Universitas Pertamina

MANUAL BOOK

Benchmarking and Performance Measurement of Neural Network Models with Two Hidden Layers for Time Series Data : Case Study of RNN, LSTM and GRU-based Structure

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Benchmarking and Performance Measurement of Neural Network Models with Two Hidden Layers for Time Series Data : Case Study of RNN, LSTM and GRU-based Structure

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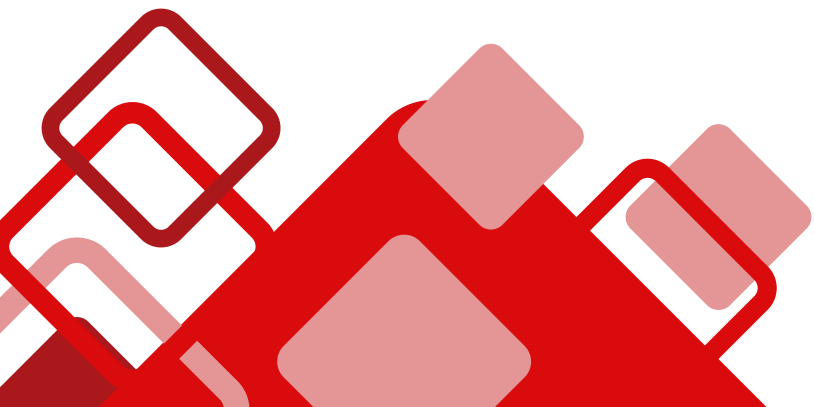


Manual Book

Menu dan Cara Penggunaan

Menyiapkan *workspace* yang dapat menjalankan *file* dengan ekstensi .ipynb. Anda dapat menggunakan *Google Colab (Colaboratory)* untuk menjalankan *file* dengan ekstensi .ipynb, dengan langkah-langkah berikut :

1. Buka *Google Colab* : Buka perambanan web yang ada di device Anda dan pergi ke *Google Colab.*
2. *Log In :*

   Pastikan Anda sudah masuk menggunakan akun *Google* Anda. Jika belum, Anda perlu memasukkan akun Anda terlebih dahulu untuk menggunakan *Google Colab*.
3. Buat *notebook* baru atau *import* dari *file* dari *device* Anda :

   Anda dapat membuat *notebook* baru dengan mengklik "*File*">"*New Notebook*" di *Google Colab*. Jika Anda sudah memiliki *file* .ipynb yang ingin dijalankan, Anda dapat mengimportnya dengan mengklik "*File*">"*Upload Notebook*".
4. Jalankan Program :

   Dalam *notebook colab*, Anda dapat menjalankan program dengan beberapa cara:

   4.1. Menjalankan *cell* secara individual :

   Klik pada *cell code* yang ingin Anda jalankan, dan tekan tombol "*Shift*"+"*Enter*" atau klik tombol "*Run*" yang ada disamping *cell code*.

   4.2. Menjalankan semua cell :

   Klik "*Runtime*" di atas, kempudian pilih "*Run All*" untuk menjalankan semua *cell code* dalam *notebook* secara otomatis.
5. Mengunggah Dataset (*Optional*) :

   Dataset sudah disediakan, apabila memiliki dataset lain, unggah dataset baru dan sesuaikan dengan nama *file*.

Benchmarking and Performance Measurement of Neural Networks Models With Two Hidden Layers For Time-Series Data: Case Study of RNN, LSTM, and GRU-based Structure

1. Import Libraries

List of libraries that will be used.

In [1]:
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import csv
import random
```

Using Utilites of Data Visualization

In [2]:
```
def plot_series(x, y, format="-", start=0, end=None,
                title=None, xlabel=None, ylabel=None, legend=None ):
    plt.figure(figsize=(10, 6))
    if type(y) is tuple:
      for y_curr in y:
        plt.plot(x[start:end], y_curr[start:end], format)
    else:
      plt.plot(x[start:end], y[start:end], format)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    if legend:
      plt.legend(legend)
    plt.title(title)
    plt.grid(True)
    plt.show()
```

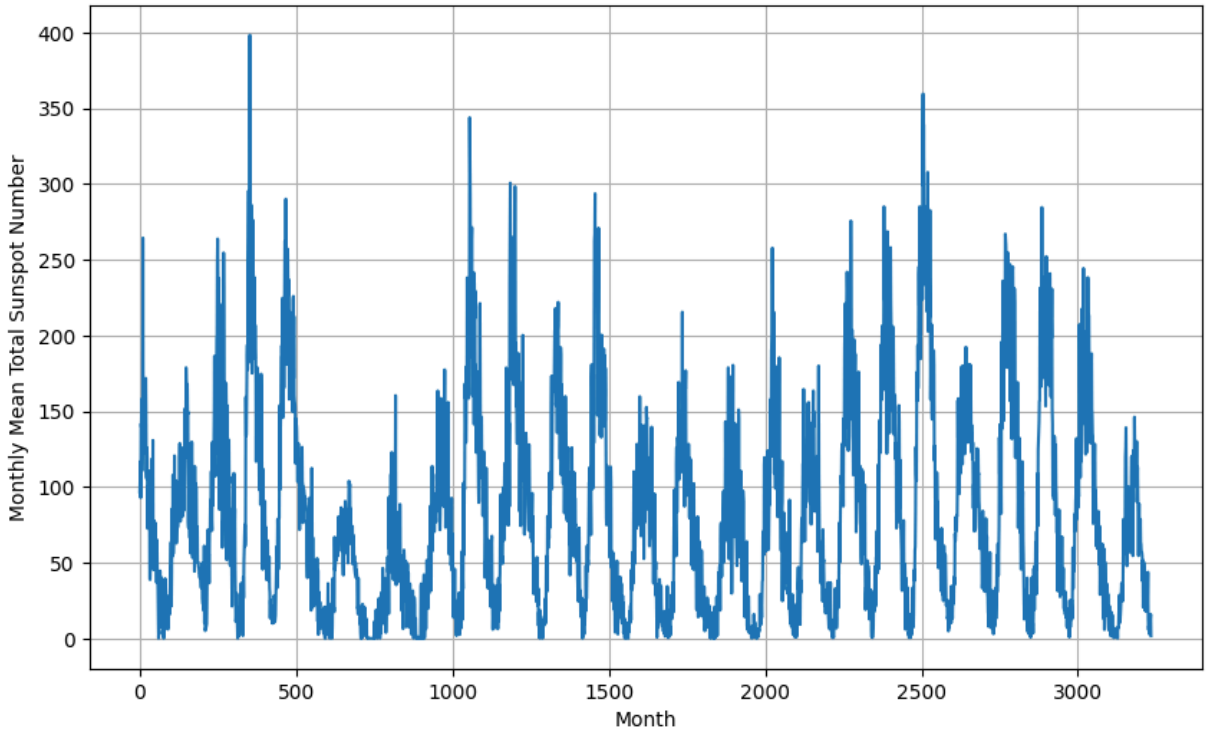
2. Get DATA

Take Data from Upstream (Local, Gdrive, Github, etc).

In [ ]:
```
!wget https://storage.googleapis.com/tensorflow-1-public/course4/Sunspots.csv
```

Data Visualize

In [4]:
```
time_step = []
sunspots = []

with open('./Sunspots.csv') as csvfile:
  reader = csv.reader(csvfile, delimiter=',')
  next(reader)

  for row in reader:
    time_step.append(int(row[0]))
    sunspots.append(float(row[2]))

time = np.array(time_step)
series = np.array(sunspots)

plot_series(time, series, xlabel='Month', ylabel='Monthly Mean Total Sunspot Number')
```



3. Data Prerocessing

Analysis and Cleaning Data -> Extract, Transform, Load.

Split Data

In [5]:
```
indices_to_change = np.where((series >= 0) & (series <= 1))
for index in indices_to_change[0]:
  series[index] = random.random() * 10

split_time = int(len(time)*0.8)

time_train = time[:split_time]
x_train = series[:split_time]

time_valid = time[split_time:]
x_valid = series[split_time:]
```

Prepare Features and Labels

In [6]:
```
def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
    dataset = tf.data.Dataset.from_tensor_slices(series)
    dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
    dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
    dataset = dataset.map(lambda window: (window[:-1], window[-1]))
    dataset = dataset.shuffle(shuffle_buffer)
    dataset = dataset.batch(batch_size).prefetch(1)
    return dataset

window_size = 30
batch_size = 32
shuffle_buffer_size = 1000

train_set = windowed_dataset(x_train, window_size, batch_size, shuffle_buffer_size)
```

4. Model Architechture

Using library from Scikit-learn, Tensorflow(?).

RNN Model

In [7]:
```
model_RNN = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.SimpleRNN(64, return_sequences=True),
  tf.keras.layers.SimpleRNN(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_RNN.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWa
rning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential mode
ls, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 30, 64)	256
simple_rnn (SimpleRNN)	(None, 30, 64)	8,256
simple_rnn_1 (SimpleRNN)	(None, 64)	8,256
dense (Dense)	(None, 1)	65
lambda (Lambda)	(None, 1)	0

Total params: 16,833 (65.75 KB)

Trainable params: 16,833 (65.75 KB)

Non-trainable params: 0 (0.00 B)

LSTM Model

In [8]:
```
model_LSTM = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.LSTM(64, return_sequences=True),
  tf.keras.layers.LSTM(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_LSTM.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	(None, 30, 64)	256
lstm (LSTM)	(None, 30, 64)	33,024
lstm_1 (LSTM)	(None, 64)	33,024
dense_1 (Dense)	(None, 1)	65
lambda_1 (Lambda)	(None, 1)	0

Total params: 66,369 (259.25 KB)

Trainable params: 66,369 (259.25 KB)

GRU Model

In [9]:
```
model_GRU = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.GRU(64, return_sequences=True),
  tf.keras.layers.GRU(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_GRU.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv1d_2 (Conv1D)	(None, 30, 64)	256
gru (GRU)	(None, 30, 64)	24,960
gru_1 (GRU)	(None, 64)	24,960
dense_2 (Dense)	(None, 1)	65
lambda_2 (Lambda)	(None, 1)	0

Total params: 50,241 (196.25 KB)

Trainable params: 50,241 (196.25 KB)

Non-trainable params: 0 (0.00 B)

RNN-LSTM Model

In [10]:
```
model_RNN_LSTM = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.SimpleRNN(64, return_sequences=True),
  tf.keras.layers.LSTM(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
```

```
])
model_RNN_LSTM.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
conv1d_3 (Conv1D)	(None, 30, 64)	256
simple_rnn_2 (SimpleRNN)	(None, 30, 64)	8,256
lstm_2 (LSTM)	(None, 64)	33,024
dense_3 (Dense)	(None, 1)	65
lambda_3 (Lambda)	(None, 1)	0

Total params: 41,601 (162.50 KB)

Trainable params: 41,601 (162.50 KB)

Non-trainable params: 0 (0.00 B)

RNN-GRU Model

In [11]:
```
model_RNN_GRU = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.SimpleRNN(64, return_sequences=True),
  tf.keras.layers.GRU(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_RNN_GRU.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv1d_4 (Conv1D)	(None, 30, 64)	256
simple_rnn_3 (SimpleRNN)	(None, 30, 64)	8,256
gru_2 (GRU)	(None, 64)	24,960
dense_4 (Dense)	(None, 1)	65
lambda_4 (Lambda)	(None, 1)	0

Total params: 33,537 (131.00 KB)

Trainable params: 33,537 (131.00 KB)

Non-trainable params: 0 (0.00 B)

LSTM-RNN

In [12]:
```
model_LSTM_RNN = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
```

```
                      input_shape=[window_size, 1]),
  tf.keras.layers.LSTM(64, return_sequences=True),
  tf.keras.layers.SimpleRNN(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_LSTM_RNN.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv1d_5 (Conv1D)	(None, 30, 64)	256
lstm_3 (LSTM)	(None, 30, 64)	33,024
simple_rnn_4 (SimpleRNN)	(None, 64)	8,256
dense_5 (Dense)	(None, 1)	65
lambda_5 (Lambda)	(None, 1)	0

Total params: 41,601 (162.50 KB)

Trainable params: 41,601 (162.50 KB)

Non-trainable params: 0 (0.00 B)

LSTM-GRU Model

In [13]:
```
model_LSTM_GRU = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                      strides=1,
                      activation="relu",
                      padding='causal',
                      input_shape=[window_size, 1]),
  tf.keras.layers.LSTM(64, return_sequences=True),
  tf.keras.layers.GRU(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_LSTM_GRU.summary()
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
conv1d_6 (Conv1D)	(None, 30, 64)	256
lstm_4 (LSTM)	(None, 30, 64)	33,024
gru_3 (GRU)	(None, 64)	24,960
dense_6 (Dense)	(None, 1)	65
lambda_6 (Lambda)	(None, 1)	0

Total params: 58,305 (227.75 KB)

Trainable params: 58,305 (227.75 KB)

Non-trainable params: 0 (0.00 B)

GRU-RNN Model

In [14]:
```
model_GRU_RNN = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.GRU(64, return_sequences=True),
  tf.keras.layers.SimpleRNN(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_GRU_RNN.summary()
```

Model: "sequential_7"

Layer (type)	Output Shape	Param #
conv1d_7 (Conv1D)	(None, 30, 64)	256
gru_4 (GRU)	(None, 30, 64)	24,960
simple_rnn_5 (SimpleRNN)	(None, 64)	8,256
dense_7 (Dense)	(None, 1)	65
lambda_7 (Lambda)	(None, 1)	0

Total params: 33,537 (131.00 KB)

Trainable params: 33,537 (131.00 KB)

Non-trainable params: 0 (0.00 B)

GRU-LSTM Model

In [15]:
```
model_GRU_LSTM = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.GRU(64, return_sequences=True),
  tf.keras.layers.LSTM(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_GRU_LSTM  .summary()
```

Model: "sequential_8"

Layer (type)	Output Shape	Param #
conv1d_8 (Conv1D)	(None, 30, 64)	256
gru_5 (GRU)	(None, 30, 64)	24,960
lstm_5 (LSTM)	(None, 64)	33,024
dense_8 (Dense)	(None, 1)	65
lambda_8 (Lambda)	(None, 1)	0

Total params: 58,305 (227.75 KB)

Trainable params: 58,305 (227.75 KB)

Non-trainable params: 0 (0.00 B)

5. Model Training

In [16]:
```
tf.keras.backend.clear_session()
learning_rate = 8e-7
```

In [ ]:
```
optimizer_RNN = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_RNN.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_RNN,
              metrics=["mae", "mse", "mape"])
history_RNN = model_RNN.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_LSTM = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_LSTM.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_LSTM,
              metrics=["mae", "mse", "mape"])
history_LSTM = model_LSTM.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_GRU= tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_GRU.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_GRU,
              metrics=["mae", "mse", "mape"])
history_GRU = model_GRU.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_RNN_LSTM = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_RNN_LSTM.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_RNN_LSTM,
              metrics=["mae", "mse", "mape"])
history_RNN_LSTM = model_RNN_LSTM.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_RNN_GRU = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_RNN_GRU.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_RNN_GRU,
              metrics=["mae", "mse", "mape"])
history_RNN_GRU = model_RNN_GRU.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_LSTM_RNN = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_LSTM_RNN.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_LSTM_RNN,
              metrics=["mae", "mse", "mape"])
history_LSTM_RNN = model_LSTM_RNN.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_LSTM_GRU = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_LSTM_GRU.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_LSTM_GRU,
              metrics=["mae", "mse", "mape"])
history_LSTM_GRU = model_LSTM_GRU.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_GRU_RNN= tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_GRU_RNN.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_GRU_RNN,
              metrics=["mae", "mse", "mape"])
history_GRU_RNN = model_GRU_RNN.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_GRU_LSTM= tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_GRU_LSTM.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_GRU_LSTM,
              metrics=["mae", "mse", "mape"])
history_GRU_LSTM = model_GRU_LSTM.fit(train_set,epochs=100)
```

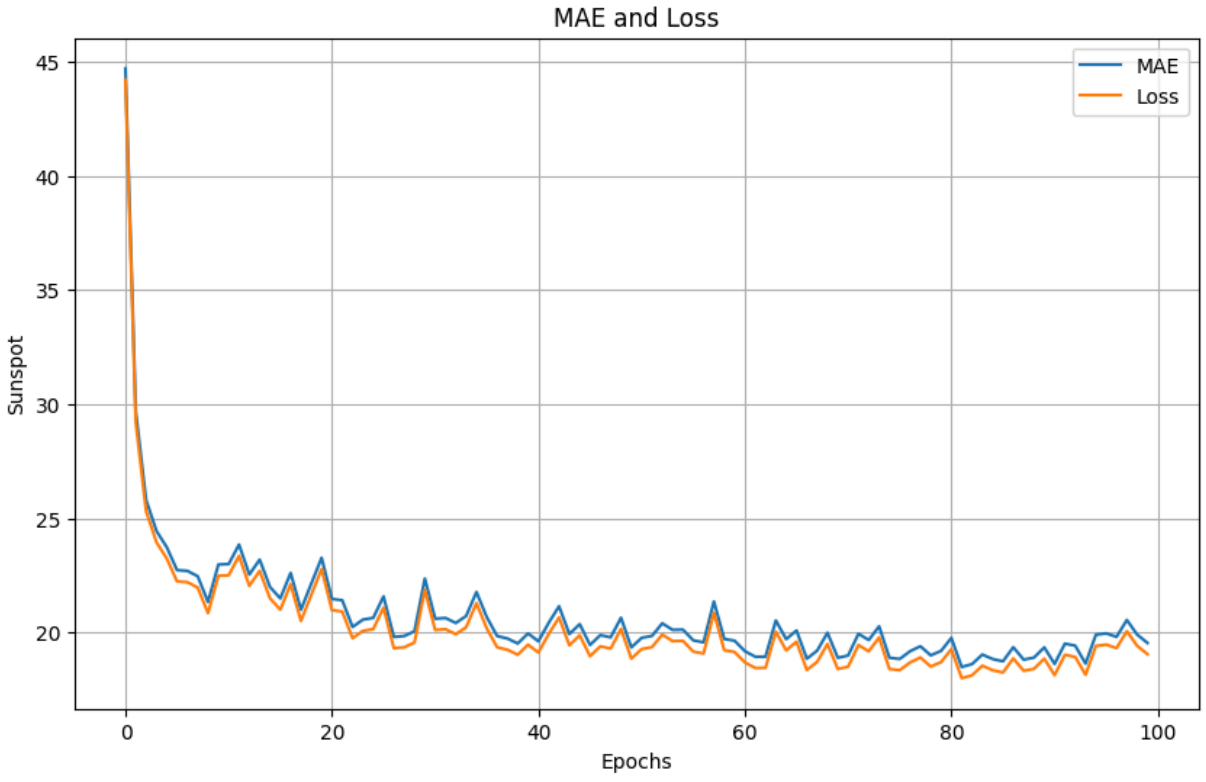
6. Model Evaluation

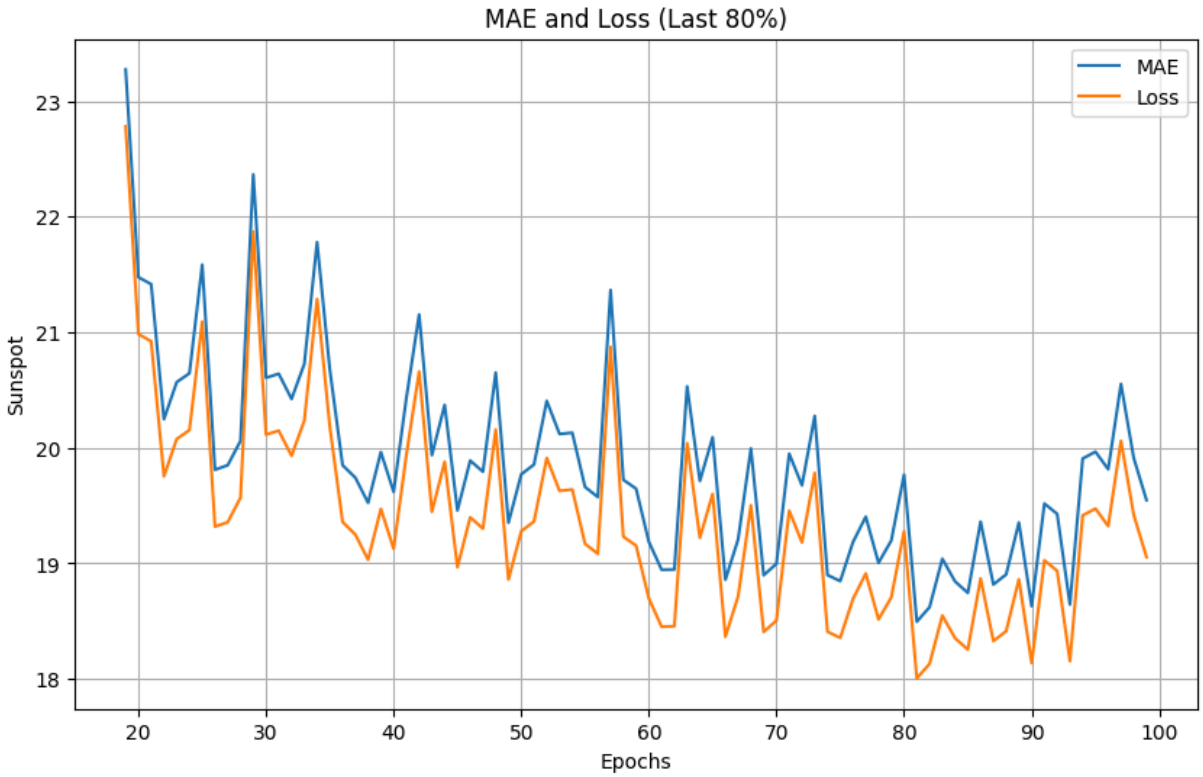
Loss evaluation using Scatter Plot

In [26]:
```
# Plot Function
def visualize_evaluation(history):
  mae=history.history['mae']
  loss=history.history['loss']

  epochs=range(len(loss))

  plot_series(
      x=epochs,
      y=(mae, loss),
      title='MAE and Loss',
      xlabel='Epochs',
      ylabel='Sunspot',
      legend=['MAE', 'Loss'])

  zoom_split = int(epochs[-1] * 0.2)
  epochs_zoom = epochs[zoom_split:]
  mae_zoom = mae[zoom_split:]
  loss_zoom = loss[zoom_split:]

  plot_series(
      x=epochs_zoom,
      y=(mae_zoom, loss_zoom),
      title='MAE and Loss (Last 80%)',
      xlabel='Epochs',
      ylabel='Sunspot',
      legend=['MAE', 'Loss'])
```

