dataset2
```

[97]:
```
                Day Month.Name  Returning.Visits  Returning.Visits[t-1]  \
Date
2014-09-17  Wednesday  September               287                  278.0
2014-09-18   Thursday  September               236                  287.0
2014-09-19     Friday  September               241                  236.0
2014-09-20   Saturday  September               133                  241.0
2014-09-21     Sunday  September               175                  133.0
…                …        …                   …                      …
2020-01-12     Sunday    January               277                  253.0
2020-01-13     Monday    January               515                  277.0
2020-01-14    Tuesday    January               434                  515.0
2020-01-15  Wednesday    January               394                  434.0
2020-01-16   Thursday    January               441                  394.0

            Returning.Visits[t-2]  Returning.Visits[t-3]
Date
```

```
2014-09-17                  231.0                  152.0
2014-09-18                  278.0                  231.0
2014-09-19                  287.0                  278.0
2014-09-20                  236.0                  287.0
2014-09-21                  241.0                  236.0
…                             …                      …
2020-01-12                  372.0                  464.0
2020-01-13                  253.0                  372.0
2020-01-14                  277.0                  253.0
2020-01-15                  515.0                  277.0
2020-01-16                  434.0                  515.0

[1948 rows x 6 columns]
```

[98]:
```
rv_cols = [f"Returning.Visits[t-{i+1}]" for i in range(WINDOW_SIZE)]

dataset2_rv_history_features = dataset2[rv_cols]
dataset2_rv_history_features
```

[98]:
```
            Returning.Visits[t-1]  Returning.Visits[t-2]  \
Date
2014-09-17                  278.0                  231.0
2014-09-18                  287.0                  278.0
2014-09-19                  236.0                  287.0
2014-09-20                  241.0                  236.0
2014-09-21                  133.0                  241.0
…                             …                      …
2020-01-12                  253.0                  372.0
2020-01-13                  277.0                  253.0
2020-01-14                  515.0                  277.0
2020-01-15                  434.0                  515.0
2020-01-16                  394.0                  434.0

            Returning.Visits[t-3]
Date
2014-09-17                  152.0
2014-09-18                  231.0
2014-09-19                  278.0
2014-09-20                  287.0
2014-09-21                  236.0
…                             …
2020-01-12                  464.0
2020-01-13                  372.0
2020-01-14                  253.0
2020-01-15                  277.0
2020-01-16                  515.0
```

```
[1948 rows x 3 columns]
```

[99]:
```
dataset2_cat_features =  dataset2[['Day', 'Month.Name']]
dataset2_cat_features
```

[99]:
```
                  Day Month.Name
Date
2014-09-17  Wednesday  September
2014-09-18   Thursday  September
2014-09-19     Friday  September
2014-09-20   Saturday  September
2014-09-21     Sunday  September
…                 …          …
2020-01-12     Sunday    January
2020-01-13     Monday    January
2020-01-14    Tuesday    January
2020-01-15  Wednesday    January
2020-01-16   Thursday    January

[1948 rows x 2 columns]
```

[100]:
```
train_dataset2 = dataset2['Returning.Visits']
train_dataset2
```

[100]:
```
Date
2014-09-17    287
2014-09-18    236
2014-09-19    241
2014-09-20    133
2014-09-21    175
              …
2020-01-12    277
2020-01-13    515
2020-01-14    434
2020-01-15    394
2020-01-16    441
Name: Returning.Visits, Length: 1948, dtype: int64
```

Building the model

[101]:
```
from keras.layers import Concatenate, Dropout