RNN Evaluation

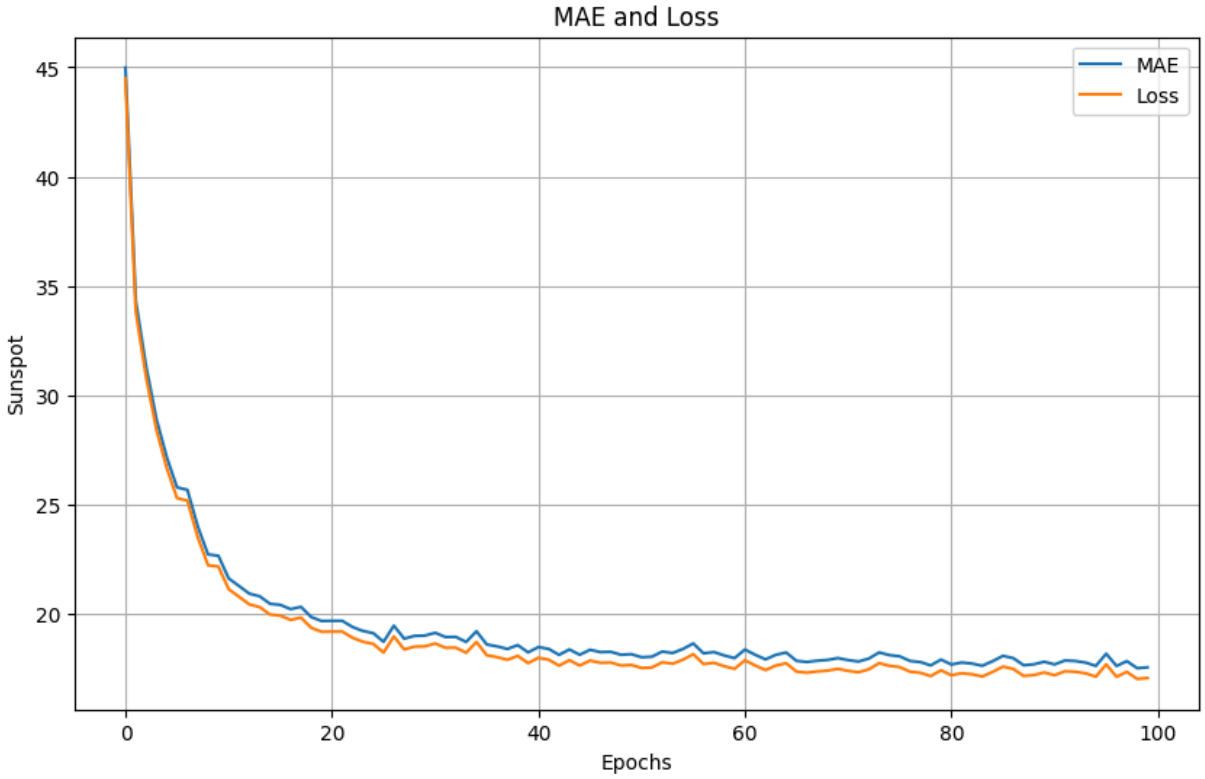
In [27]:
```
visualize_evaluation(history_RNN)
```

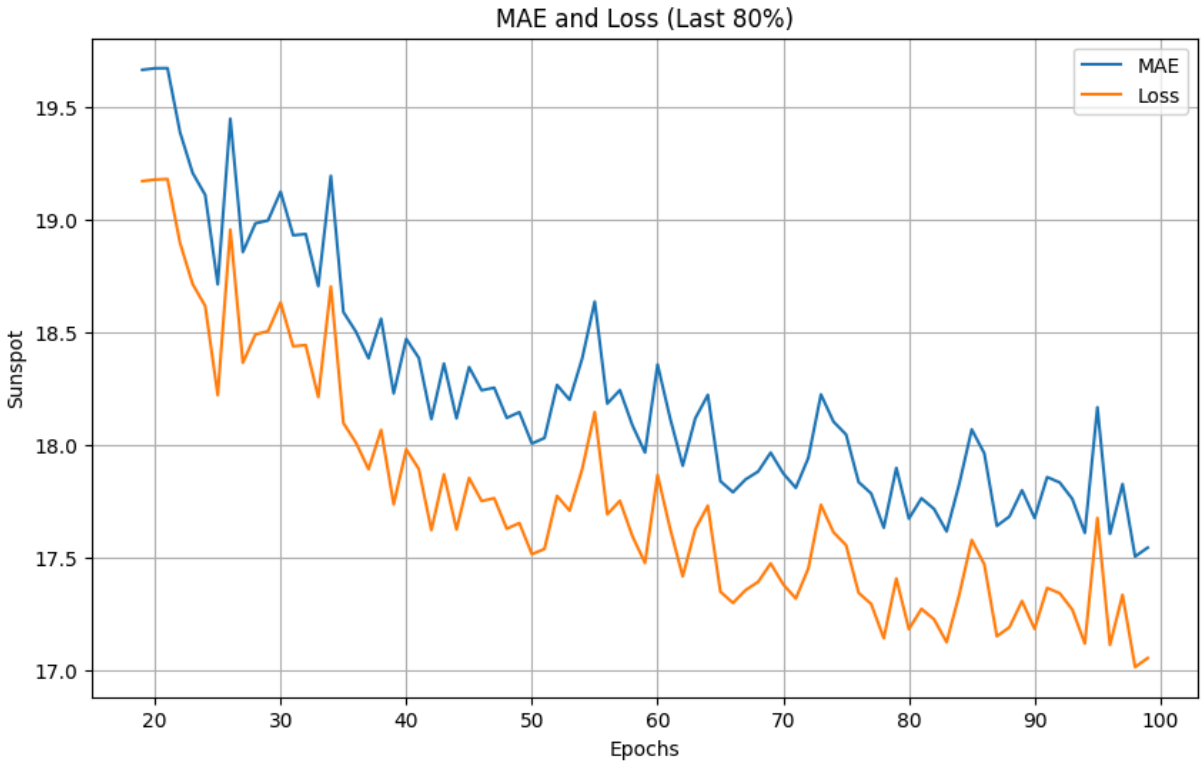




LSTM Evaluation

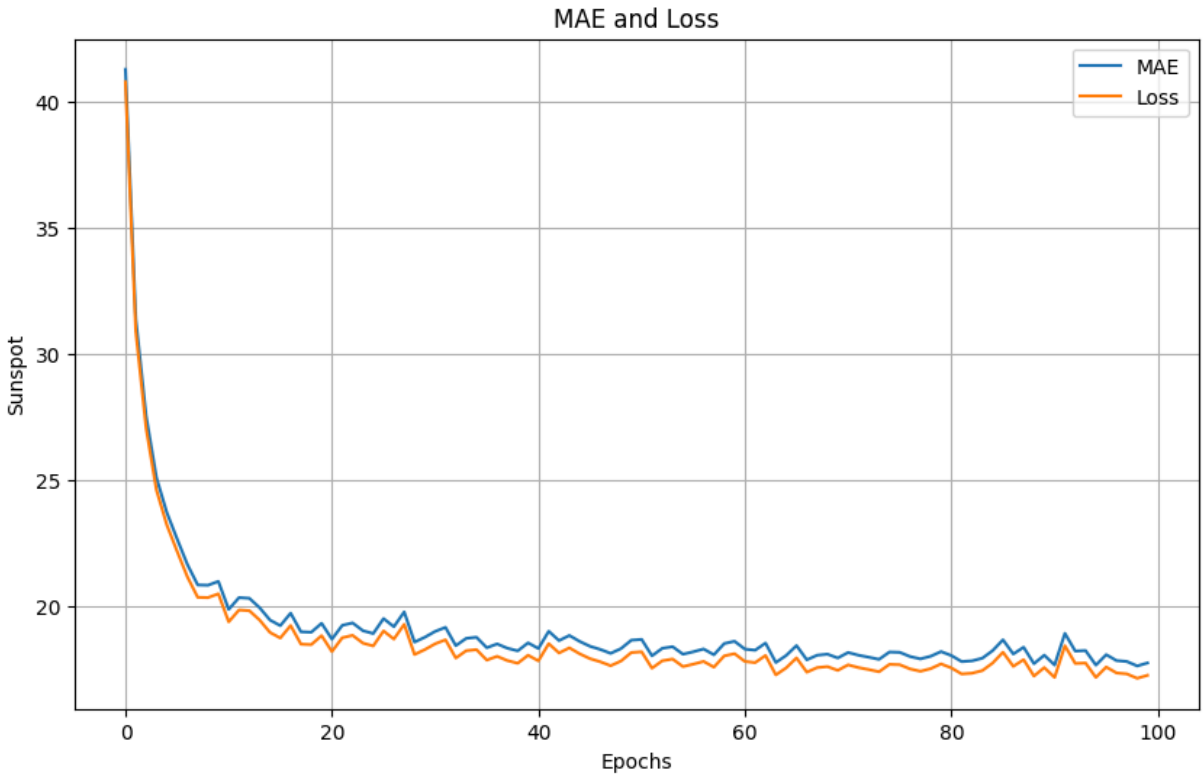
In [28]:
```
visualize_evaluation(history_LSTM)
```





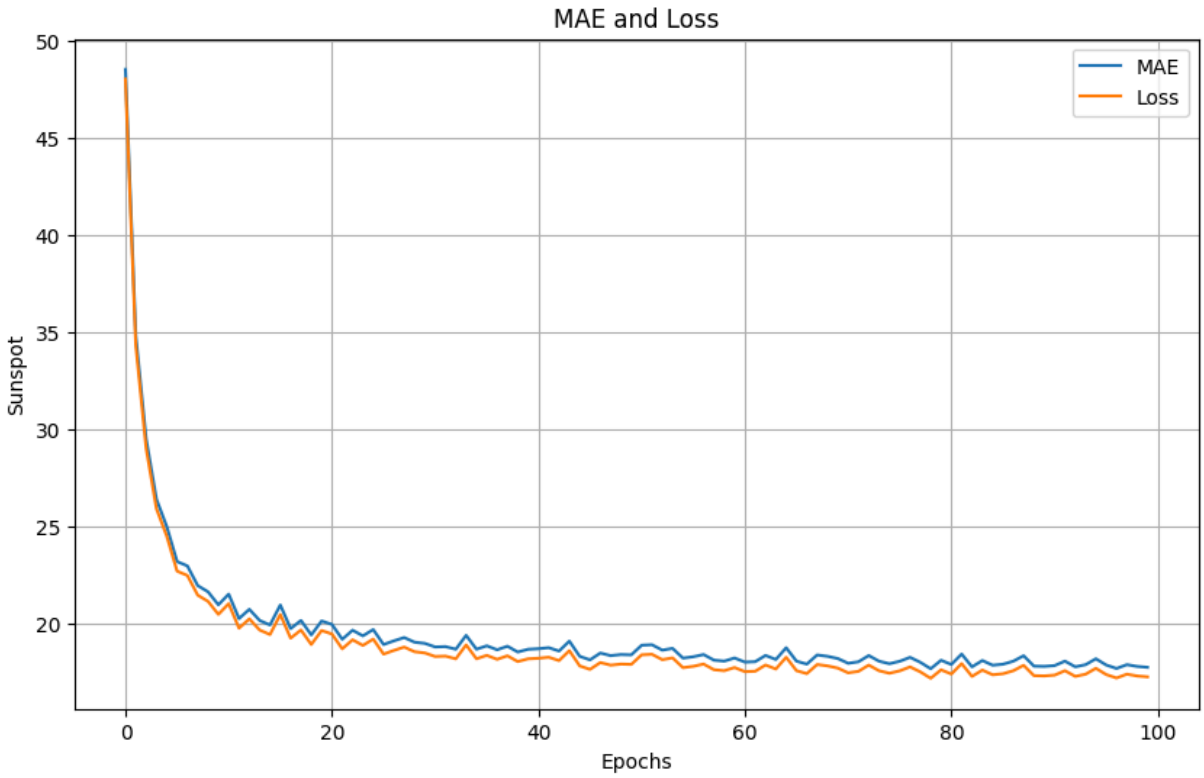
GRU Evaluation

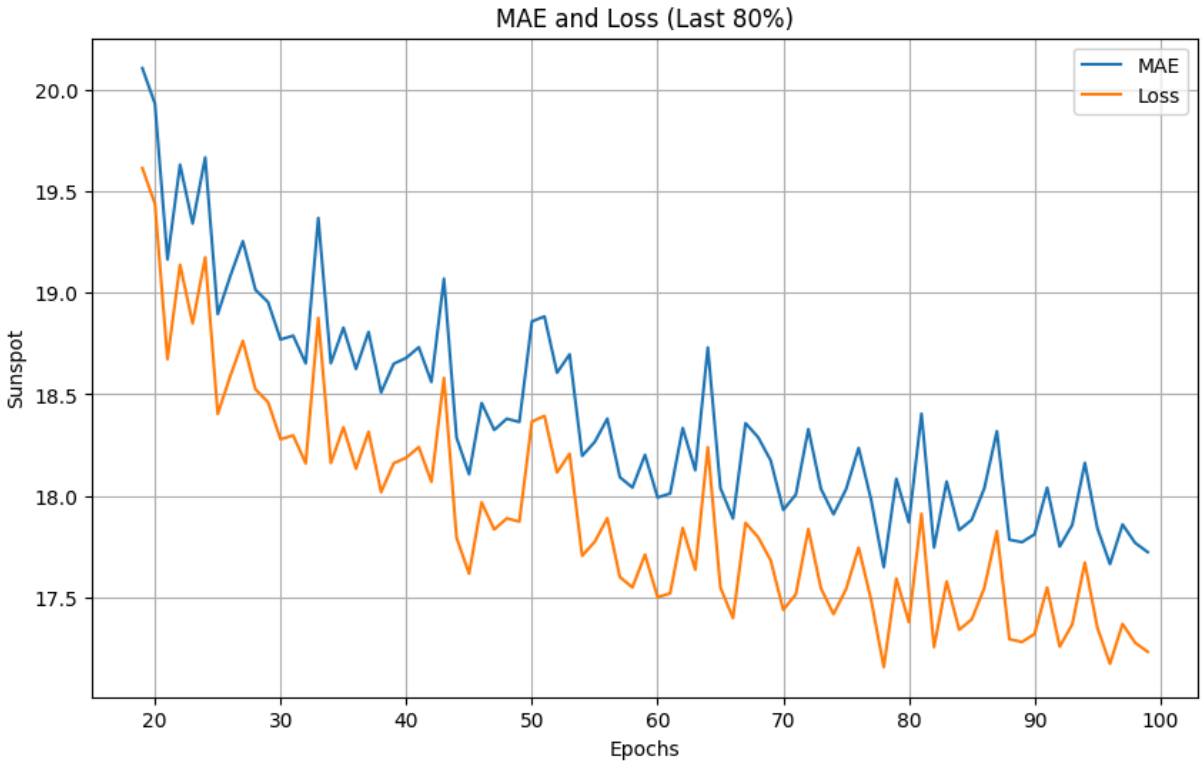
In [29]:
```
visualize_evaluation(history_GRU)
```



RNN-LSTM Evaluation

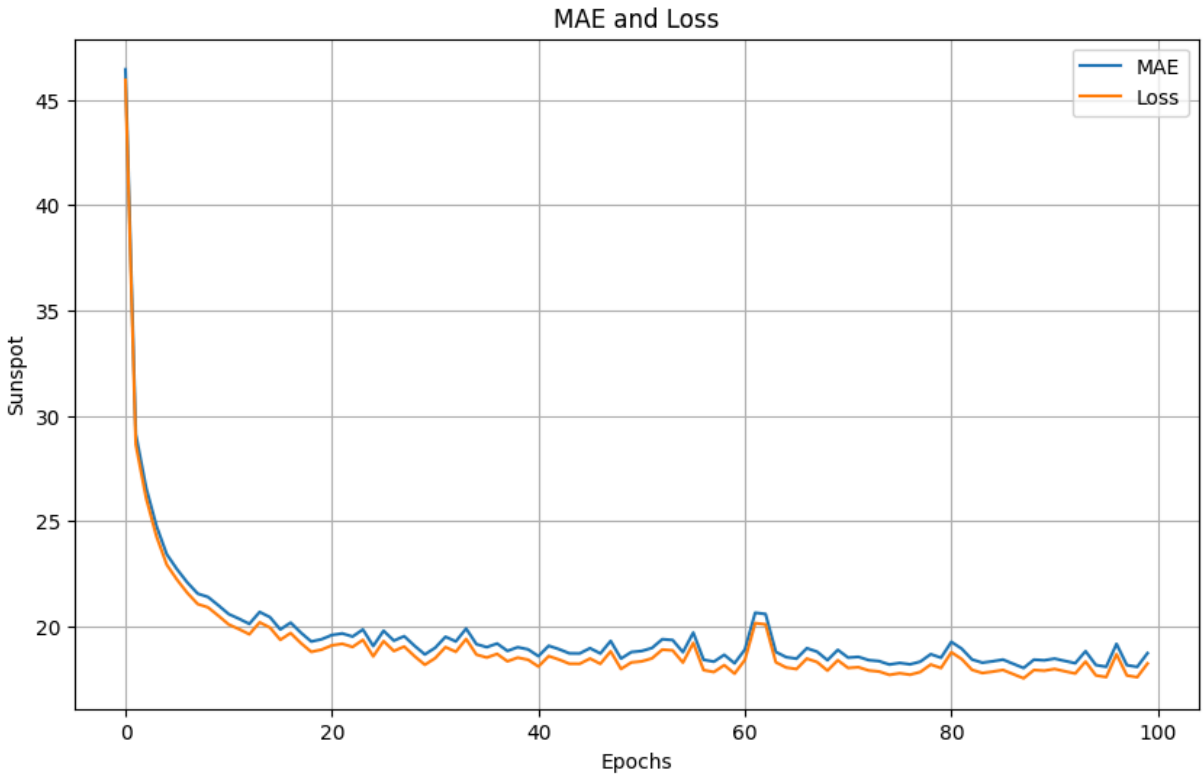
In [30]:
```
visualize_evaluation(history_RNN_LSTM)
```

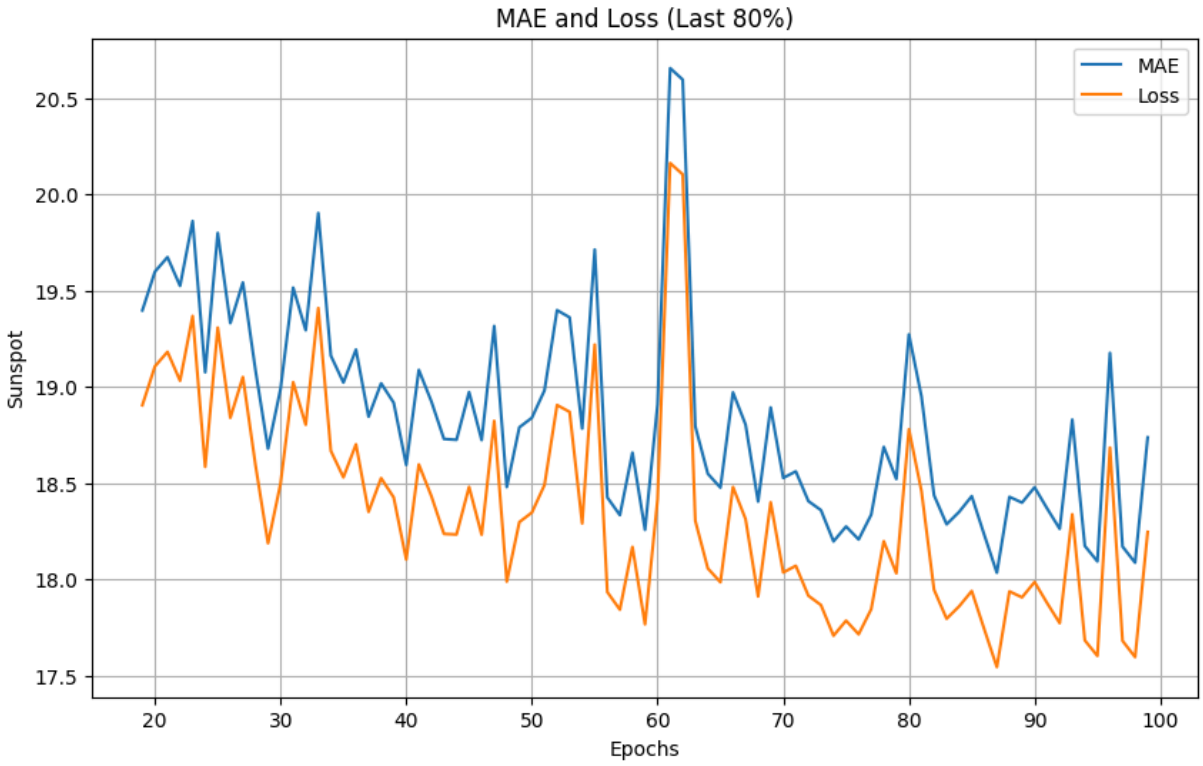




RNN-GRU Evaluation

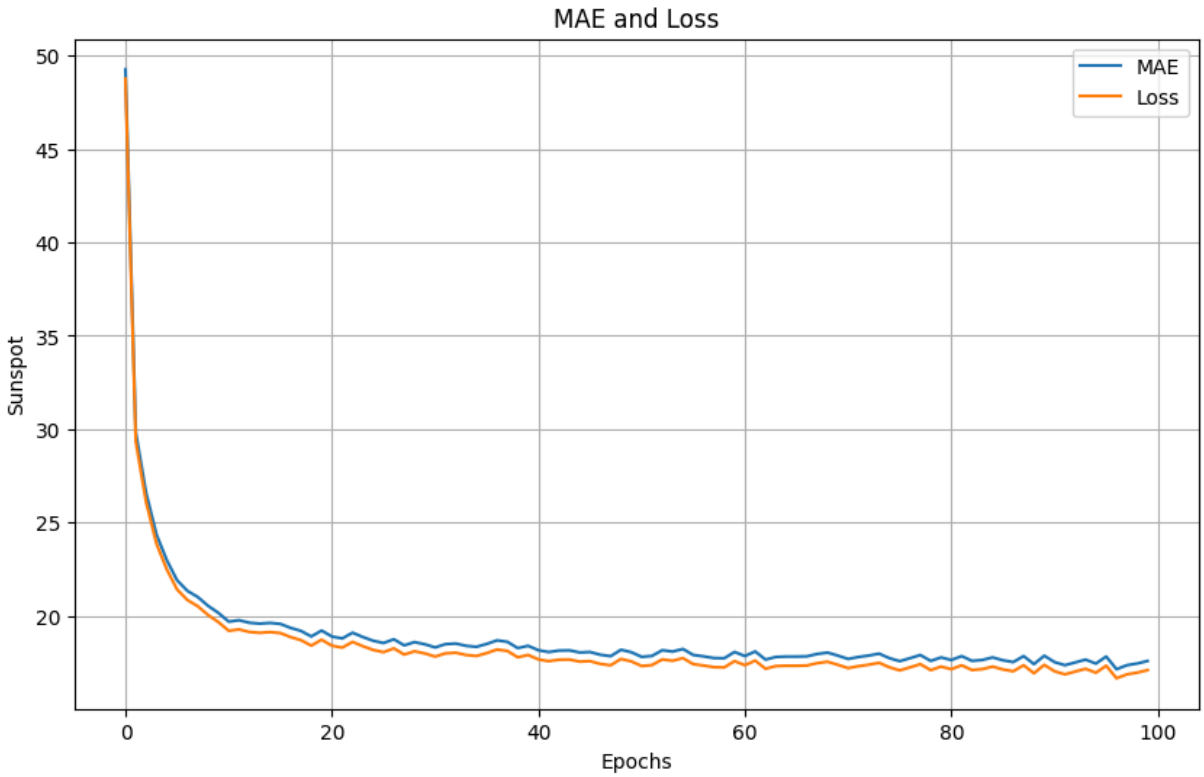
In [31]:
```
visualize_evaluation(history_RNN_GRU)
```