tf.random.set_seed(42)
def build_model_3():
    seq_input = Input(shape=(WINDOW_SIZE,))
    lambda_layer = Lambda(lambda x: x[:, tf.newaxis])(seq_input)
    rnn_layer = GRU(64, activation='relu')(lambda_layer)
```

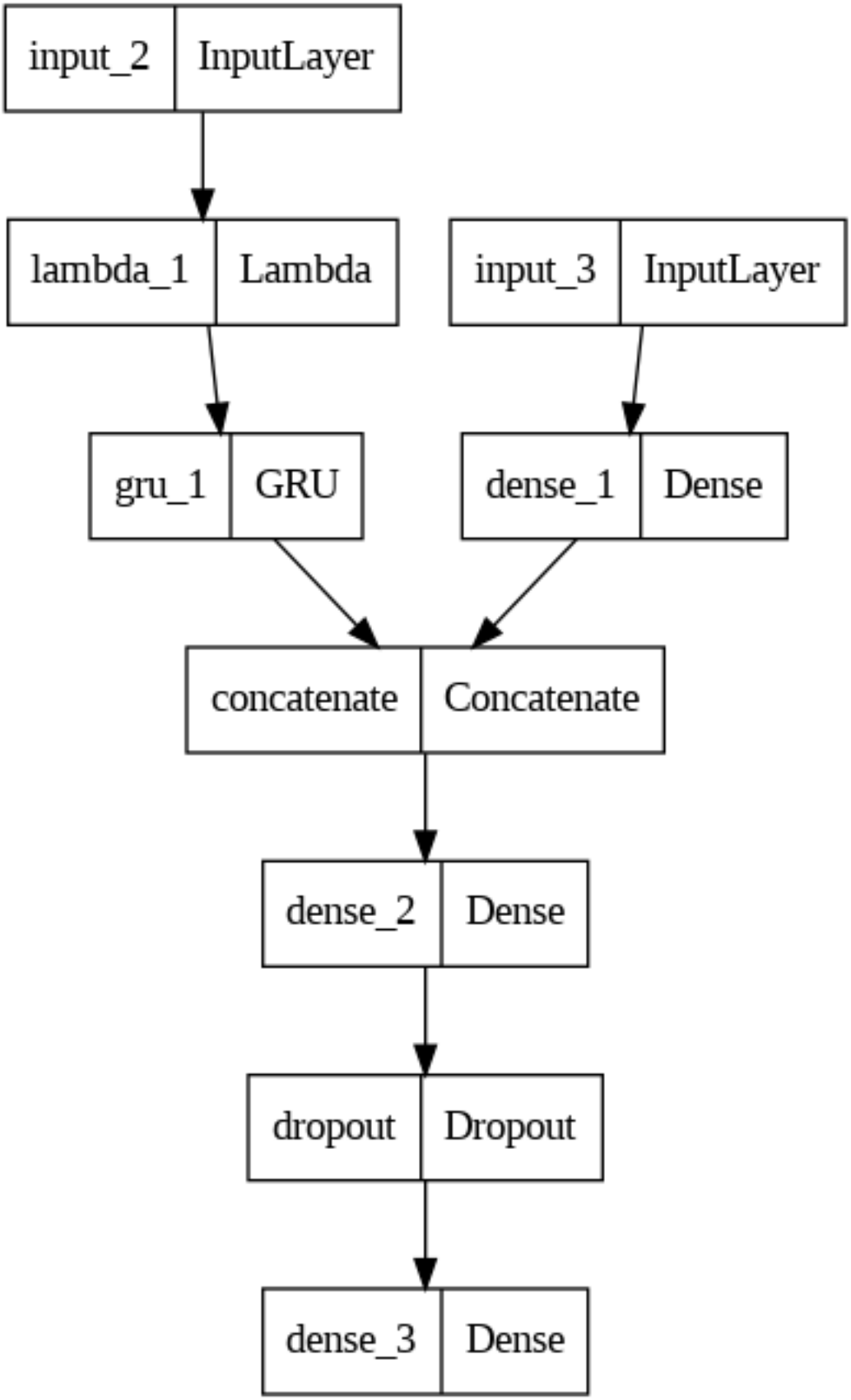
```
    cat_input = Input(shape=(2,))
    cat_dense_layer = Dense(32, activation='relu')(cat_input)