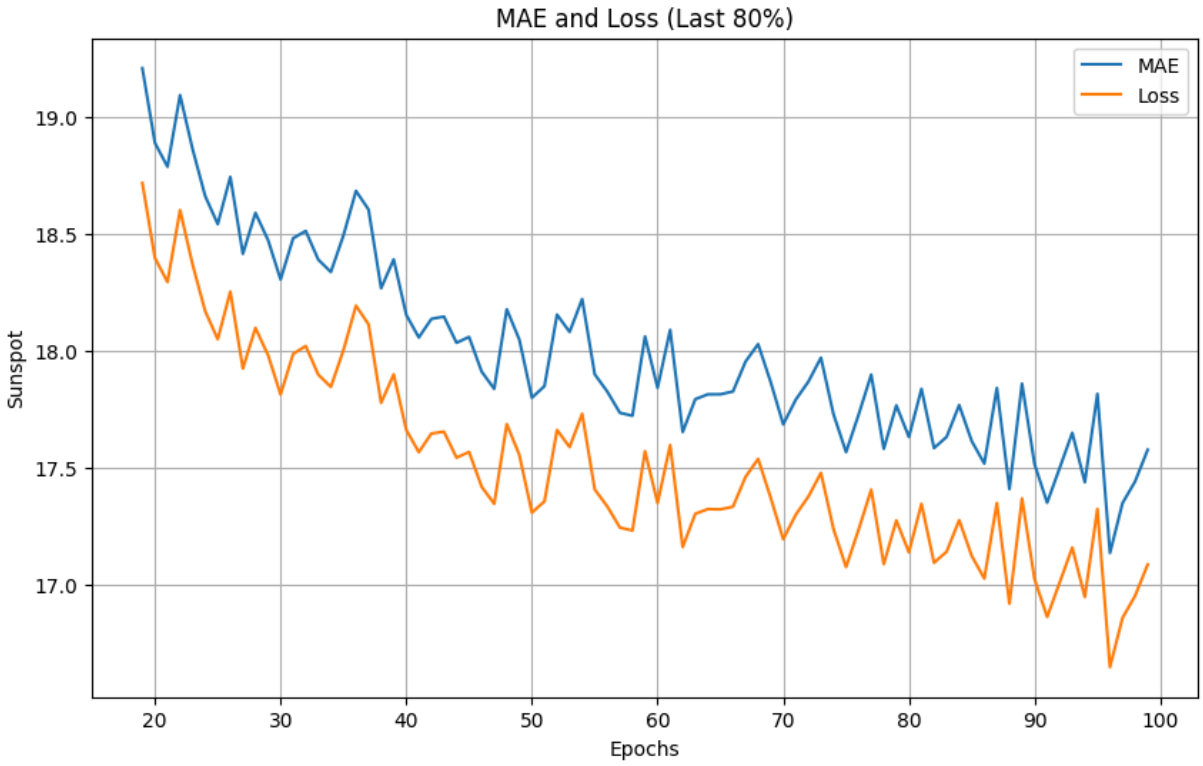




LSTM-RNN Evaluation

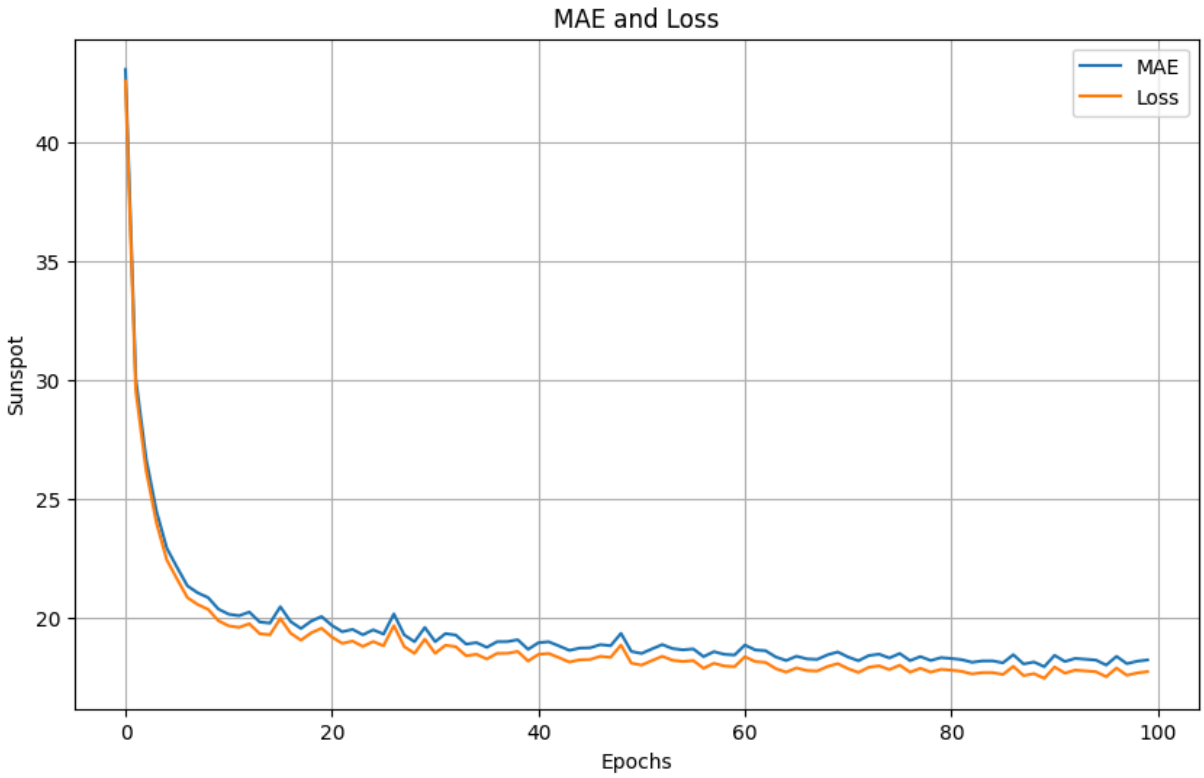
In [32]:
```
visualize_evaluation(history_LSTM_RNN)
```





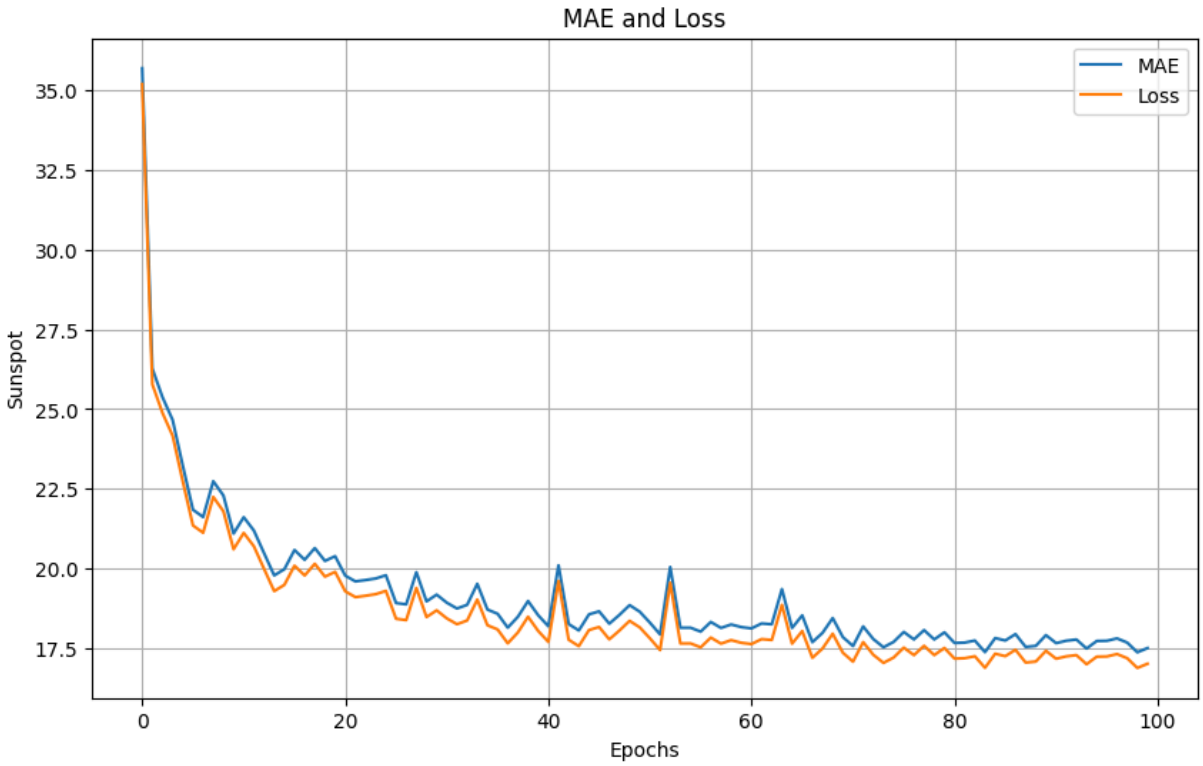
LSTM-GRU Evaluation

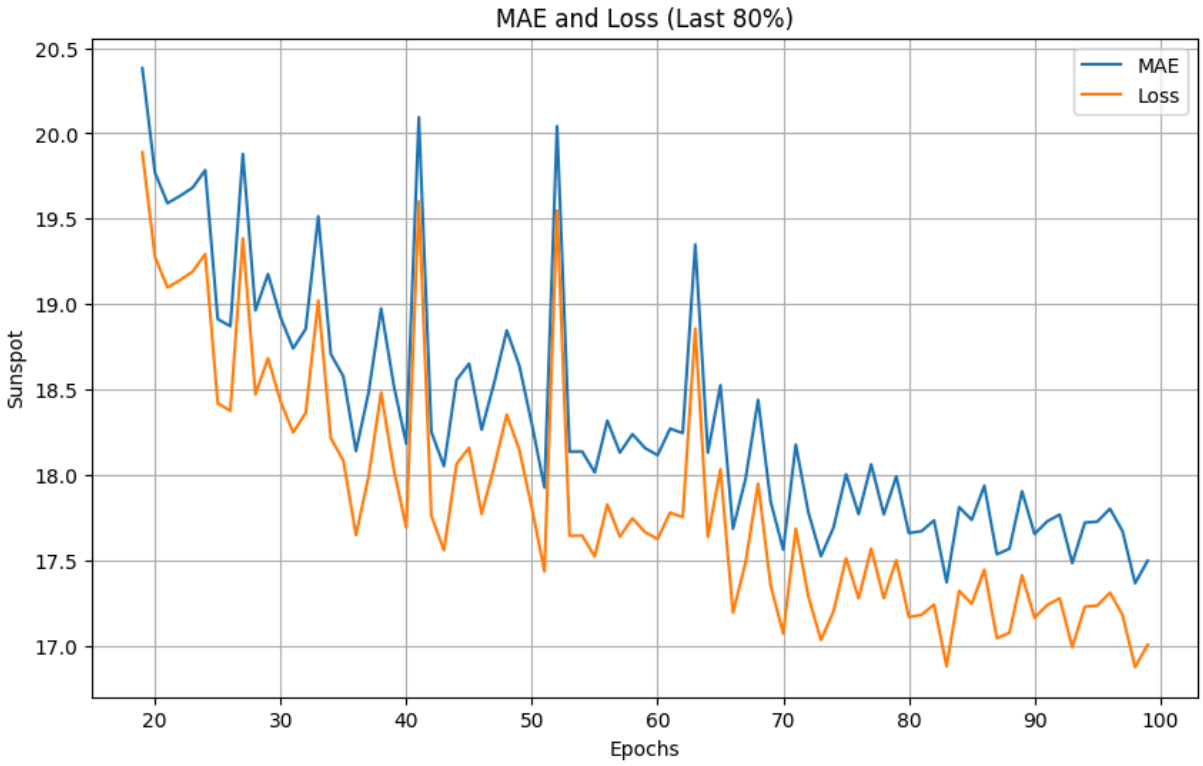
In [33]:
```
visualize_evaluation(history_LSTM_GRU)
```



GRU-RNN Evaluation

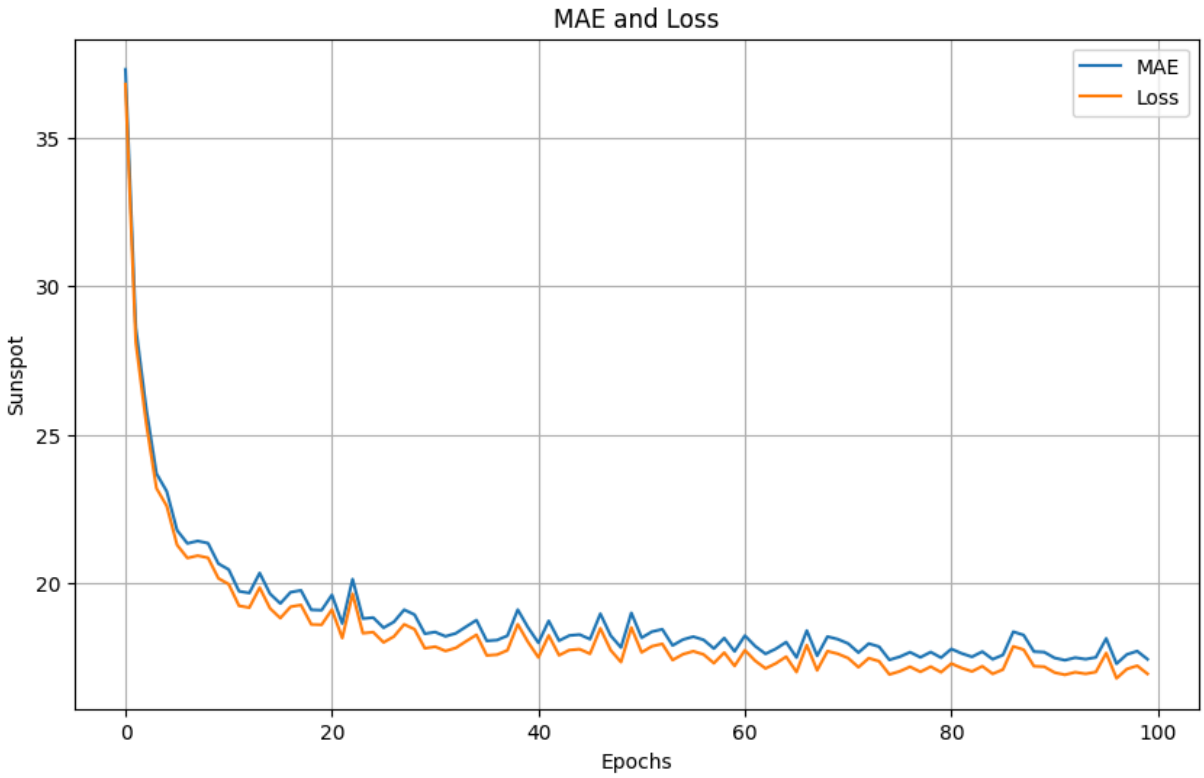
In [34]:
```
visualize_evaluation(history_GRU_RNN)
```

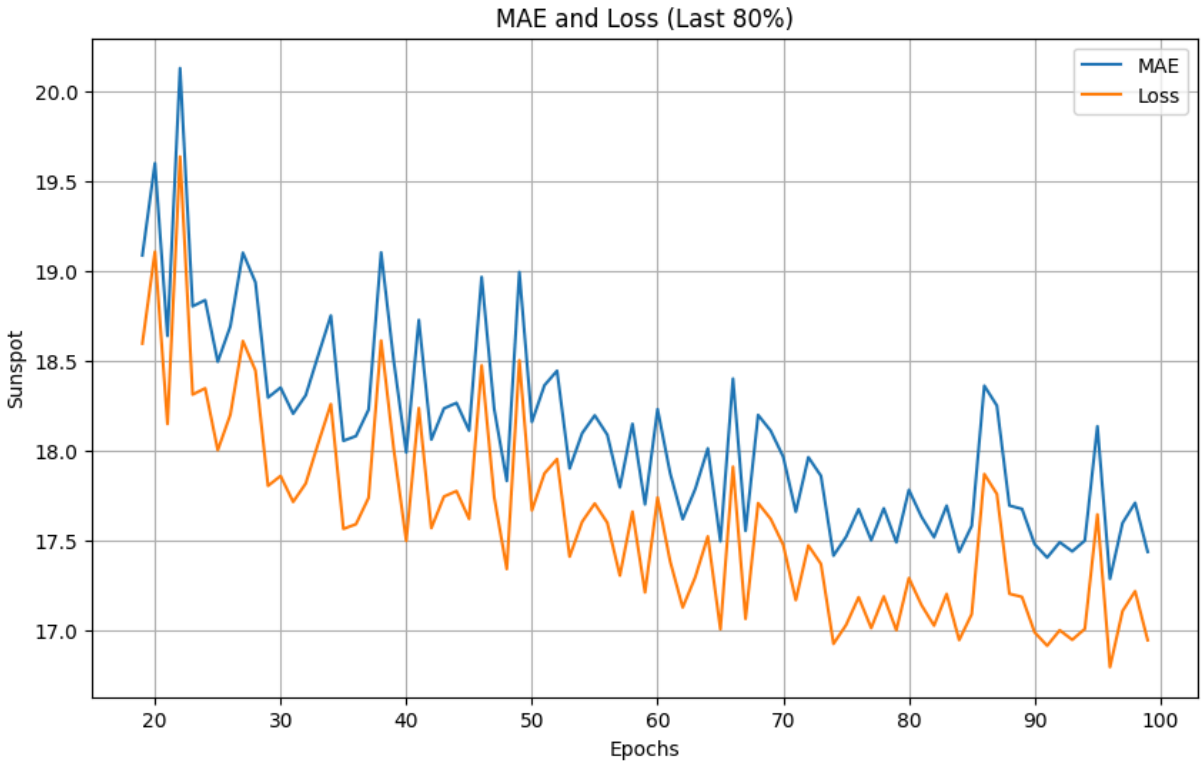




GRU-LSTM Evaluation

In [36]:
```
visualize_evaluation(history_GRU_LSTM)
```





7. Model Prediction

Analysis outcome of clustering for whale transaction characteristic

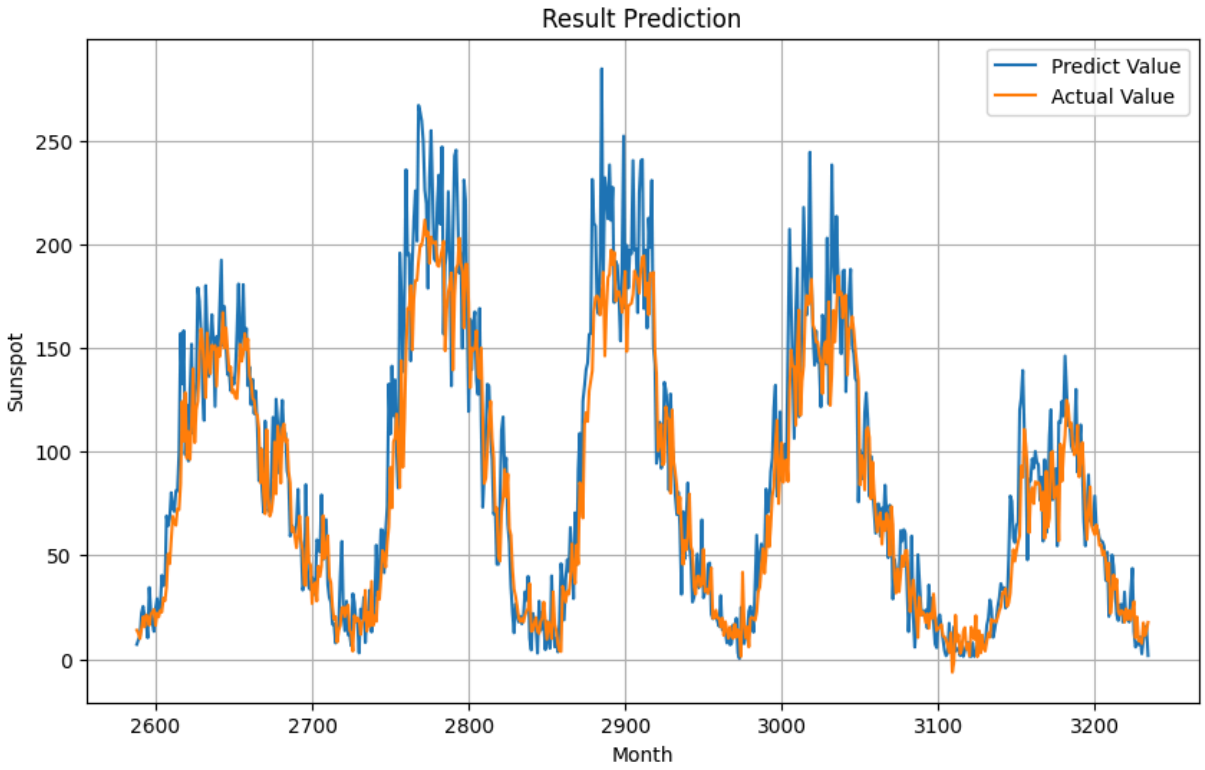
In [37]:
```
def model_forecast(model, series, window_size, batch_size):
    dataset = tf.data.Dataset.from_tensor_slices(series)
    dataset = dataset.window(window_size, shift=1, drop_remainder=True)
    dataset = dataset.flat_map(lambda w: w.batch(window_size))
    dataset = dataset.batch(batch_size).prefetch(1)
    forecast = model.predict(dataset)
    return forecast
```

In [38]:
```
def predict(model):
  forecast_series = series[split_time-window_size:-1]
  forecast = model_forecast(model, forecast_series, window_size, batch_size)
  results = forecast.squeeze()
  plot_series(time_valid, (x_valid, results, ), title='Result Prediction',
  xlabel='Month',
  ylabel='Sunspot',
  legend=['Predict Value', 'Actual Value'])
```

RNN Prediction

In [39]:
```
predict(model_RNN)
```

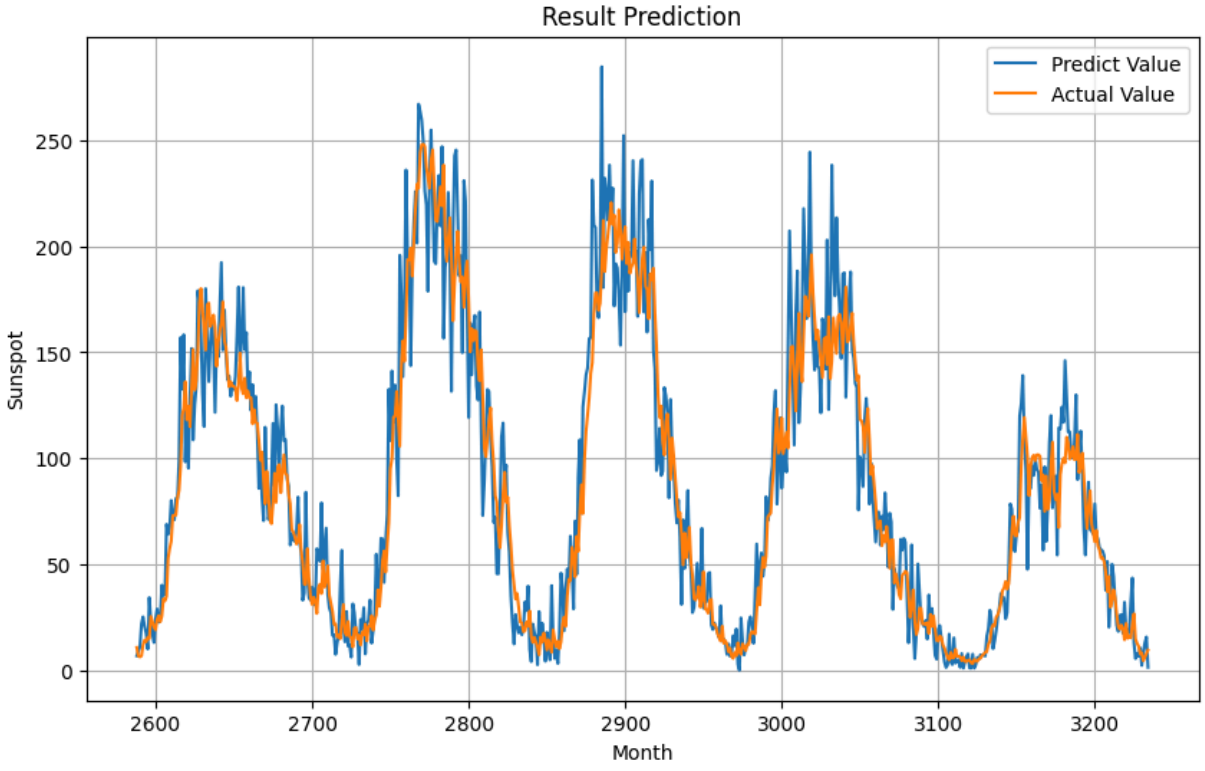
```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 21ms/step
```



LSTM Prediction

In [40]:
```
predict(model_LSTM)
```

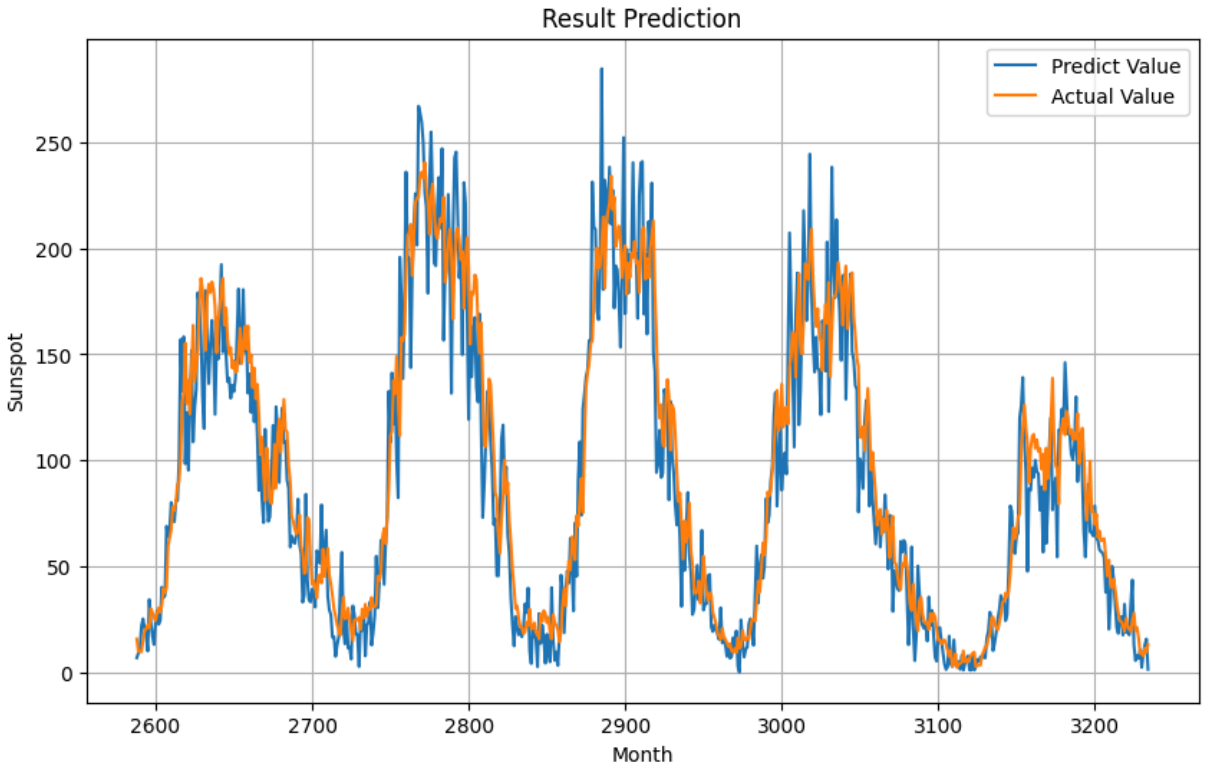
```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 44ms/step
```



GRU Prediction

In [41]:
```
predict(model_GRU)
```

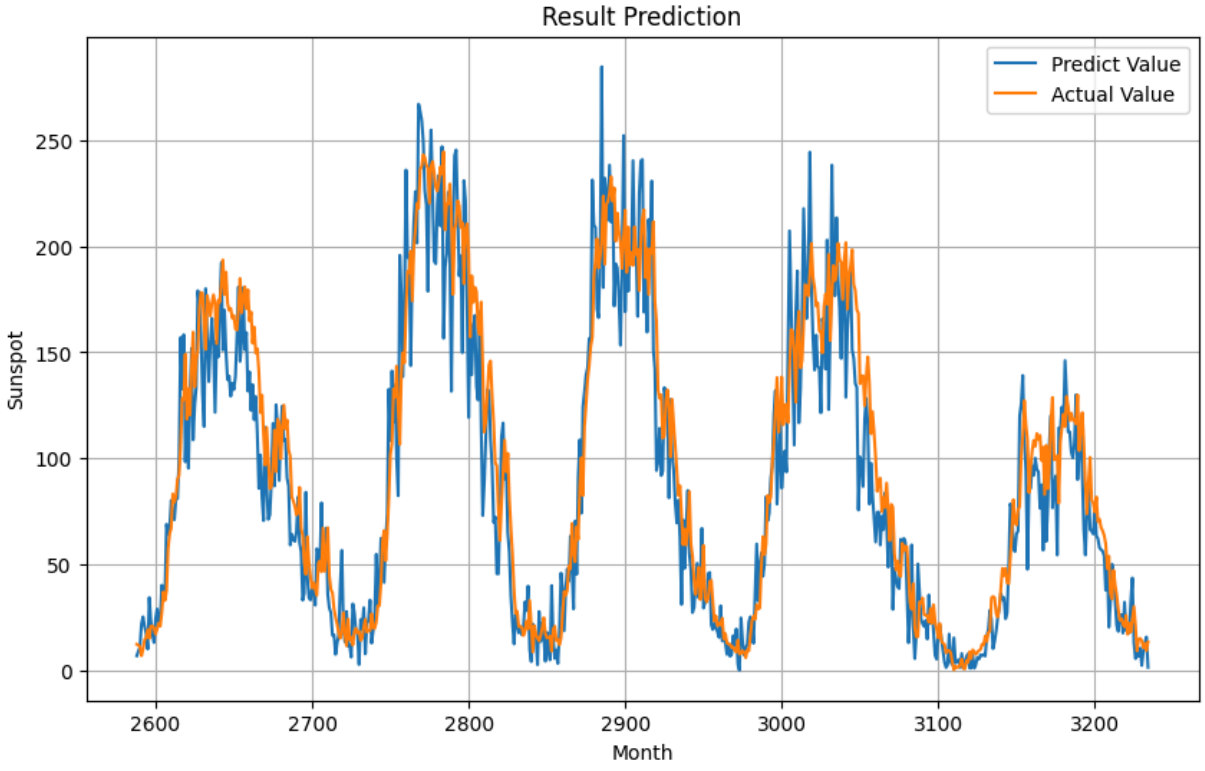
```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 30ms/step
```



RNN-LSTM Prediction

In [42]:
```
predict(model_RNN_LSTM)
```

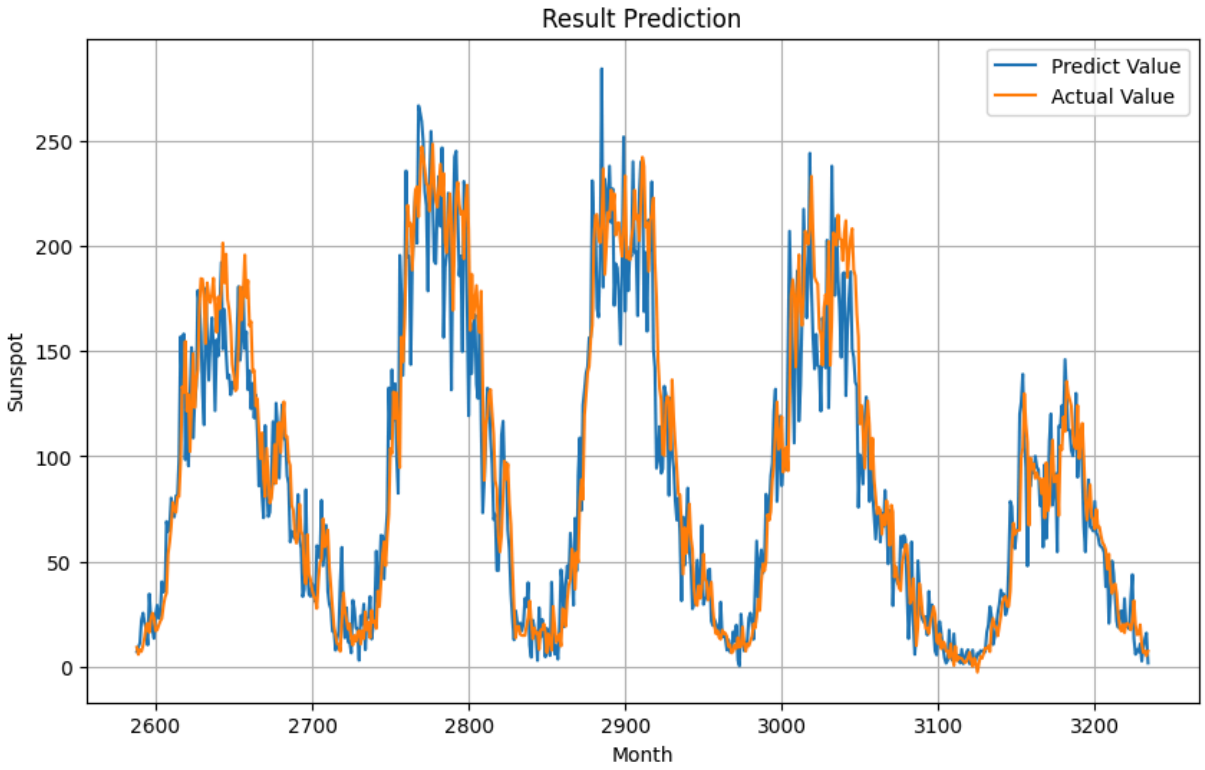
```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 26ms/step
```



RNN-GRU Prediction

In [43]:
```
predict(model_RNN_GRU)
```

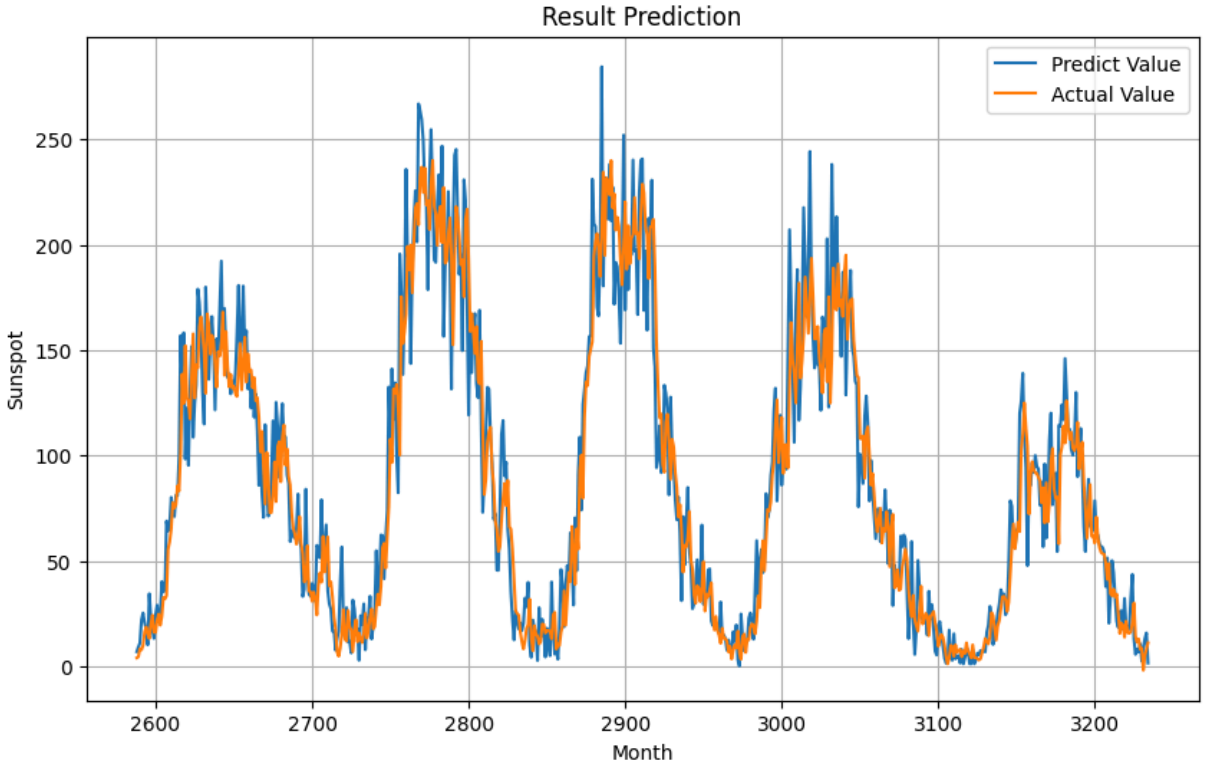
```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 27ms/step
```



LSTM-RNN Prediction

In [44]:
```
predict(model_LSTM_RNN)
```

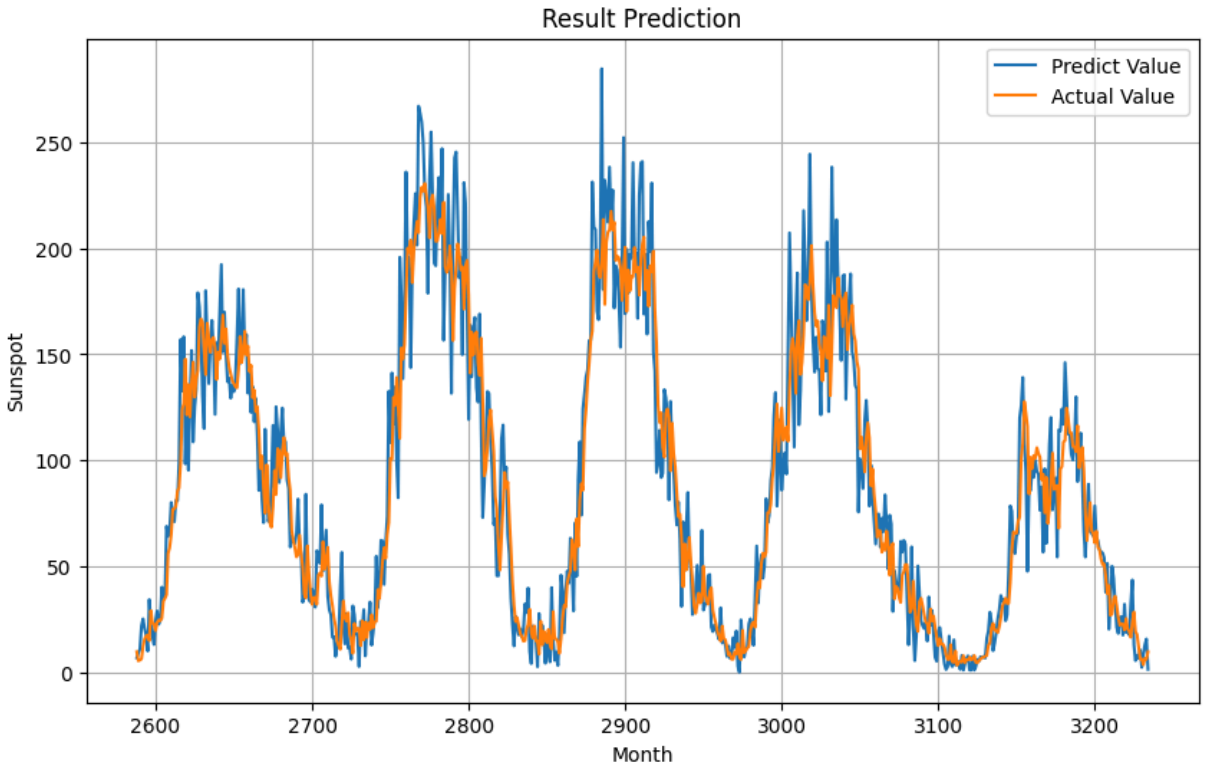
```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 27ms/step
```



LSTM-GRU Prediction

In [45]:
```
predict(model_LSTM_GRU)
```

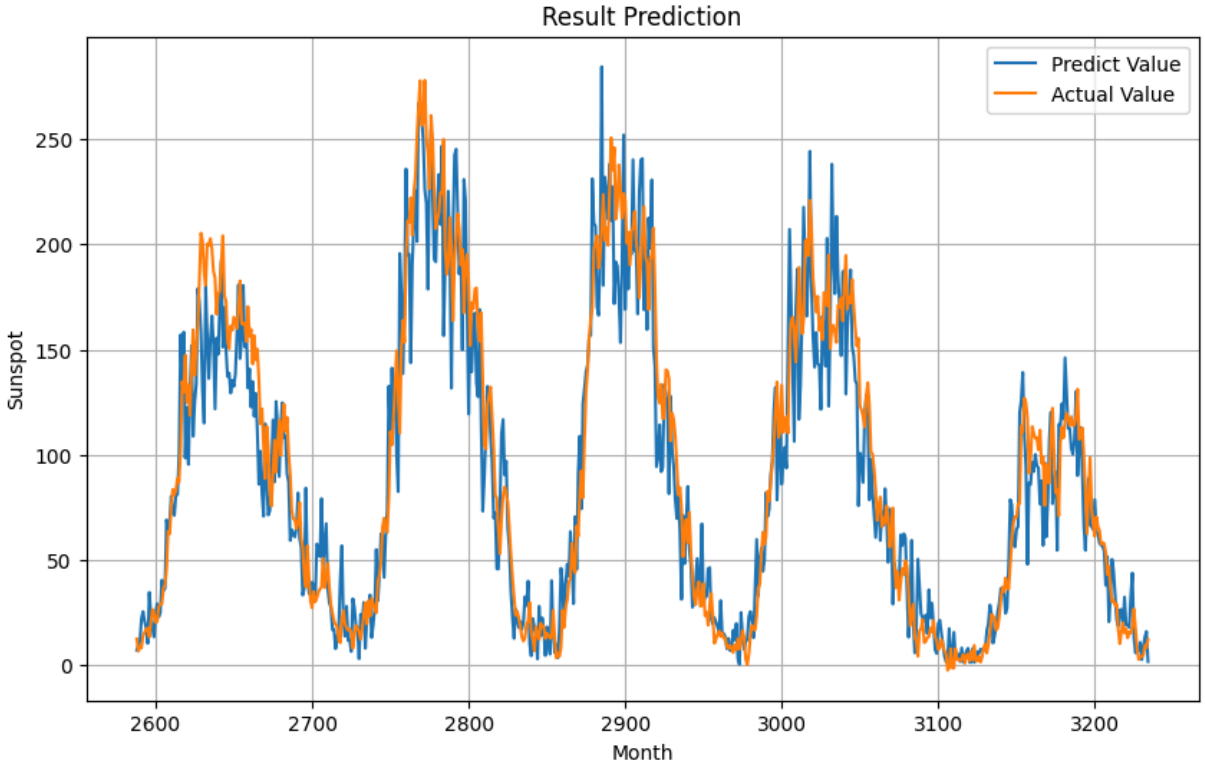
```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 31ms/step
```



GRU-RNN Prediction

In [46]:
```
predict(model_GRU_RNN)
```

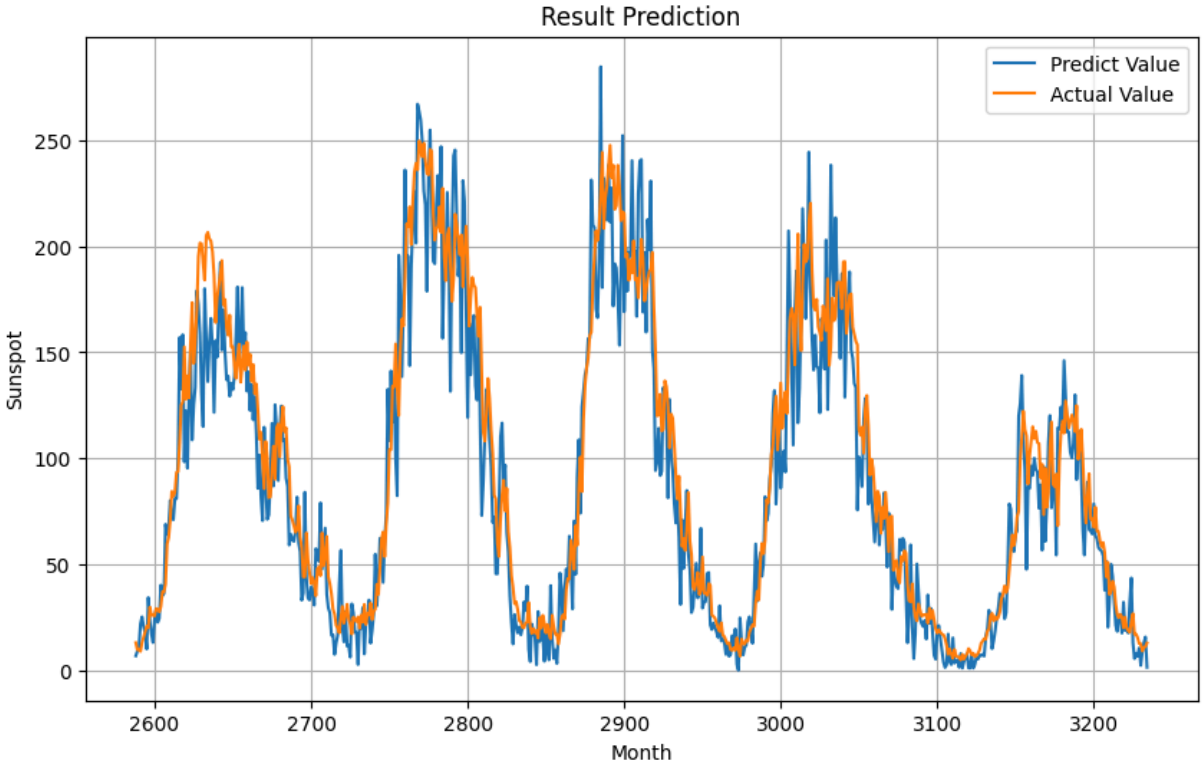
```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 25ms/step
```



GRU-LSTM Prediction

In [47]:
```
predict(model_GRU_LSTM)
```

```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 30ms/step
```


Result Prediction
Predict Value
Actual Value
Sunspot
Month
0
50
100
150
200
250
2600
2700
2800
2900
3000
3100
3200