    concat_layer = Concatenate()([rnn_layer, cat_dense_layer])
    dense_layer1 = Dense(128, activation='relu')(concat_layer)
    dropout_layer = Dropout(0.5)(dense_layer1)
    output_layer = Dense(1, activation='linear')(dropout_layer)

    return Model(inputs=[seq_input, cat_input], outputs=output_layer,␣
 ↪name="model_3")

model_3 = build_model_3()
model_3.compile(
    loss=tf.keras.losses.MeanAbsoluteError(),
    optimizer=tf.keras.optimizers.Adam()
)

model_3.summary()
```

```
Model: "model_3"
__________________________________________________________________________________
__________________
 Layer (type)                Output Shape              Param #   Connected to
==================================================================================
==================
 input_2 (InputLayer)        [(None, 3)]               0         []

 lambda_1 (Lambda)           (None, 1, 3)              0
['input_2[0][0]']

 input_3 (InputLayer)        [(None, 2)]               0         []

 gru_1 (GRU)                 (None, 64)                13248
['lambda_1[0][0]']

 dense_1 (Dense)             (None, 32)                96
['input_3[0][0]']

 concatenate (Concatenate)   (None, 96)                0
['gru_1[0][0]',
'dense_1[0][0]']

 dense_2 (Dense)             (None, 128)               12416
['concatenate[0][0]']

 dropout (Dropout)           (None, 128)               0
```

```
['dense_2[0][0]']

 dense_3 (Dense)             (None, 1)                 129
['dropout[0][0]']

==================================================================================
==================
Total params: 25889 (101.13 KB)
Trainable params: 25889 (101.13 KB)
Non-trainable params: 0 (0.00 Byte)
----------------------------------------------------------------------------------
------------------
```

[102]:
```
tf.keras.utils.plot_model(model_3)
```

[102]:


input_2
InputLayer
lambda_1
Lambda
input_3
InputLayer
gru_1
GRU
dense_1
Dense
concatenate
Concatenate
dense_2
Dense
dropout
Dropout
dense_3
Dense

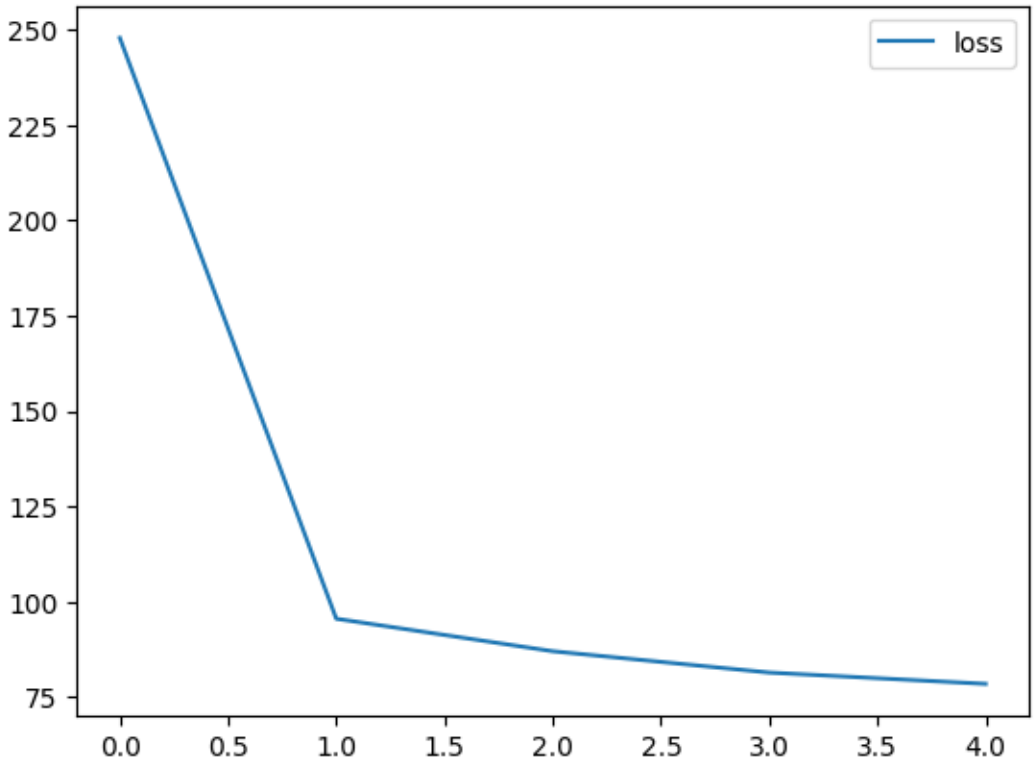
[103]:
```
from sklearn.preprocessing import LabelEncoder, OrdinalEncoder
X_cat_encoder = OrdinalEncoder(categories = [DAYS_OF_WEEK, MONTH_NAMES])
X_cat_encoded = X_cat_encoder.fit_transform(dataset2_cat_features)
X_cat_encoded, X_cat_encoder.categories_
```

[103]:
```
(array([[2., 8.],
        [3., 8.],
        [4., 8.],
        …,
        [1., 0.],
        [2., 0.],
        [3., 0.]]),
 [array(['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',
         'Sunday'], dtype=object),
  array(['January', 'February', 'March', 'April', 'May', 'June', 'July',
         'August', 'September', 'October', 'November', 'December'],
        dtype=object)])
```

[104]:
```
from tensorflow.data import Dataset