Confident Interval

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import files
import time
```

Donwload Data

In [ ]:
```
!gdown 1tPJuX6Fe-PXCxzLE-xw9jxnWwUErcA4F
!gdown 1wFyMh0P9bT08fdaB1AoVv6tDvPSuYY8d
!gdown 1HmdOvr2q03rC4w7qEAdNqYWjJK7gXhHD
!gdown 1JkwqKnS0ubAns2XJH_A8lHbOE8-ThOhx
!gdown 1JnE3zsGCpFG9eFK4c9meG7Ox0zF7p5Ao
!gdown 10s6qULX0pCdZsXqiVVaqHoyUuOdlzzls
!gdown 1cG7s3oX6jHgKcTdfAJ8J1O1XKTq38KeN
!gdown 1CKUWag2iDSmHlYdaYiGIFd6_E8zjli7c
!gdown 1p-EagHjp7NyEVGNXM3mStH5QAXGpN-gI
```

In [ ]:
```
!gdown 1IZId_e5nCMviLsGv9aM3nyaDQmEqYjLq
!gdown 13H7TwY8WZLF6Xd9I0ZZtS1orAGhKM4lC
!gdown 1nyVHyU8D7vRyMBXsQ4xQxcGaw1uSiCIK
!gdown 1fnLwDBh8FfROEK9JJsJsUMWb4_FST0Mh
!gdown 1kXFAubzTacey_WrduvpAkysM8N9iLw6F
!gdown 1Kyt7pNxSQpPjQCRxbMzqUNuYjv8qASnM
!gdown 1B4fj3dEbEeByqF1vUs-r2bQNJ2jFScou
!gdown 1_-e4A9LH13DVTbNLz-cFbunZo1iuYMHB
!gdown 11Mr2-77o-UwP5uxI3n5VwcJlWZac8-hx
```

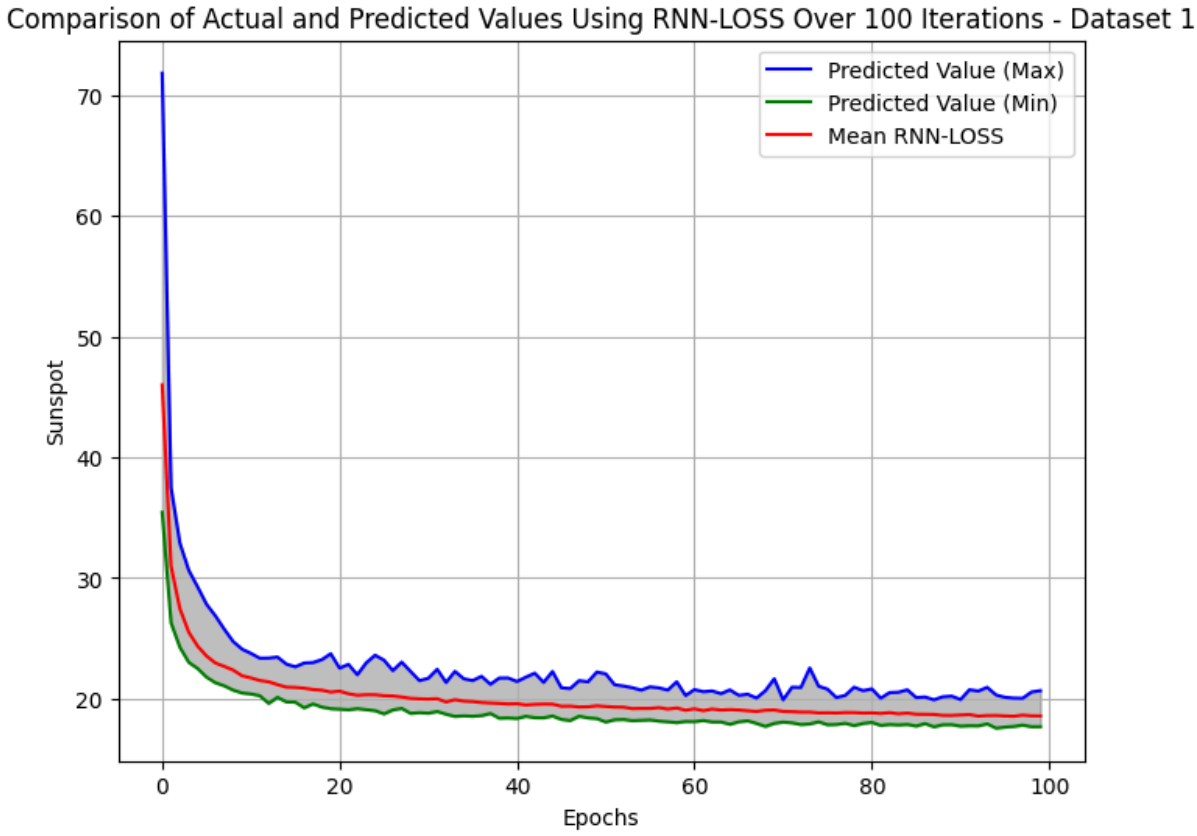
Viz

In [ ]:
```
from re import X
def shade_plot(temp, x_valid='0', line='MAE', predict=''):
  import matplotlib.pyplot as plt

  if predict == '':
    redline = f'Mean {line}'
    axis = 'Epochs'
  else:
    redline = 'Actual Value'
    axis = 'Days'

  #SORT
  temp = temp.apply(lambda x: x.sort_values().reset_index(drop=True))

  #CUT 2.5%
  n = int(len(temp) * 0.025)
  temp = temp.iloc[n:-n]

  batas_atas = temp.max().tolist()
  batas_bawah = temp.min().tolist()
  rata = temp.mean().tolist()

  # Replace these lists with your actual data
  # Dataset 1
  x1 = [i for i in range(0,len(batas_atas))]
  y1 = batas_atas

  # Dataset 2
  x2 = [i for i in range(0,len(batas_bawah))]
  y2 = batas_bawah

  if(x_valid=='0'):
```

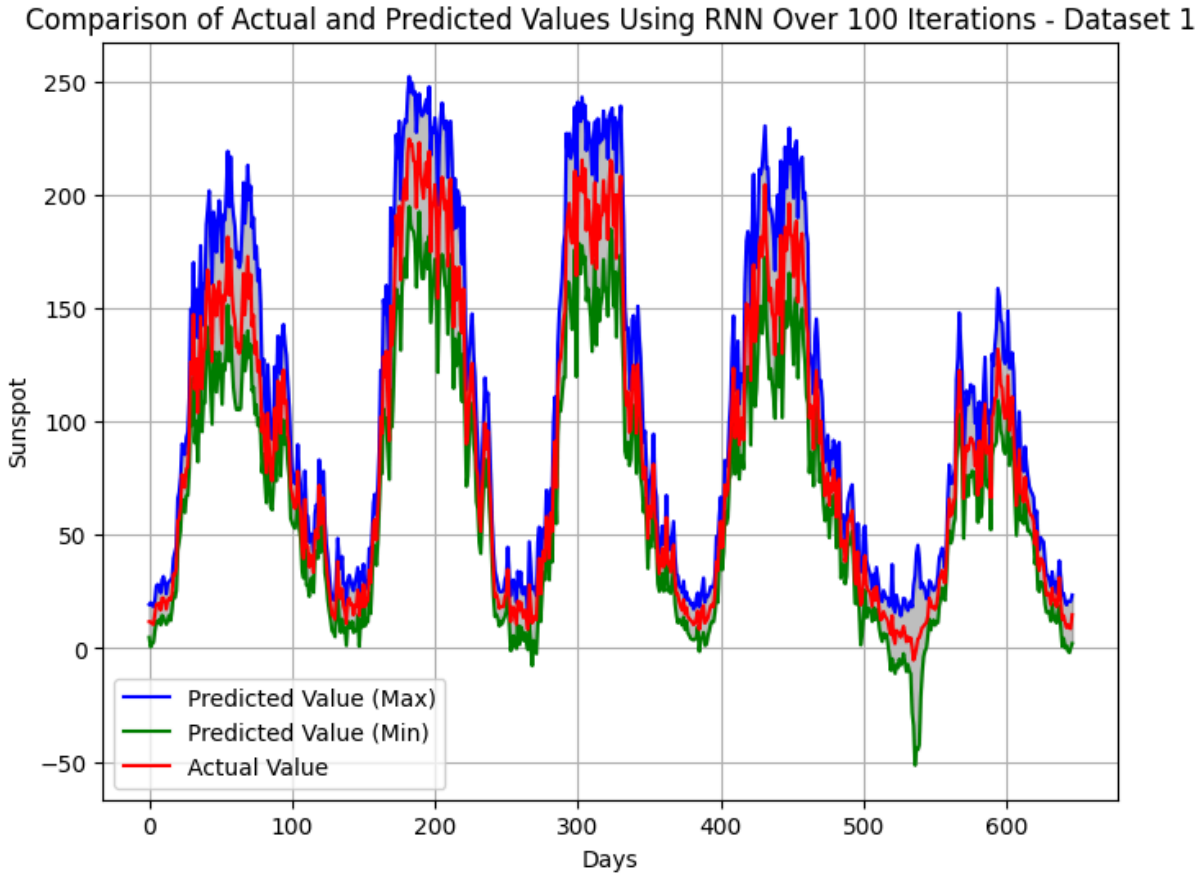
```
    # Dataset 3
    x3 = [i for i in range(0,len(rata))]
    y3 = rata
  else:
    x3 = [i for i in range(0,len(x_valid))]
    y3 = x_valid

  # Create the plot
  plt.figure(figsize=(8, 6))

  # Plot the first linear dataset
  plt.plot(x1, y1, label=f'Predicted Value (Max)', color='blue')

  # Plot the second linear dataset
  plt.plot(x2, y2, label=f'Predicted Value (Min)', color='green')

  plt.plot(x3, y3, label=f'{redline}', color='red')

  # Create a mask for the shaded area where y1 >= y2
  mask = [y1_val >= y2_val for y1_val, y2_val in zip(y1, y2)]

  # Shade the area between the two datasets
  plt.fill_between(x1, y1, y2, where=mask, interpolate=True, color='gray', alpha=0.5)

  # Add labels and legend
  plt.xlabel(f'{axis}')
  plt.ylabel('Sunspot')
  plt.title(f'Comparison of Actual and Predicted Values Using {line} Over 100 Iterations - Data
  plt.legend()
  plt.savefig(f"Predicted_Actual_Value_Dataset1_{line}.pdf", dpi=300)
  files.download(f"Predicted_Actual_Value_Dataset1_{line}.pdf")
  # Show the plot
  plt.grid(True)
  plt.show()
```

RNN

In [ ]:
```
temp = pd.read_excel('RNN_LOSS.xlsx')
shade_plot(temp, line = 'RNN-LOSS')
```

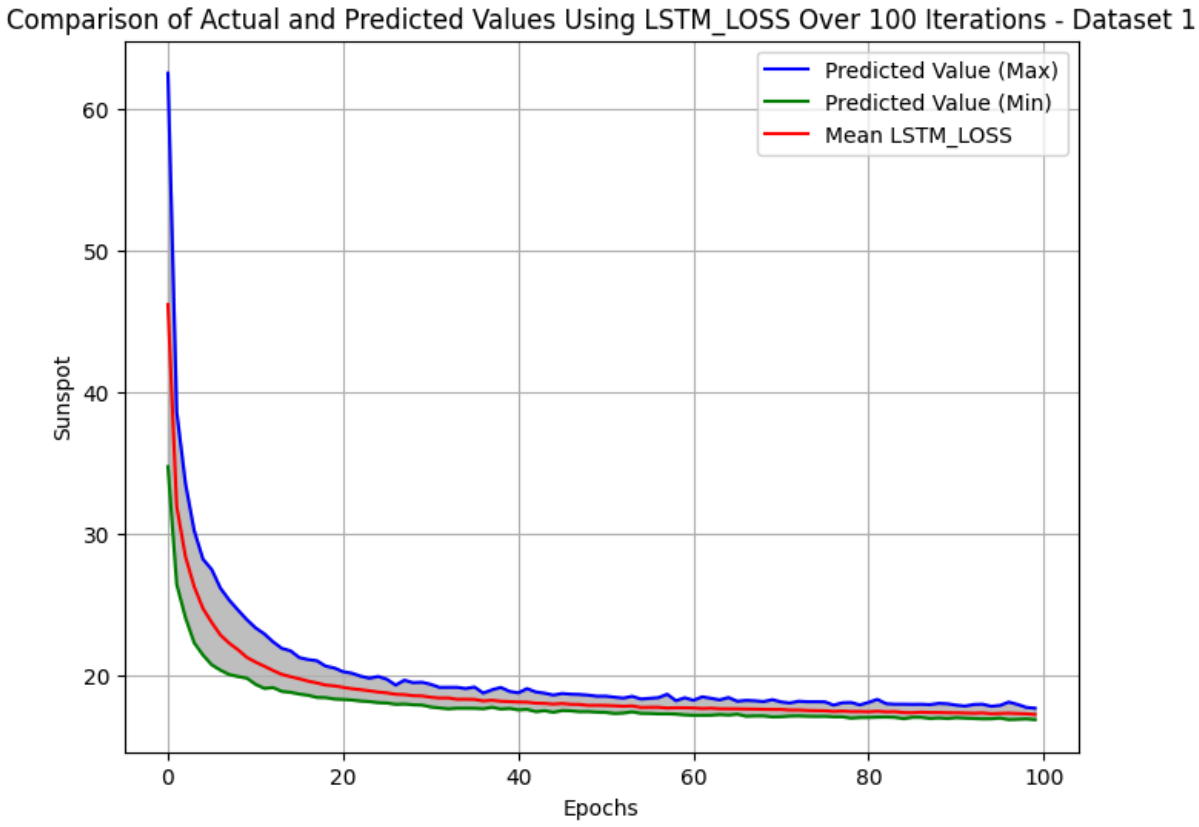


In [ ]:
```
temp = pd.read_excel('RNN_PREDICT.xlsx')
shade_plot(temp, line='RNN', predict='YES')
```

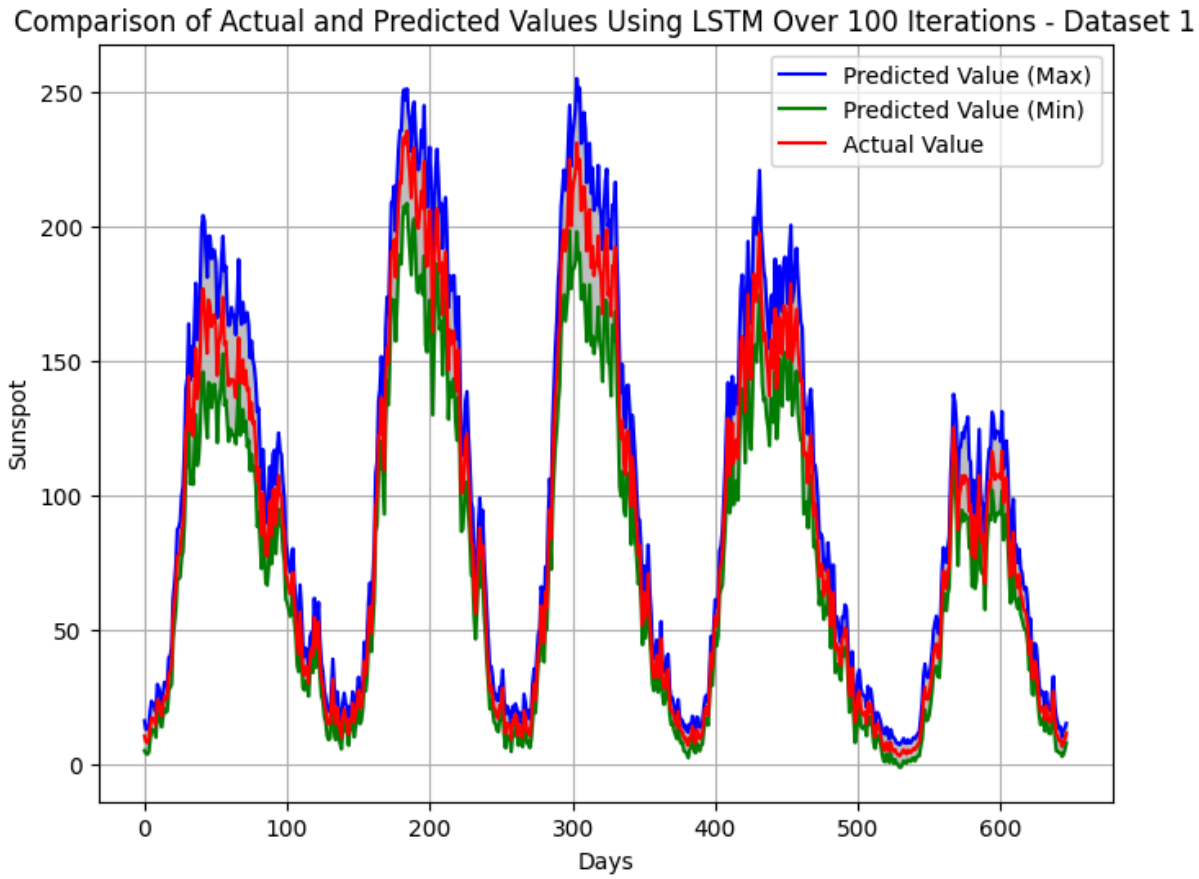


LSTM

In [ ]:
```
temp = pd.read_excel('LSTM_LOSS.xlsx')
shade_plot(temp, line = 'LSTM_LOSS')
```

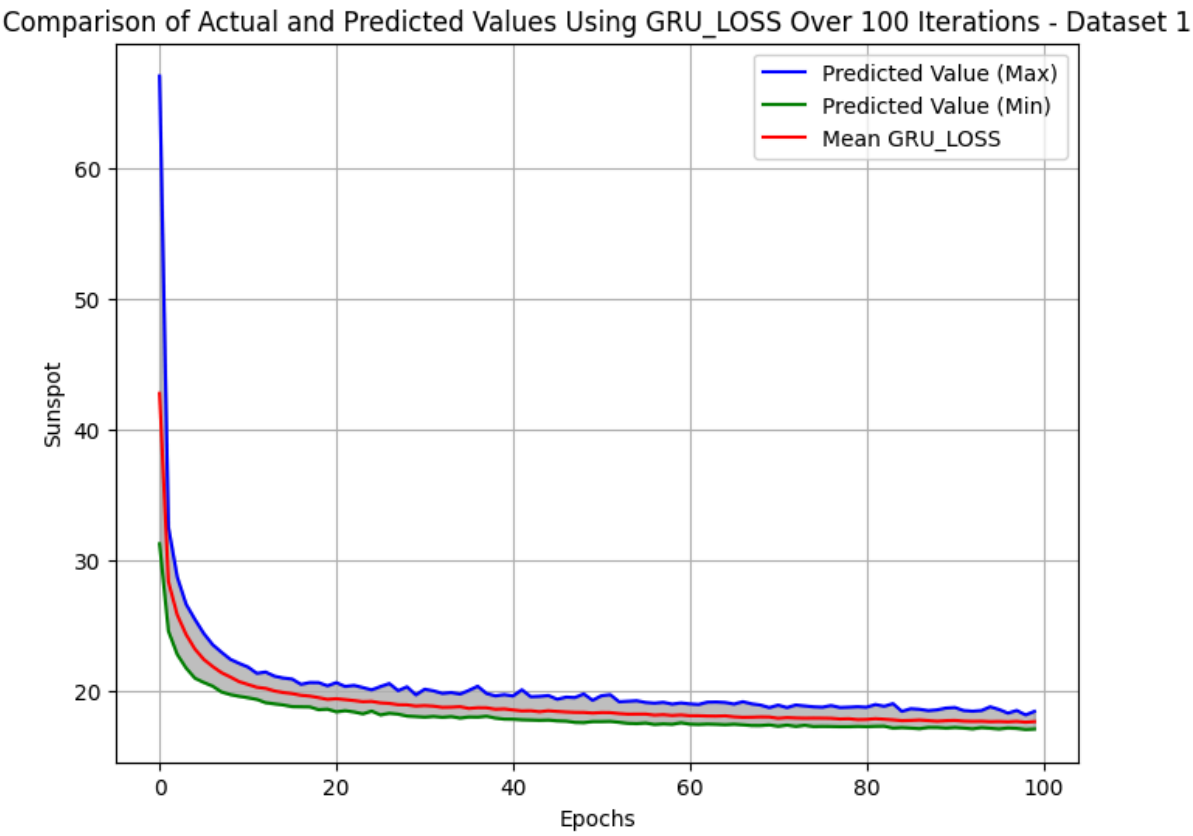


In [ ]:
```
temp = pd.read_excel('LSTM_PREDICT.xlsx')
shade_plot(temp, line='LSTM', predict='YES')
```

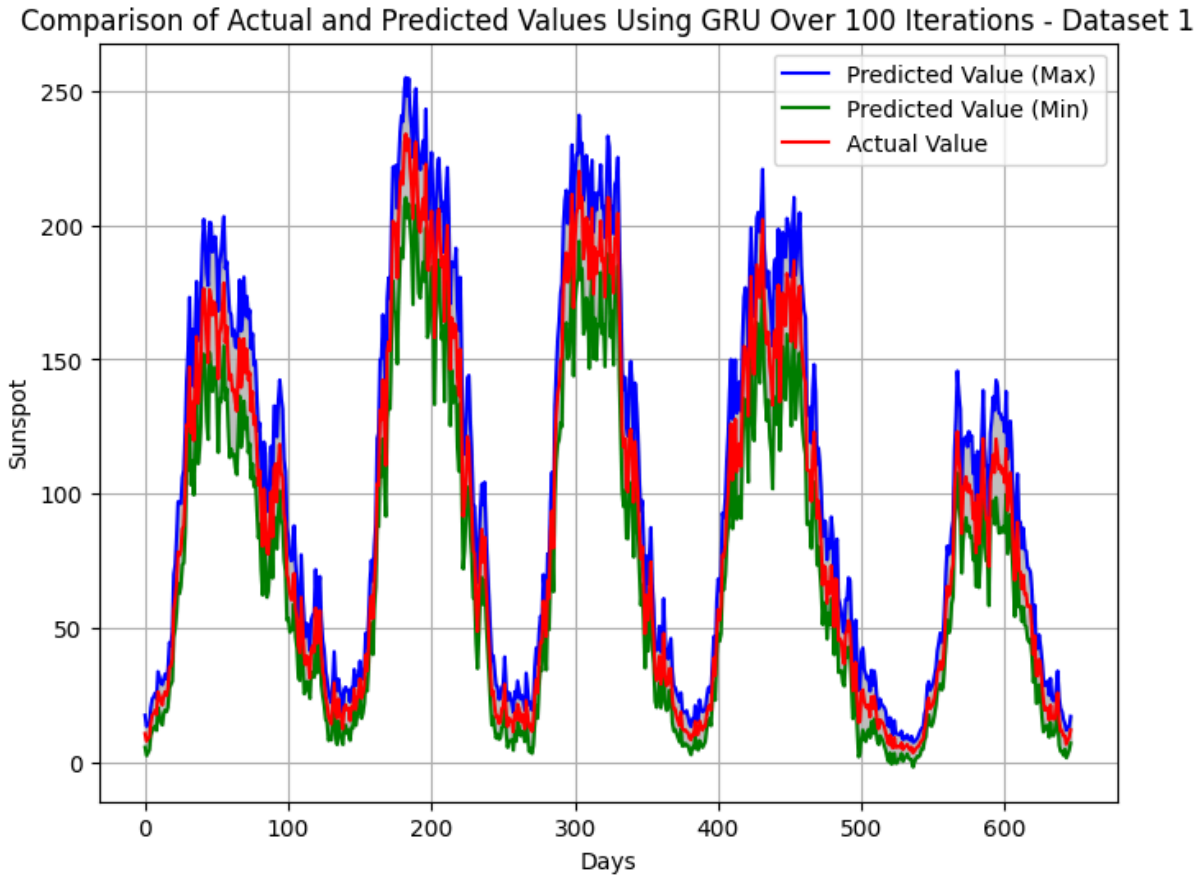


GRU

In [ ]:
```
temp = pd.read_excel('GRU_LOSS.xlsx')
shade_plot(temp, line = 'GRU_LOSS')
```



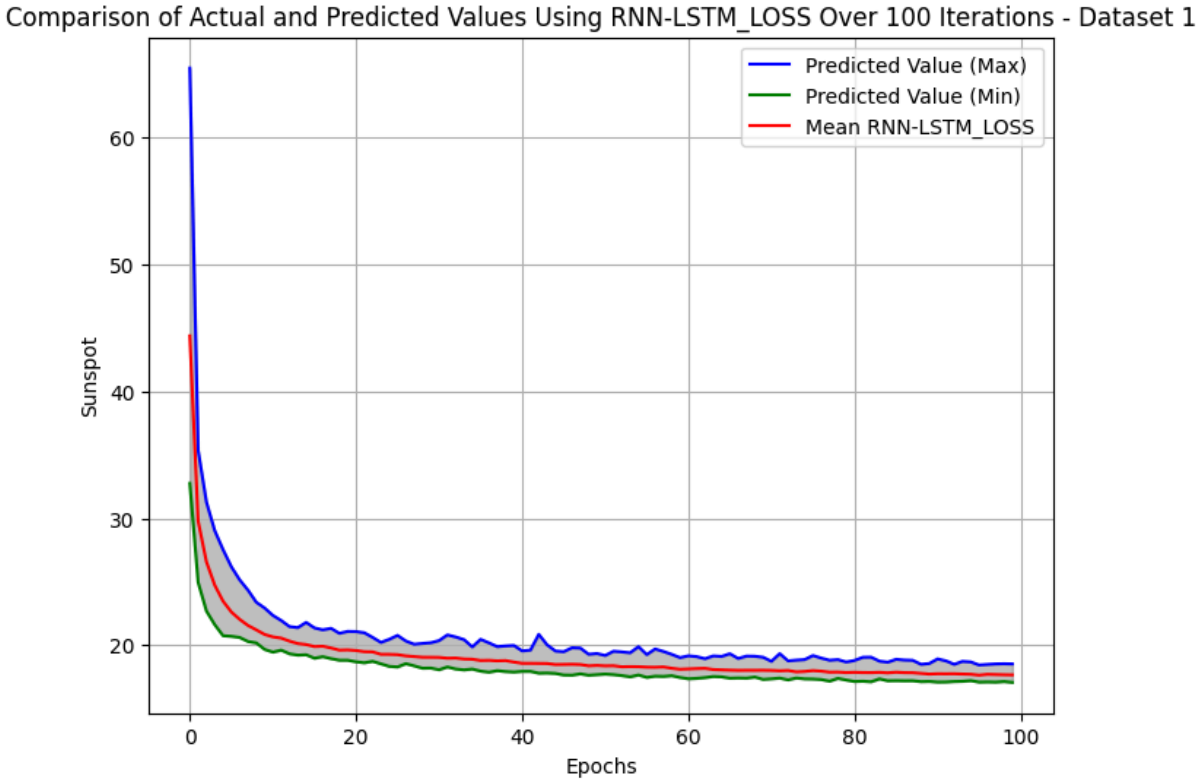
In [ ]:
```
temp = pd.read_excel('GRU_PREDICT.xlsx')
shade_plot(temp, line='GRU', predict='YES')
```



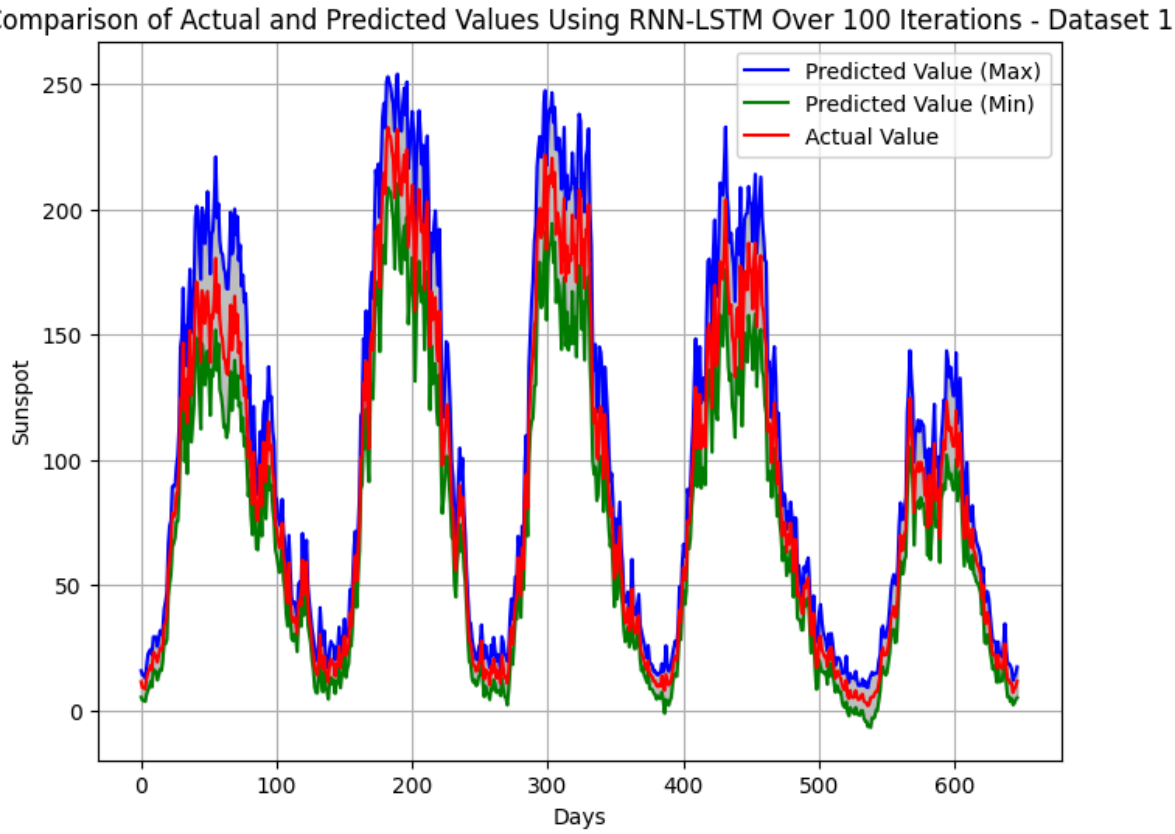
In [ ]:
```
!gdown 1Jcj7_vtMQ2foct0YPmWC6nO9q4T_x3bl
!gdown 1d-M7kCjRcggRBII-8o9WUhbWPaFxcPRg
```

RNN-LSTM

In [ ]:
```
temp = pd.read_excel('RNN-LSTM_LOSS.xlsx')
shade_plot(temp, line = 'RNN-LSTM_LOSS')
```

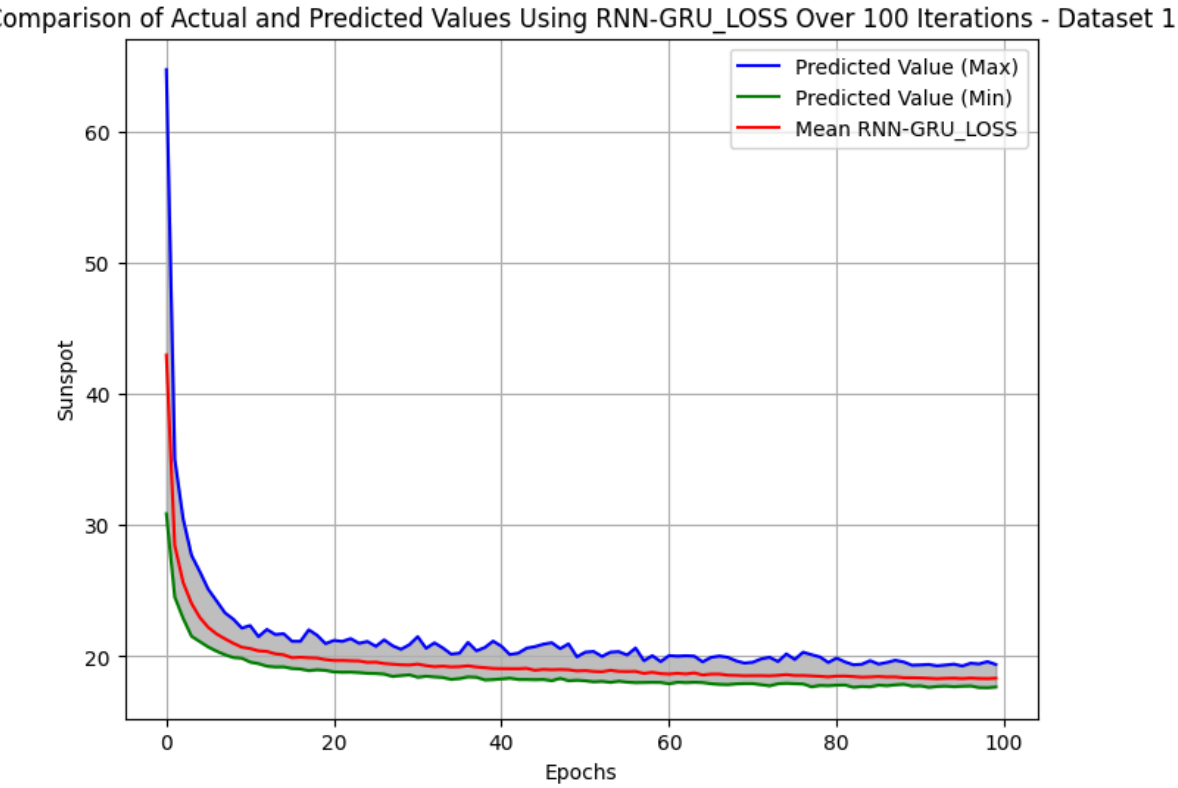


In [ ]:
```
temp = pd.read_excel('RNN-LSTM_PREDICT.xlsx')
shade_plot(temp, line='RNN-LSTM', predict='YES')
```

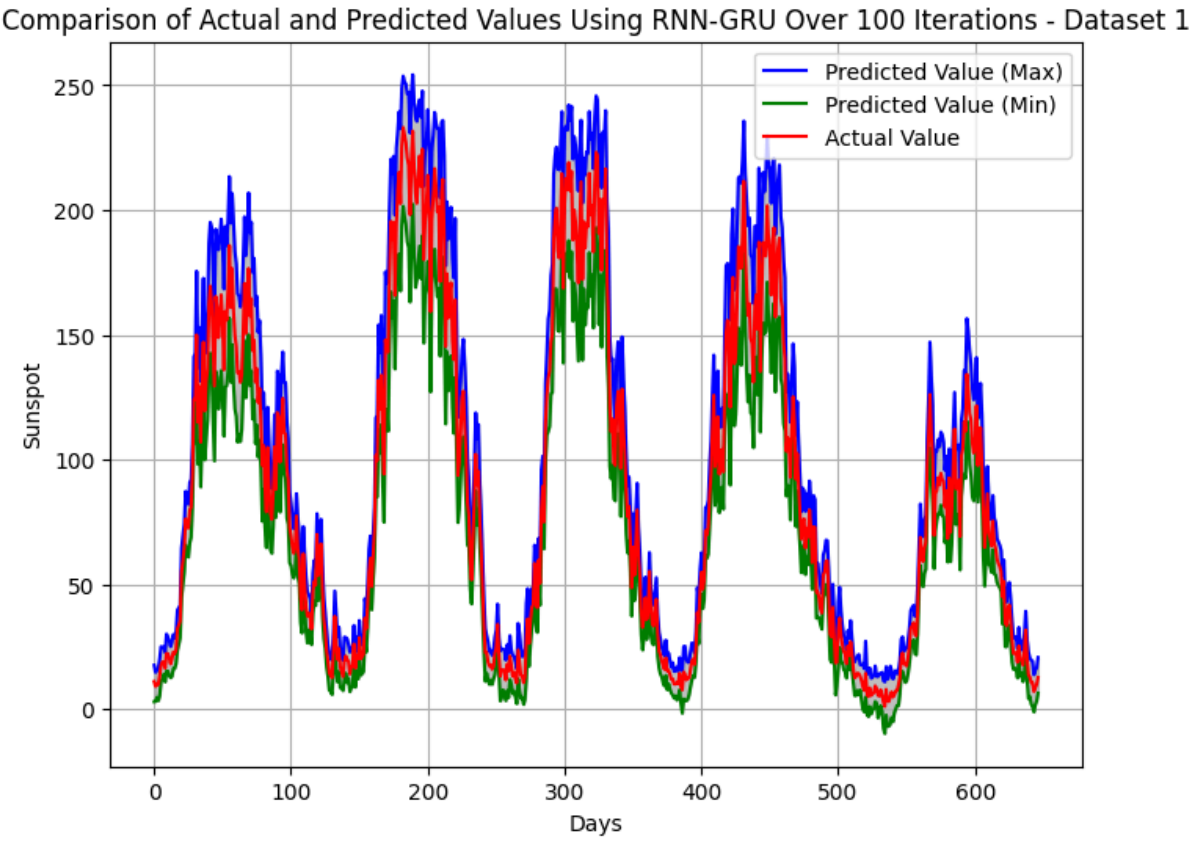


RNN-GRU

In [ ]:
```
temp = pd.read_excel('RNN-GRU_LOSS.xlsx')
shade_plot(temp, line = 'RNN-GRU_LOSS')
```

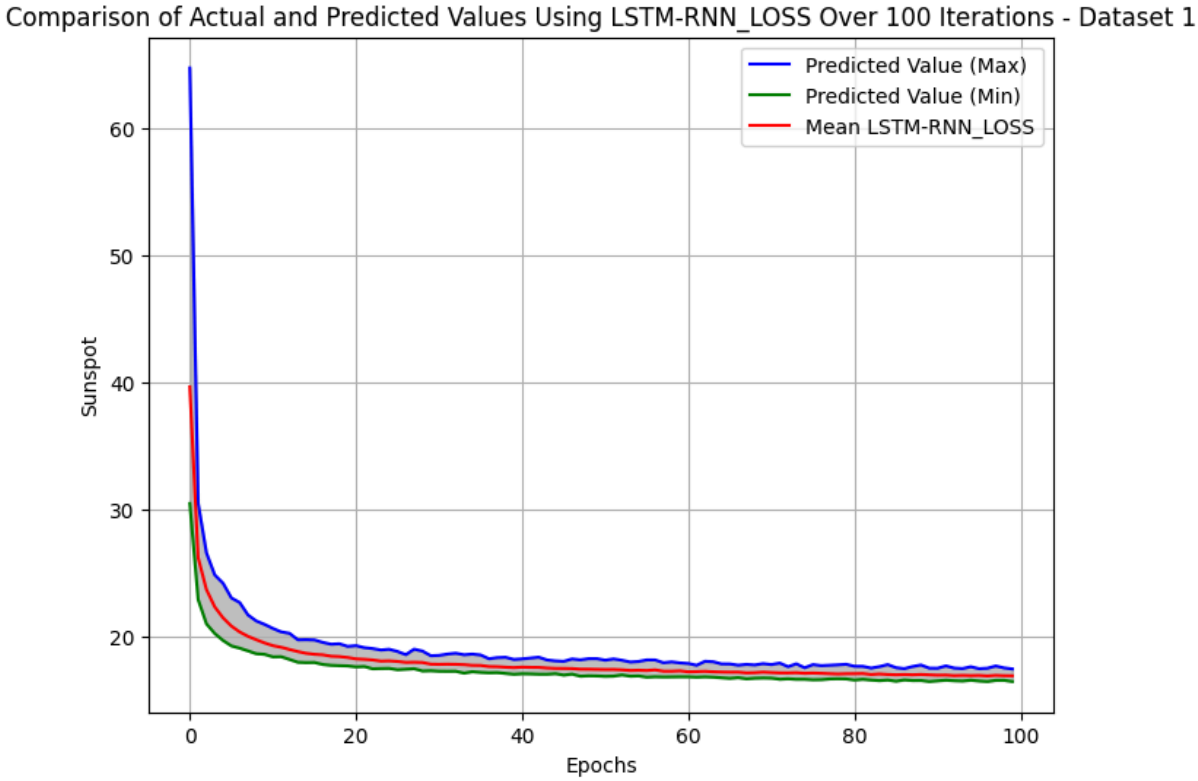


In [ ]:
```
temp = pd.read_excel('RNN-GRU_PREDICT.xlsx')
shade_plot(temp, line='RNN-GRU', predict='YES')
```

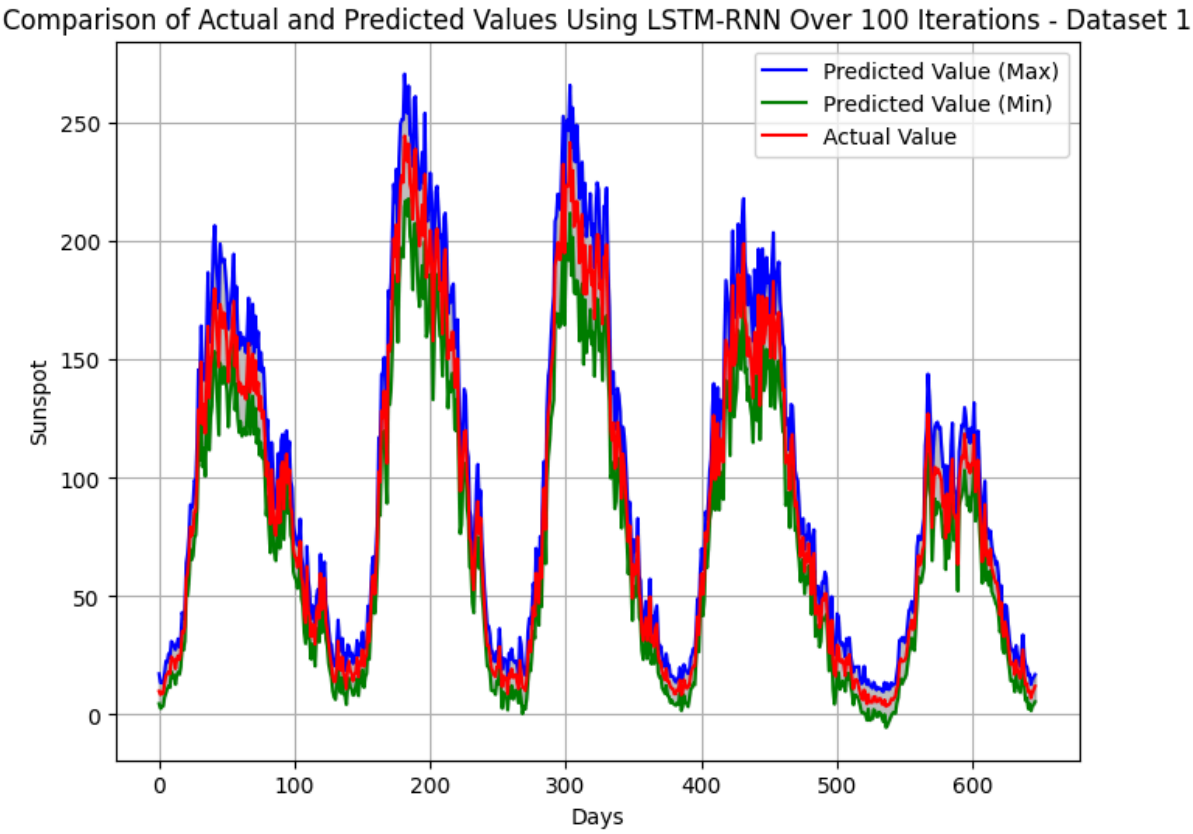


LSTM-RNN

In [ ]:
```
temp = pd.read_excel('LSTM-RNN_LOSS.xlsx')
shade_plot(temp, line = 'LSTM-RNN_LOSS')
```

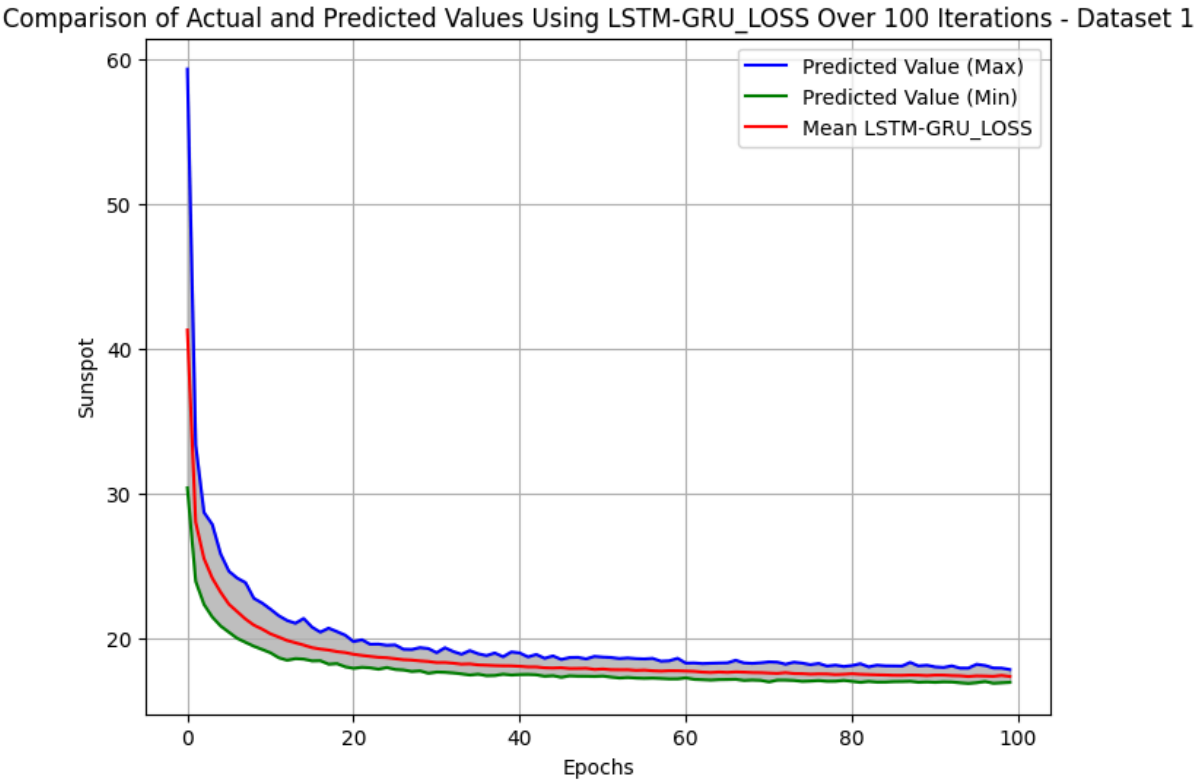


In [ ]:
```
temp = pd.read_excel('LSTM-RNN_PREDICT.xlsx')
shade_plot(temp, line='LSTM-RNN', predict='YES')
```

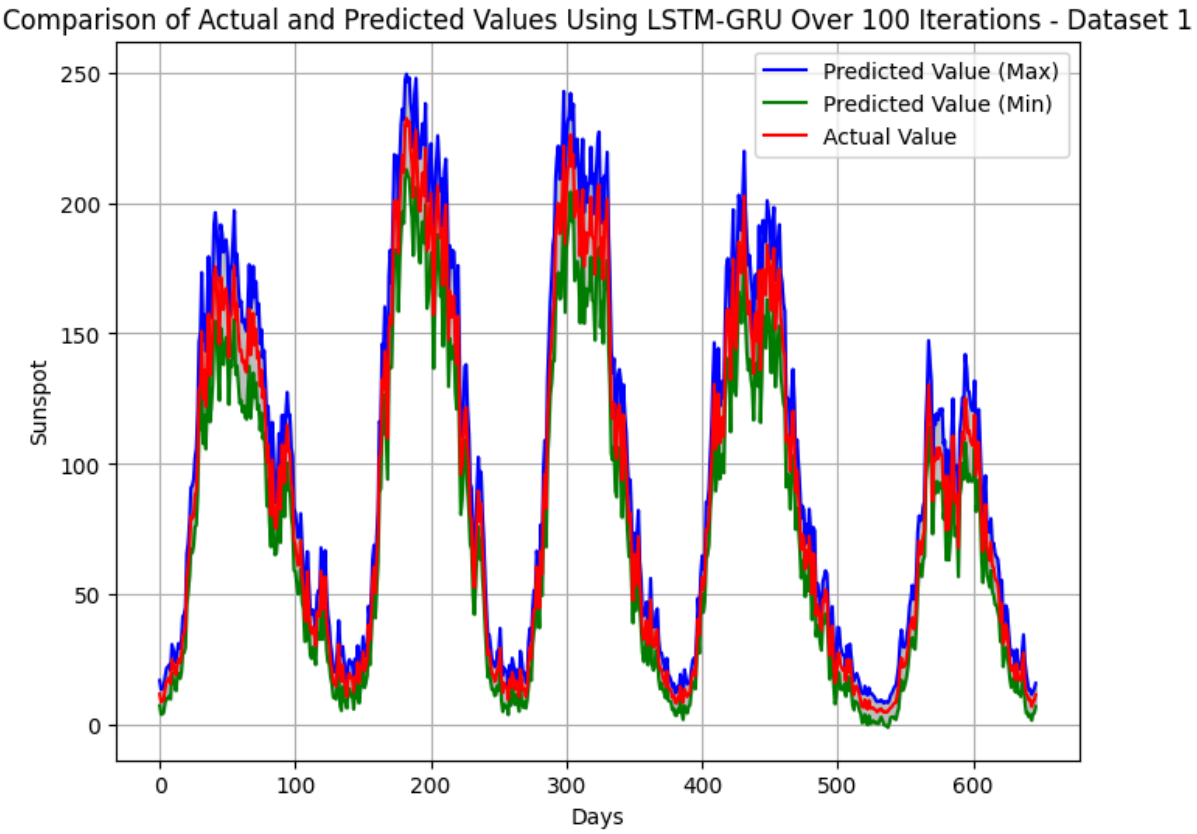


LSTM-GRU

In [ ]:
```
temp = pd.read_excel('LSTM-GRU_LOSS.xlsx')
shade_plot(temp, line = 'LSTM-GRU_LOSS')
```

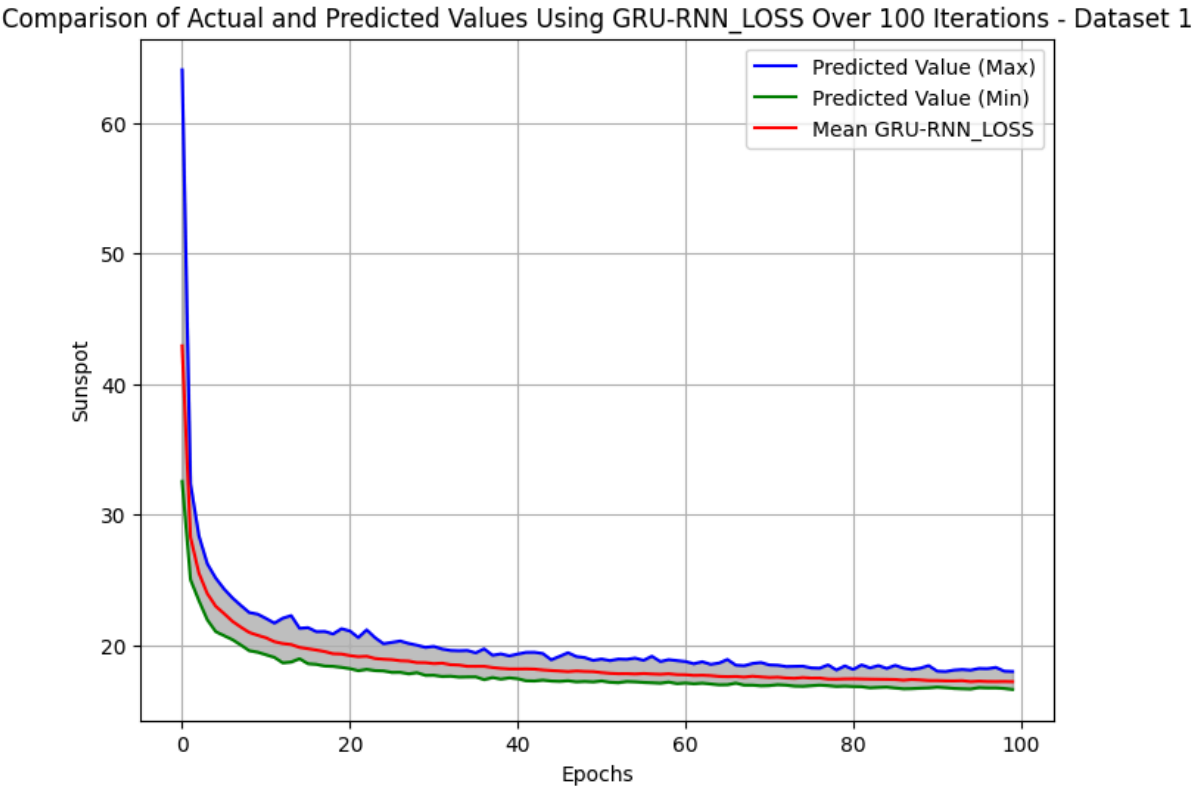


In [ ]:
```
temp = pd.read_excel('LSTM-GRU_PREDICT.xlsx')
shade_plot(temp, line='LSTM-GRU', predict='YES')
```

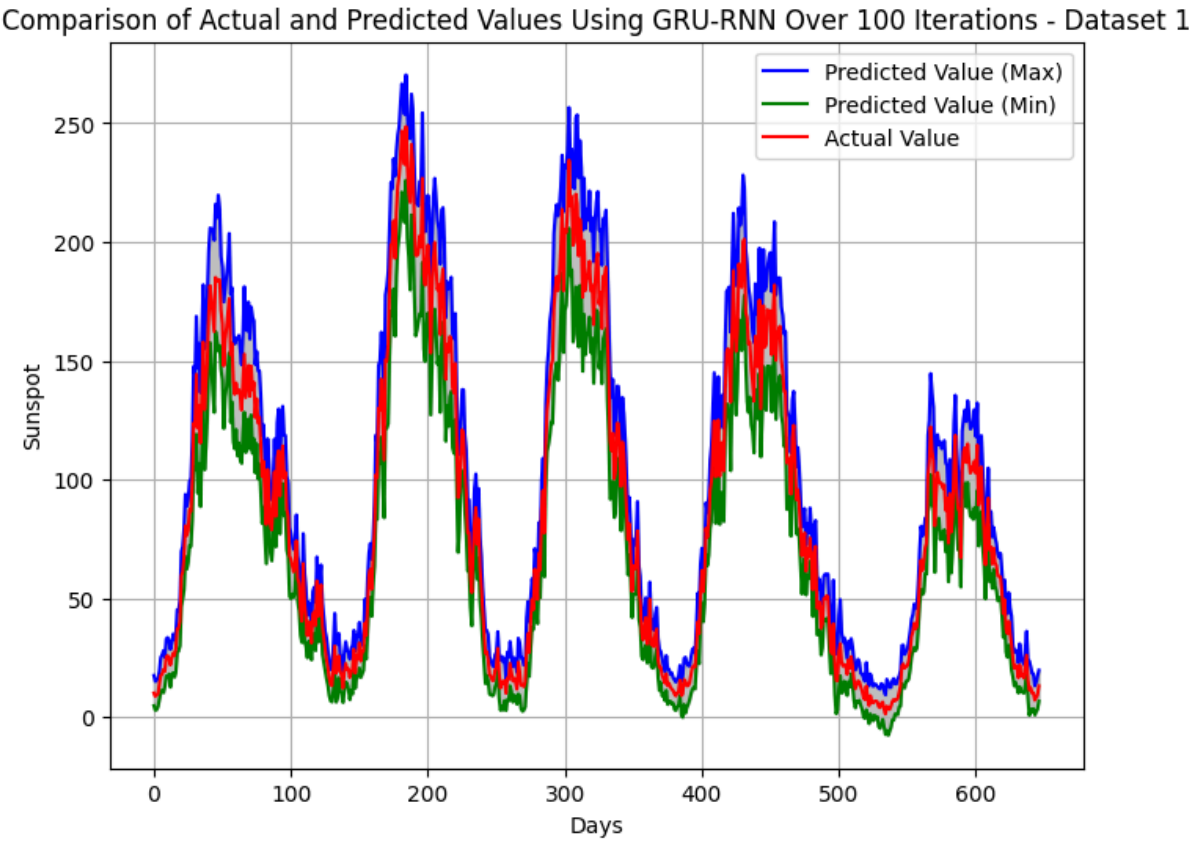


GRU-RNN

In [ ]:
```
temp = pd.read_excel('GRU-RNN_LOSS.xlsx')
shade_plot(temp, line = 'GRU-RNN_LOSS')
```

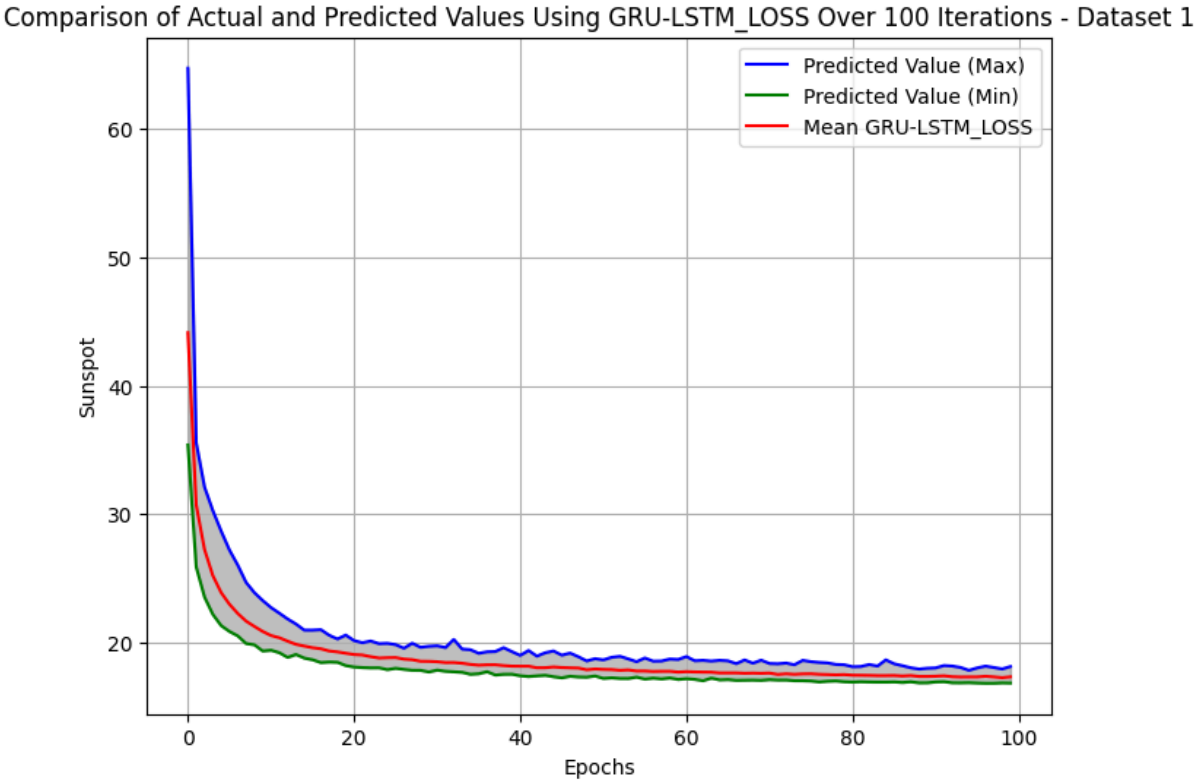


In [ ]:
```
temp = pd.read_excel('GRU-RNN_PREDICT.xlsx')
shade_plot(temp, line='GRU-RNN', predict='YES')
```

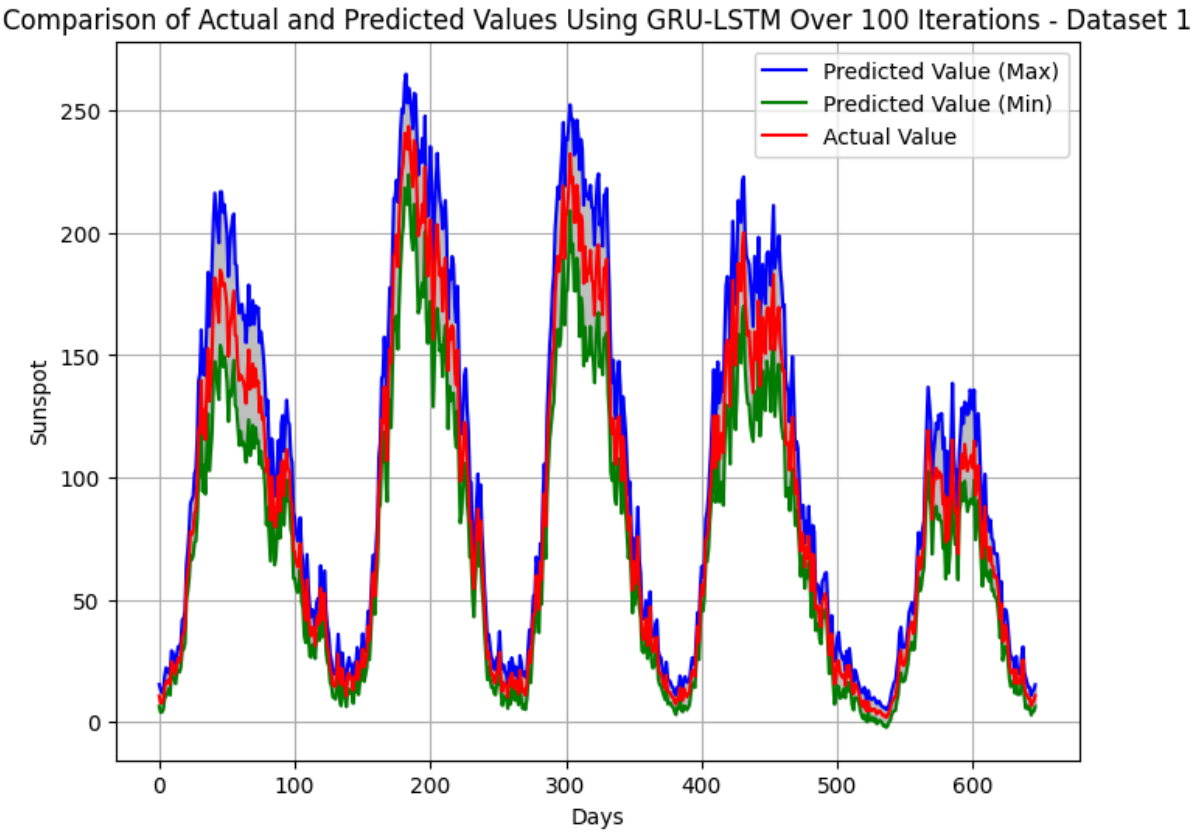


GRU-LSTM

In [ ]:
```
temp = pd.read_excel('GRU-LSTM_LOSS.xlsx')
shade_plot(temp, line = 'GRU-LSTM_LOSS')
```



In [ ]:
```
temp = pd.read_excel('GRU-LSTM_PREDICT.xlsx')
shade_plot(temp, line='GRU-LSTM', predict='YES')
```



In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import files
```