model3_history = model_3.fit(x=[dataset2_rv_history_features, X_cat_encoded],␣
 ↪y=train_dataset2, epochs=5)
pd.DataFrame(model3_history.history).plot()
```

```
Epoch 1/5
61/61 [==============================] - 4s 3ms/step - loss: 247.8772
Epoch 2/5
61/61 [==============================] - 0s 4ms/step - loss: 95.5574
Epoch 3/5
61/61 [==============================] - 0s 4ms/step - loss: 87.0351
Epoch 4/5
61/61 [==============================] - 0s 4ms/step - loss: 81.4419
Epoch 5/5
61/61 [==============================] - 0s 4ms/step - loss: 78.4773
```

[104]:
```
<Axes: >
```



[106]:
```
test_dataset2 = windowize_dataset(dataset[TEST_DATA_BOUNDARY_INDEX-WINDOW_SIZE:
 ↪].copy())
test_dataset2['Month.Name'] = pd.Series(test_dataset2.index,␣
 ↪index=test_dataset2.index)\
                        .apply(lambda x: calendar.month_name[x.month])
test_dataset2 = test_dataset2.dropna()
test_dataset2
```

[106]:

Date	Row	Day	Day.Of.Week	Page.Loads	Unique.Visits	\
2020-01-16	1951	Thursday	5	3817	2951	
2020-01-17	1952	Friday	6	3175	2419	
2020-01-18	1953	Saturday	7	2336	1927	
2020-01-19	1954	Sunday	1	2597	2031	
2020-01-20	1955	Monday	2	3715	2948	
…	…	…	…	…	…	
2020-08-15	2163	Saturday	7	2221	1696	
2020-08-16	2164	Sunday	1	2724	2037	
2020-08-17	2165	Monday	2	3456	2638	
2020-08-18	2166	Tuesday	3	3581	2683	
2020-08-19	2167	Wednesday	4	2064	1564	

```
            First.Time.Visits  Returning.Visits  Returning.Visits[t-1]  \
Date
2020-01-16               2510               441                   394.0
2020-01-17               2006               413                   441.0
2020-01-18               1681               246                   413.0
2020-01-19               1717               314                   246.0
2020-01-20               2505               443                   314.0
…                         …                  …                      …
2020-08-15               1373               323                   386.0
2020-08-16               1686               351                   323.0
2020-08-17               2181               457                   351.0
2020-08-18               2184               499                   457.0
2020-08-19               1297               267                   499.0