DONWLOAD DATA

In [ ]:
```
!gdown 1OHO_beLZo7QnekysxZa-JNAIjwAPfJj_
!gdown 1KM5U2pnghQeuIBGwa1SbmzvrMT18b91M
!gdown 1Lg6Gz_kXvypCKqjCxZOz1WalPGzapraV
!gdown 1Lg6Gz_kXvypCKqjCxZOz1WalPGzapraV
!gdown 1pBcD816adMQW1TxbokeRjJin8xGQGYer
!gdown 1rCcIouPG_QtA7OidY3HGQmRPooWpFJsp
!gdown 1m_5WyP0jU98vUgh124zyxCD67TEk_6zR
!gdown 1fsHt6tVw2ebOO_k0Xe4nkChJYKt8y1Ur
!gdown 1u0ywQUQAa69DcBPq_u9tcr7jePd98xiZ
!gdown 1H4KHj3giWcM8lPhU_AIQ32QyrOjY1JSh
!gdown 1RvkRM9vxddIDred7d56wJ2-aGe31u6uD
```

In [ ]:
```
!gdown 1y-VzDoWFEGmUOFWVpagg5CB0qkSzMiJB
!gdown 1Tls80_AHsKCkG4rR34y1hslf5rfOWif4
!gdown 1XOyVcuzMBwhitCjazcyemz33ZjoAOsvi
!gdown 11uxmJoYWW-9srCdDs-s9mSHk1i6AWBp0
!gdown 1mGXeE6uOVT3Pyvte7Lgqhn19hlYpybQH
!gdown 1bknN4MJf-puQAiEsvn1Hccdwmpqg1QkR
!gdown 1BakteERQlZYVln7buOHrMxcC2NL2aPCr
!gdown 1kbX7JzrmTkjlwX-NslbDxFSGZvT3sbpF
```

In [ ]:
```
!gdown 1HHSVdJzYWT93d_0qmeXE4VhOx5OYc0x0
!gdown 1En9dH6c-vmq72JmzAzcLlWHtI4X9xcT6
!gdown 172z5EOqrM8ACjr3g1JjSu-Oj5pwHdoxz
!gdown 1THv3DAS6EhuOsvKrqdKJ9PSZNoIweWfs
!gdown 1zgeDDSPKE4JF_rM3b29dE3ryy7M1W9gl
!gdown 1-f_PDTK891JK2vZOwTO5fuwl8GEC1Bh6
!gdown 1rRSz3vn4Y7ml5X9y57RbogUv5pipdVre
!gdown 1OYTOub9vv35Wiuxx3vgBAEIjOQzCksXK
!gdown 1lCYQvasS5ORVzdPbIm9Ipmj3qCXPcxjR
```

In [ ]:
```
!gdown 1GjhlV9cldg6dGRuPyyCctR5tTF-MHV1a
!gdown 1i_CkunKD18a04P0FF2EM-NxNyAKA5NZt
!gdown 1PAU06DAruF8R3xcG3DLytuGSL-gVmbB_
!gdown 198a4VKQm4fRFHE5EXWilcQdC5sBMv0qC
!gdown 13-Wt96xDZW3_jRi0bgctXclYNy0UOLUg
!gdown 1kScpmncOvzJnVa9x--jEP8bCG92bMPnI
!gdown 1G29FRXkxuHYEGn_PyshQ5oWxk59eH9Rk
!gdown 1G56MJL6SOOaYRjRrgml4vVPVdueLiE90
!gdown 1GqQs02UGzh1f_ZycvmVCPVdoc4JTOk4x
!gdown 1lCYQvasS5ORVzdPbIm9Ipmj3qCXPcxjR
```

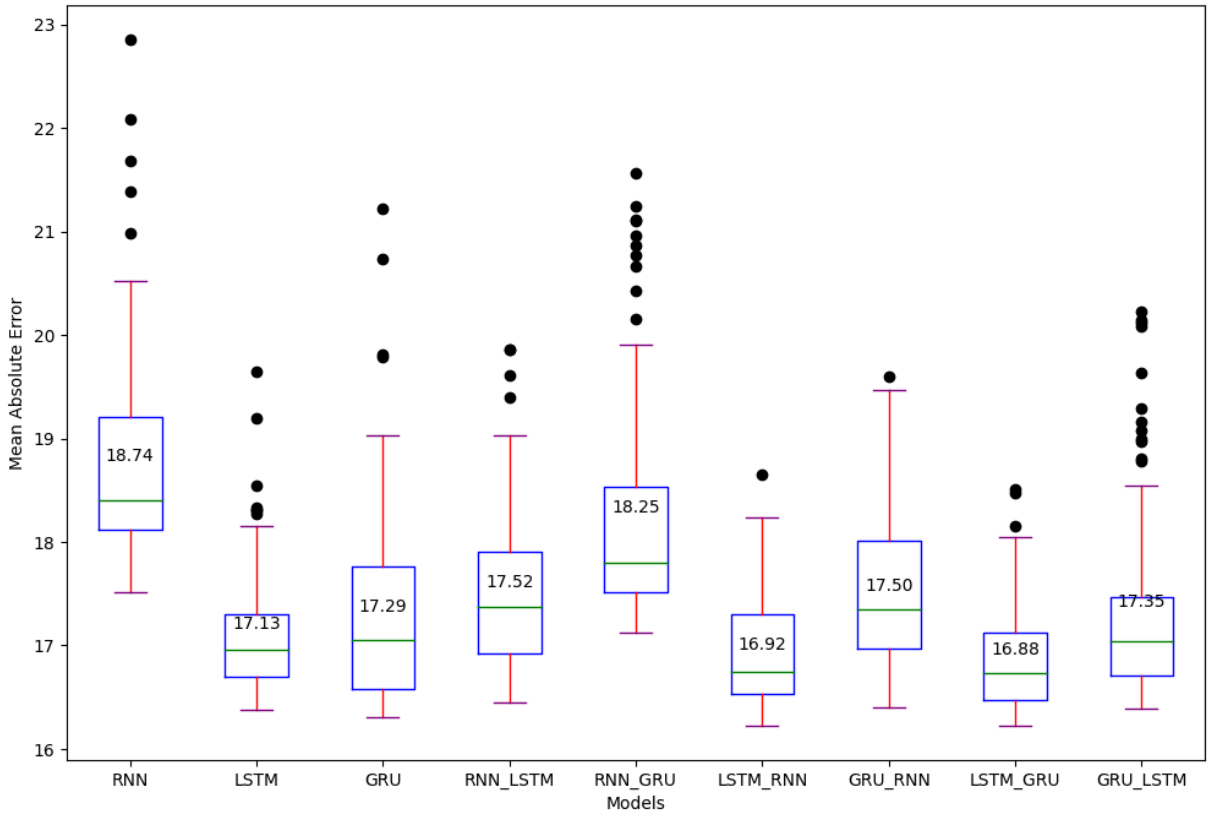
Metrik Evaluation

MAE

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_FORECASTMae.xlsx')
df2 =  pd.read_excel('/content/LSTM_FORECASTMae.xlsx')
df3 =  pd.read_excel('/content/GRU_FORECASTMae.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_FORECASTMae.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_FORECASTMae.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_FORECASTMae.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_FORECASTMae.xlsx')
df8 =  pd.read_excel('/content/LSTM-GRU_FORECASTMae.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_FORECASTMae.xlsx')
```

In [ ]:
```
df = pd.DataFrame()
df['RNN'] =  df1[0]
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]