            Returning.Visits[t-2]  Returning.Visits[t-3] Month.Name
Date
2020-01-16                  434.0                  515.0    January
2020-01-17                  394.0                  434.0    January
2020-01-18                  441.0                  394.0    January
2020-01-19                  413.0                  441.0    January
2020-01-20                  246.0                  413.0    January
…                             …                      …        …
2020-08-15                  458.0                  427.0     August
2020-08-16                  386.0                  458.0     August
2020-08-17                  323.0                  386.0     August
2020-08-18                  351.0                  323.0     August
2020-08-19                  457.0                  351.0     August

[217 rows x 11 columns]
```

[107]:
```
X_test_rv_history_input = test_dataset2[rv_cols]
X_test_rv_history_input
```

[107]:
```
            Returning.Visits[t-1]  Returning.Visits[t-2]  \
Date
2020-01-16                  394.0                  434.0
2020-01-17                  441.0                  394.0
2020-01-18                  413.0                  441.0
2020-01-19                  246.0                  413.0
2020-01-20                  314.0                  246.0
…                             …                      …
2020-08-15                  386.0                  458.0
2020-08-16                  323.0                  386.0
2020-08-17                  351.0                  323.0
2020-08-18                  457.0                  351.0
2020-08-19                  499.0                  457.0
```

```
            Returning.Visits[t-3]
Date
2020-01-16                  515.0
2020-01-17                  434.0
2020-01-18                  394.0
2020-01-19                  441.0
2020-01-20                  413.0
…                           …
2020-08-15                  427.0
2020-08-16                  458.0
2020-08-17                  386.0
2020-08-18                  323.0
2020-08-19                  351.0

[217 rows x 3 columns]
```

[108]:
```
X_test_cat_input = test_dataset2[['Day', 'Month.Name']]
X_test_cat_input = X_cat_encoder.transform(X_test_cat_input)
X_test_cat_input.shape, X_test_cat_input[:5]
```

[108]:
```
((217, 2),
 array([[3., 0.],
        [4., 0.],
        [5., 0.],
        [6., 0.],
        [0., 0.]]))
```

[109]:
```
model_3_preds = model_3.predict([X_test_rv_history_input, X_test_cat_input])
model_3_preds[:15]
```

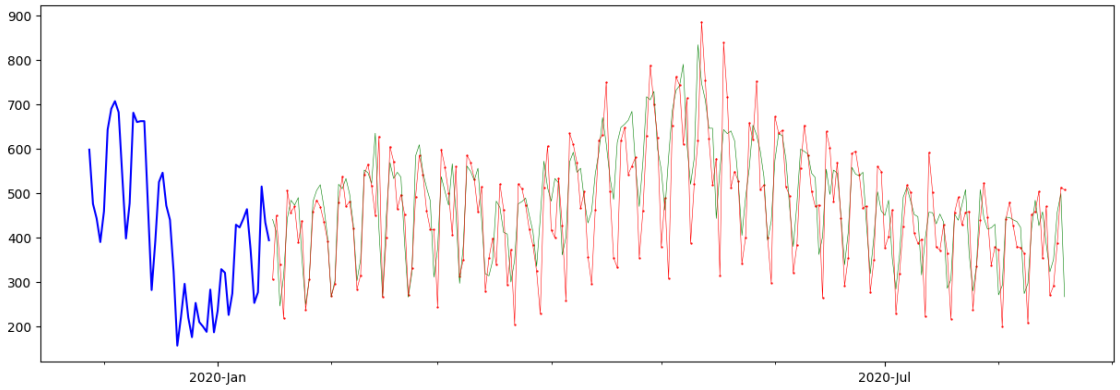
```
7/7 [==============================] - 1s 5ms/step
```

[109]:
```
array([[305.5503 ],
       [449.51257],
       [340.03714],
       [218.20609],
       [506.13654],
       [457.20728],
       [470.06744],
       [389.448  ],
       [438.15656],
       [237.35915],
       [306.98065],
       [457.7482 ],
       [484.1681 ],
       [469.60846],
       [435.30145]], dtype=float32)
```

[110]:
```
y_dataset = test_dataset2['Returning.Visits']
```

[111]:
```
def evaluate_model_predictions(y_true, predictions, model_name):
    metrics = evaluate_predictions(y_true, predictions)

    MODEL_METRICS.loc[model_name] = metrics
    plot_time_series(predictions.ravel(), start_index=1900)
    return metrics

evaluate_model_predictions(y_dataset, model_3_preds, 'model_3 (multi-input)')
```

[111]:
```
{'mae': 66.37921923096829,
 'mse': 7288.542556140803,
 'rmse': 85.3729615050386,
 'mape': 0.143966483112374}
```



[112]:
```
MODEL_METRICS
```

[112]:

	mae	mse	rmse	mape
model_0	72.198157	8508.622120	92.242193	0.167139
model_1	88.477570	11614.890893	107.772403	0.194746
model_3 (multi-input)	66.379219	7288.542556	85.372962	0.143966

ensemble methods

[113]:
```
def build_model_5(n_models, loss_fns):
    models = []
    for loss_fn in loss_fns:
        print(f"Training {n_models} models for {loss_fn} loss...")
        for i in range(n_models):
            model = Sequential([
                Input(shape=(WINDOW_SIZE,)),
                Lambda(lambda x: tf.expand_dims(x, axis=1)),
                GRU(128, activation='relu'),
```

```
                Dense(1, activation='linear')
            ])

            model.compile(loss=loss_fn, optimizer=tf.keras.optimizers.Adam())
            models.append(model)


    return models


model_5 = build_model_5(n_models=5, loss_fns=['mae', 'mse', 'mape'])
model_5
```

```
Training 5 models for mae loss…
Training 5 models for mse loss…
Training 5 models for mape loss…
```

[113]:
```
[<keras.src.engine.sequential.Sequential at 0x7be49a576f20>,
 <keras.src.engine.sequential.Sequential at 0x7be49a559d20>,
 <keras.src.engine.sequential.Sequential at 0x7be49a5757e0>,
 <keras.src.engine.sequential.Sequential at 0x7be49a93fa00>,
 <keras.src.engine.sequential.Sequential at 0x7be49a6f1db0>,
 <keras.src.engine.sequential.Sequential at 0x7be499098220>,
 <keras.src.engine.sequential.Sequential at 0x7be4990a8b50>,
 <keras.src.engine.sequential.Sequential at 0x7be4990cd060>,
 <keras.src.engine.sequential.Sequential at 0x7be49a5f3040>,
 <keras.src.engine.sequential.Sequential at 0x7be4990c0850>,
 <keras.src.engine.sequential.Sequential at 0x7be4990c2380>,
 <keras.src.engine.sequential.Sequential at 0x7be4990ced10>,
 <keras.src.engine.sequential.Sequential at 0x7be498f4a710>,
 <keras.src.engine.sequential.Sequential at 0x7be498f4b8e0>,
 <keras.src.engine.sequential.Sequential at 0x7be498f4b700>]
```

[114]:
```
model_5[0].summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lambda_2 (Lambda)           (None, 1, 3)              0

 gru_2 (GRU)                 (None, 128)               51072

 dense_4 (Dense)             (None, 1)                 129

=================================================================
Total params: 51201 (200.00 KB)
Trainable params: 51201 (200.00 KB)
```

```
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[115]:
```python
for i, model in enumerate(model_5):
    print(f"Training model {i+1} out of {len(model_5)} models")
    model.fit(train_dataset, epochs=5, verbose=0)
```

```
Training model 1 out of 15 models
Training model 2 out of 15 models
Training model 3 out of 15 models
Training model 4 out of 15 models
Training model 5 out of 15 models
Training model 6 out of 15 models
Training model 7 out of 15 models
Training model 8 out of 15 models
Training model 9 out of 15 models
Training model 10 out of 15 models
Training model 11 out of 15 models
Training model 12 out of 15 models
Training model 13 out of 15 models
Training model 14 out of 15 models
Training model 15 out of 15 models
```

[116]:
```python
def ensemble_prediction(models):
    predictions = []
    for model in models:
        pred = model.predict(test_dataset, verbose=0)
        predictions.append(pred)

    return np.array(predictions)

model_5_all_preds = ensemble_prediction(model_5)
model_5_all_preds.shape
```

```
WARNING:tensorflow:5 out of the last 14 calls to <function
Model.make_predict_function.<locals>.predict_function at 0x7be495e8cd30>
triggered tf.function retracing. Tracing is expensive and the excessive number
of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2)
passing tensors with different shapes, (3) passing Python objects instead of
tensors. For (1), please define your @tf.function outside of the loop. For (2),
@tf.function has reduce_retracing=True option that can avoid unnecessary
retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.
WARNING:tensorflow:6 out of the last 16 calls to <function
Model.make_predict_function.<locals>.predict_function at 0x7be495e8d6c0>
triggered tf.function retracing. Tracing is expensive and the excessive number
of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2)
```

```
passing tensors with different shapes, (3) passing Python objects instead of
tensors. For (1), please define your @tf.function outside of the loop. For (2),
@tf.function has reduce_retracing=True option that can avoid unnecessary
retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.
```

[116]:
```
(15, 217, 1)
```

[118]:
```
model_5_all_preds.shape
```

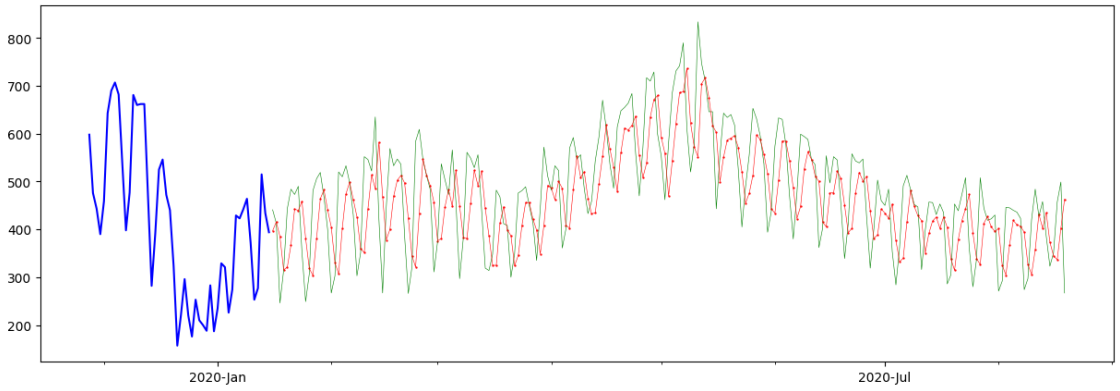
[118]:
```
(15, 217, 1)
```

[119]:
```
def aggregate_ensemble_predictions(predictions):
    return tf.reduce_mean(predictions, axis=0).numpy()

model_5_preds = aggregate_ensemble_predictions(model_5_all_preds)
model_5_preds.shape
```

[119]:
```
(217, 1)
```

[120]:
```
evaluate_model_predictions(y_true, model_5_preds, 'model_5 (ensemble)')
```

[120]:
```
{'mae': 73.04654872911867,
 'mse': 8556.55393296718,
 'rmse': 92.50164286631443,
 'mape': 0.16257963102721296}
```



[121]:
```
MODEL_METRICS
```

[121]:

	mae	mse	rmse	mape
model_0	72.198157	8508.622120	92.242193	0.167139
model_1	88.477570	11614.890893	107.772403	0.194746

```
model_3 (multi-input)  66.379219   7288.542556   85.372962  0.143966
model_5 (ensemble)     73.046549   8556.553933   92.501643  0.162580
```