# n = int(len(df) * (20 / 100))
n = int(len(df) * (2.5 / 100))
df = df.iloc[n:-n]
```

In [ ]:
```
df = pd.DataFrame()
df['RNN'] =  sorted(df1[0])
df['LSTM'] =  sorted(df2[0])
df['GRU'] =  sorted(df3[0])
df['RNN_LSTM'] =  sorted(df4[0])
df['RNN_GRU'] =  sorted(df5[0])
df['LSTM_RNN'] = sorted(df6[0])
df['GRU_RNN'] =  sorted(df7[0])
df['LSTM_GRU'] = sorted(df8[0])
df['GRU_LSTM'] = sorted(df9[0])


# n = int(len(df)*0.15)
n = int(len(df) * 0.025)
df = df[:].iloc[n:-n]
data = df[:]

box_color = 'blue'
whisker_color = 'red'
median_color = 'green'
flier_color = 'black'
cap_color = 'purple'

fig, ax = plt.subplots(figsize=(12, 8))

plt.boxplot(data.values, labels=data.columns,
            boxprops=dict(color=box_color),
            whiskerprops=dict(color=whisker_color),
            capprops=dict(color=cap_color),
            flierprops=dict(markerfacecolor=flier_color, marker='o', markersize=6),
            medianprops=dict(color=median_color))

for i, column in enumerate(data.columns):
    mean = np.mean(data[column])
    plt.text(i + 1, mean, f'{mean:.2f}', ha='center', va='bottom', color='black')

# plt.title('Predict with Boxplot')
plt.xlabel('Models')
plt.ylabel('Mean Absolute Error')
plt.savefig("Comparison_MAE_Dataset1.pdf", dpi=300)
files.download("Comparison_MAE_Dataset1.pdf")

plt.show()
```

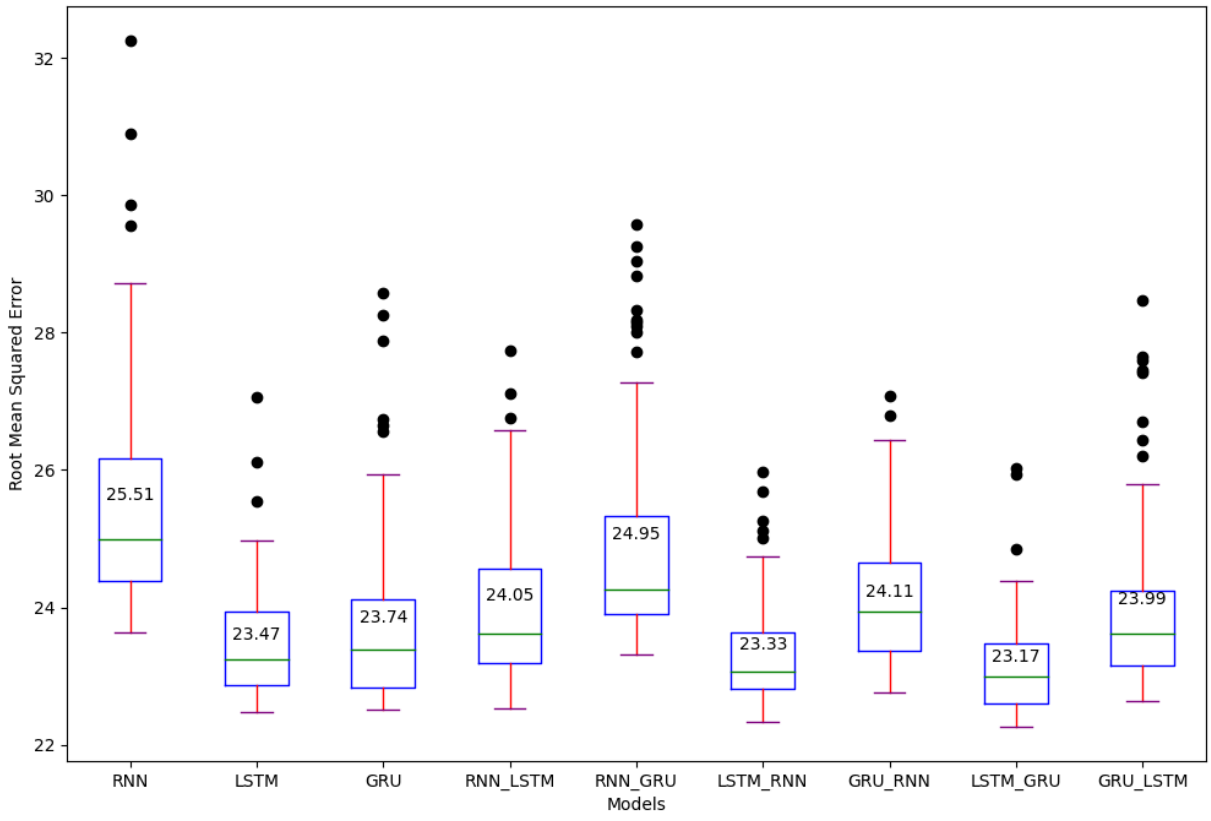


RMSE

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_FORECASTRMse.xlsx')
df2 =  pd.read_excel('/content/LSTM_FORECASTRMse.xlsx')
df3 =  pd.read_excel('/content/GRU_FORECASTRMse.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_FORECASTRMse.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_FORECASTRMse.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_FORECASTRMse.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_FORECASTRMse.xlsx')
df8 =  pd.read_excel('/content/LSTM-GRU_FORECASTRMse.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_FORECASTRMse.xlsx')
df = pd.DataFrame()
df['RNN'] =  df1[0]
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]

# n = int(len(df) * (20 / 100))
n = int(len(df) * (2.5 / 100))
df = df.iloc[n:-n]
```

In [ ]:
```
df = pd.DataFrame()
df['RNN'] =  sorted(df1[0])
df['LSTM'] =  sorted(df2[0])
df['GRU'] =  sorted(df3[0])
df['RNN_LSTM'] =  sorted(df4[0])
df['RNN_GRU'] =  sorted(df5[0])
df['LSTM_RNN'] = sorted(df6[0])
df['GRU_RNN'] =  sorted(df7[0])
df['LSTM_GRU'] = sorted(df8[0])
df['GRU_LSTM'] = sorted(df9[0])


# n = int(len(df)*0.15)
n = int(len(df) * 0.025)
```

```
df = df[:].iloc[n:-n]
data = df[:]

box_color = 'blue'
whisker_color = 'red'
median_color = 'green'
flier_color = 'black'
cap_color = 'purple'

fig, ax = plt.subplots(figsize=(12, 8))

plt.boxplot(data.values, labels=data.columns,
            boxprops=dict(color=box_color),
            whiskerprops=dict(color=whisker_color),
            capprops=dict(color=cap_color),
            flierprops=dict(markerfacecolor=flier_color, marker='o', markersize=6),
            medianprops=dict(color=median_color))

for i, column in enumerate(data.columns):
    mean = np.mean(data[column])
    plt.text(i + 1, mean, f'{mean:.2f}', ha='center', va='bottom', color='black')

# plt.title('Predict with Boxplot')
plt.xlabel('Models')
plt.ylabel('Root Mean Squared Error')
plt.savefig("Comparison_RMSE_Dataset1.pdf", dpi=300)
files.download("Comparison_RMSE_Dataset1.pdf")

plt.show()
```



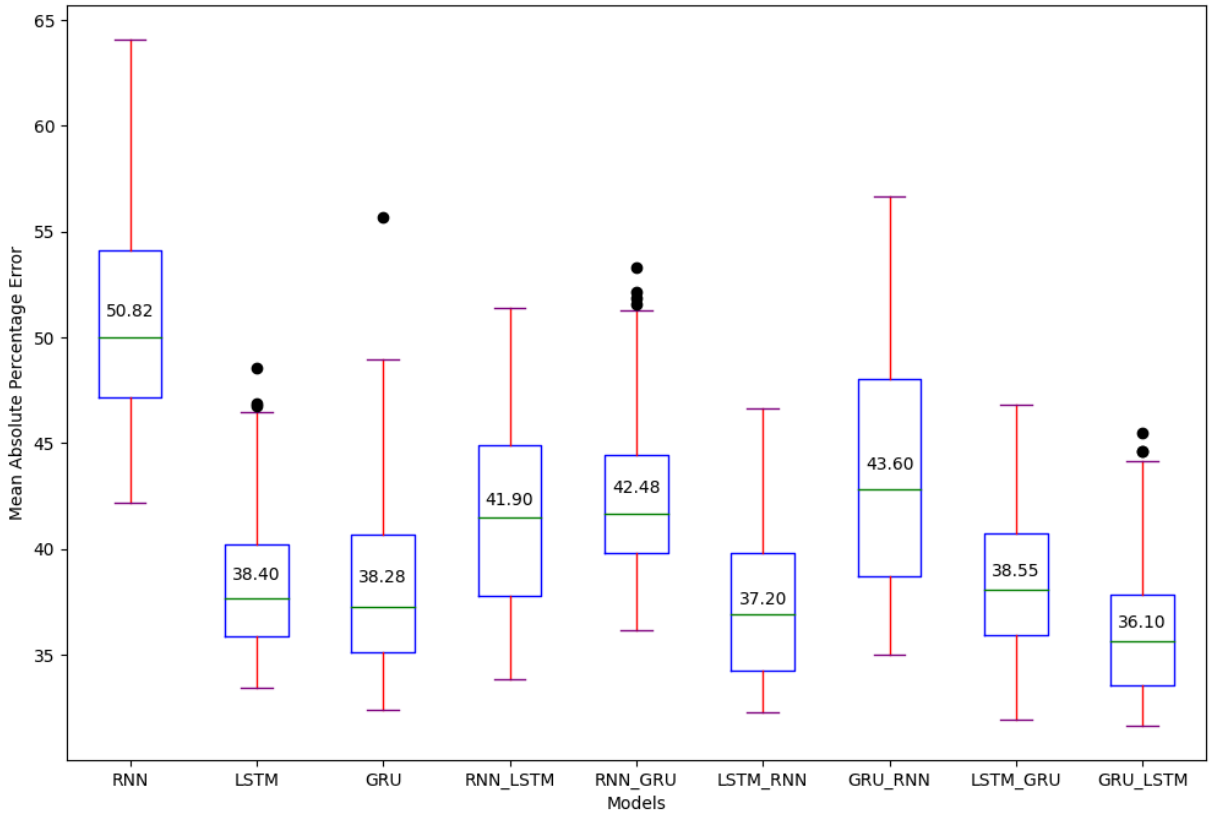
MAPE

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_FORECASTMpe.xlsx')
df2 =  pd.read_excel('/content/LSTM_FORECASTMpe.xlsx')
df3 =  pd.read_excel('/content/GRU_FORECASTMpe.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_FORECASTMpe.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_FORECASTMpe.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_FORECASTMpe.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_FORECASTMpe.xlsx')
```

```
df8 =  pd.read_excel('/content/LSTM-GRU_FORECASTMpe.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_FORECASTMpe.xlsx')
df = pd.DataFrame()
df['RNN'] =  df1[0]
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]

# n = int(len(df) * (20 / 100))
n = int(len(df) * (2.5 / 100))
df = df.iloc[n:-n]
```

In [ ]:

```
df = pd.DataFrame()
df['RNN'] =  sorted(df1[0])
df['LSTM'] =  sorted(df2[0])
df['GRU'] =  sorted(df3[0])
df['RNN_LSTM'] =  sorted(df4[0])
df['RNN_GRU'] =  sorted(df5[0])
df['LSTM_RNN'] = sorted(df6[0])
df['GRU_RNN'] =  sorted(df7[0])
df['LSTM_GRU'] = sorted(df8[0])
df['GRU_LSTM'] = sorted(df9[0])


# n = int(len(df)*0.15)
n = int(len(df) * 0.025)
df = df[:].iloc[n:-n]
data = df[:]

box_color = 'blue'
whisker_color = 'red'
median_color = 'green'
flier_color = 'black'
cap_color = 'purple'

fig, ax = plt.subplots(figsize=(12, 8))

plt.boxplot(data.values, labels=data.columns,
            boxprops=dict(color=box_color),
            whiskerprops=dict(color=whisker_color),
            capprops=dict(color=cap_color),
            flierprops=dict(markerfacecolor=flier_color, marker='o', markersize=6),
            medianprops=dict(color=median_color))

for i, column in enumerate(data.columns):
    mean = np.mean(data[column])
    plt.text(i + 1, mean, f'{mean:.2f}', ha='center', va='bottom', color='black')

# plt.title('Predict with Boxplot')
plt.xlabel('Models')
plt.ylabel('Mean Absolute Percentage Error')
plt.savefig("Comparison_MAPE_Dataset1.pdf", dpi=300)
files.download("Comparison_MAPE_Dataset1.pdf")

plt.show()
```

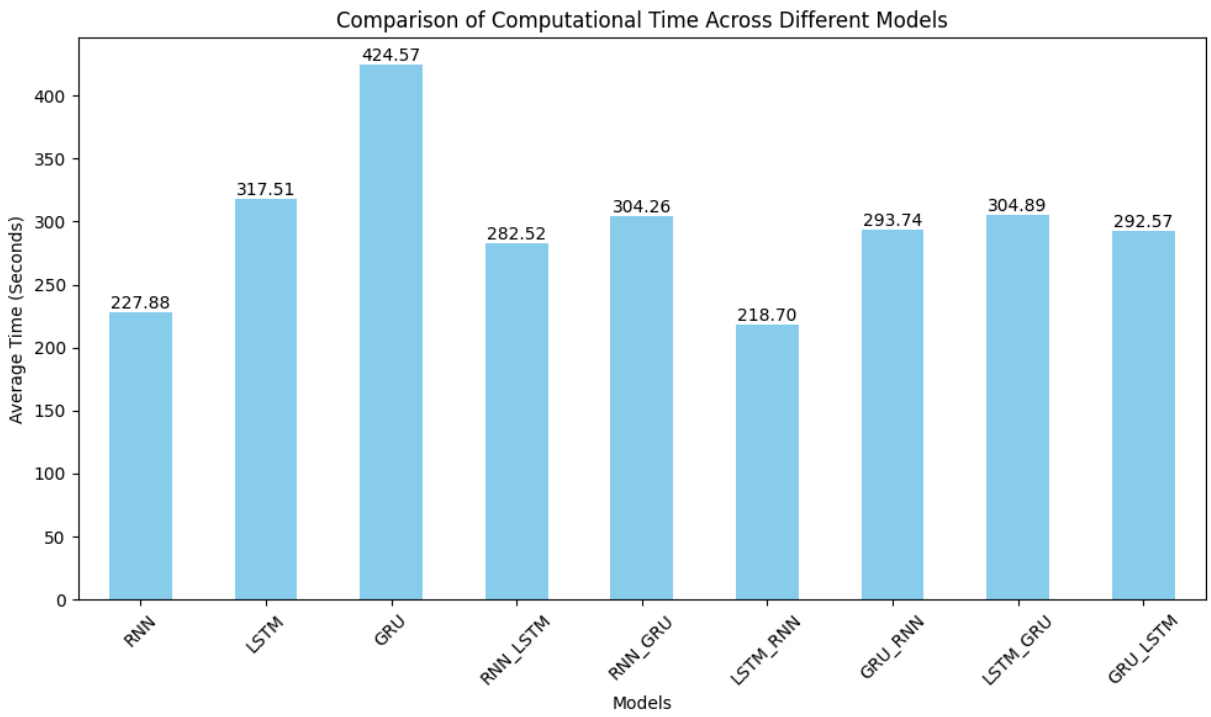


Time Comparison

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_TIME.xlsx')
df2 =  pd.read_excel('/content/LSTM_TIME.xlsx')
df3 =  pd.read_excel('/content/GRU_TIME.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_TIME.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_TIME.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_TIME.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_TIME.xlsx')
df8 =  pd.read_excel('/content/LSTM-GRU_TIME.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_TIME.xlsx')
df = pd.DataFrame()
df['RNN'] =  df1[0]
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]
```

In [ ]:
```
# Calculate the average time for each model
average_times = df.mean()

# Create a bar chart
plt.figure(figsize=(10, 6))
average_times.plot(kind='bar', color='skyblue')
plt.title('Comparison of Computational Time Across Different Models')
plt.xlabel('Models')
plt.ylabel('Average Time (Seconds)')
plt.xticks(rotation=45)
plt.tight_layout()

# Display the average times on top of the bars
for i, v in enumerate(average_times):
    plt.text(i, v, f"{v:.2f}", ha='center', va='bottom')

plt.savefig("Comparison_Time_Dataset1.pdf", dpi=300)
```

```
files.download("Comparison_Time_Dataset1.pdf")
plt.show()
```



1. Import Libraries

List of libraries that will be used.

In [6]:
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import csv
```

Using Utilites of Data Visualization

In [7]:
```
def plot_series(x, y, format="-", start=0, end=None,
                title=None, xlabel=None, ylabel=None, legend=None ):
    plt.figure(figsize=(10, 6))
    if type(y) is tuple:
      for y_curr in y:
        plt.plot(x[start:end], y_curr[start:end], format)
    else:
      plt.plot(x[start:end], y[start:end], format)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    if legend:
      plt.legend(legend)
    plt.title(title)
    plt.grid(True)
    plt.show()
```

2. Get DATA

Take Data from Upstream (Local, Gdrive, Github, etc).

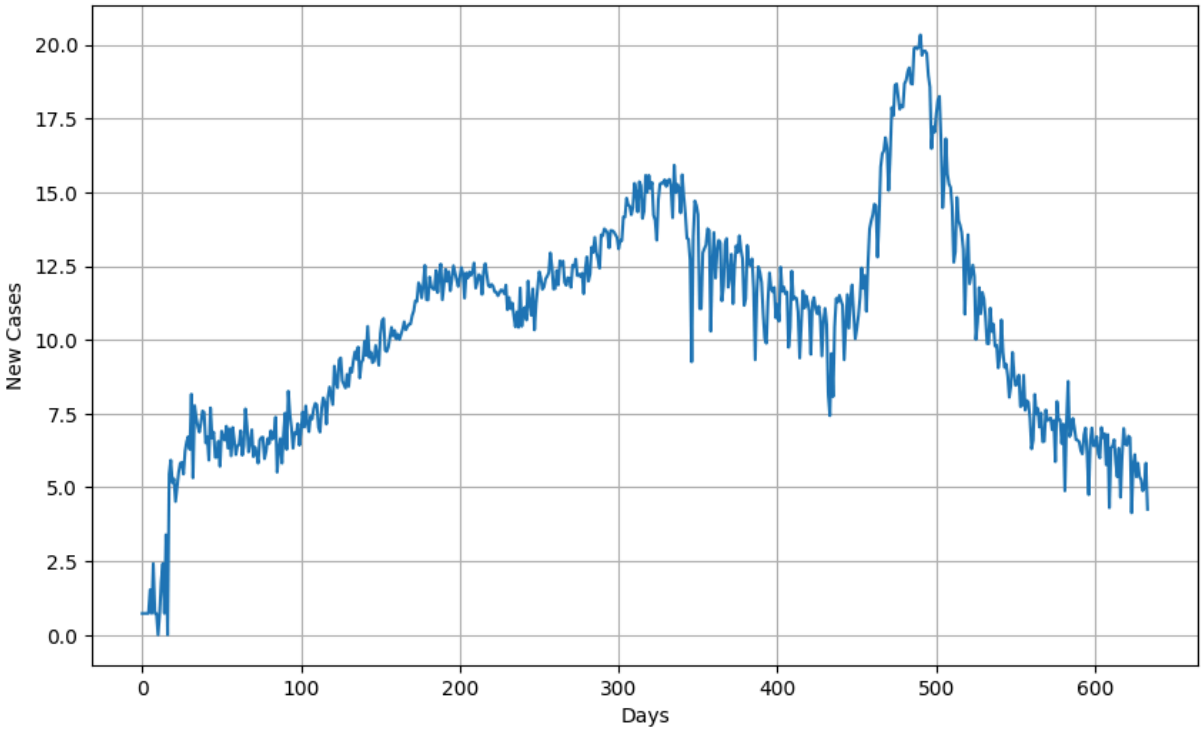
In [ ]:
```
!wget https://raw.githubusercontent.com/MhdIqbalPratama/ware-house/main/Data%20COVID-19%20Indon
```

Data Visualize

In [9]:
```
df = pd.read_csv(r"/content/Data COVID-19 Indonesia.csv", delimiter=',', parse_dates=['Date'])
df = df[df['Location'] == "DKI Jakarta"]
dx = df.groupby('Date').sum()
data =pd.DataFrame(dx).reset_index()
data.rename(columns={'New Cases' : 'New_Cases', 'New Deaths':'New_Deaths'}, inplace=True)
from scipy.stats import boxcox
data = data[data['New_Cases'] > 0]
data['New_Cases'], lambda_value = boxcox(data['New_Cases'])
```

In [10]:
```
def take(file):
  time_step = []
  data = []

  for i in range(len(file)):
    time_step.append(i)
    data.append(float(file.iloc[i][3]))
  time = np.array(time_step)
  series = np.array(data)
  return time, series
time, series = take(data)
plot_series(time, series, xlabel='Days', ylabel='New Cases')
```

```
<ipython-input-10-54f33a54f1e4>:7: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  data.append(float(file.iloc[i][3]))
```



3. Data Prerocessing

Analysis and Cleaning Data -> Extract, Transform, Load.

Split Data

In [11]:
```
split_time = int(len(time)*0.7)

time_train = time[:split_time]
x_train = series[:split_time]

time_valid = time[split_time:]
x_valid = series[split_time:]
```

Prepare Features and Labels

In [12]:
```
def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
    dataset = tf.data.Dataset.from_tensor_slices(series)
    dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
    dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
    dataset = dataset.map(lambda window: (window[:-1], window[-1]))
    dataset = dataset.shuffle(shuffle_buffer)
    dataset = dataset.batch(batch_size).prefetch(1)
    return dataset

window_size = 7
batch_size = 32
shuffle_buffer_size = 1000

train_set = windowed_dataset(x_train, window_size, batch_size, shuffle_buffer_size)
```

4. Model Architechture

Using library from Scikit-learn, Tensorflow(?).

RNN Model

In [13]:
```
model_RNN = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.SimpleRNN(64, return_sequences=True),
  tf.keras.layers.SimpleRNN(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_RNN.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 7, 64)	256
simple_rnn (SimpleRNN)	(None, 7, 64)	8,256
simple_rnn_1 (SimpleRNN)	(None, 64)	8,256
dense (Dense)	(None, 1)	65
lambda (Lambda)	(None, 1)	0

Total params: 16,833 (65.75 KB)

Trainable params: 16,833 (65.75 KB)

Non-trainable params: 0 (0.00 B)

LSTM Model

In [14]:
```
model_LSTM = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.LSTM(64, return_sequences=True),
  tf.keras.layers.LSTM(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_LSTM.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	(None, 7, 64)	256
lstm (LSTM)	(None, 7, 64)	33,024
lstm_1 (LSTM)	(None, 64)	33,024
dense_1 (Dense)	(None, 1)	65
lambda_1 (Lambda)	(None, 1)	0

Total params: 66,369 (259.25 KB)

Trainable params: 66,369 (259.25 KB)

GRU Model

In [15]:
```
model_GRU = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.GRU(64, return_sequences=True),
  tf.keras.layers.GRU(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_GRU.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv1d_2 (Conv1D)	(None, 7, 64)	256
gru (GRU)	(None, 7, 64)	24,960
gru_1 (GRU)	(None, 64)	24,960
dense_2 (Dense)	(None, 1)	65
lambda_2 (Lambda)	(None, 1)	0

Total params: 50,241 (196.25 KB)

Trainable params: 50,241 (196.25 KB)

Non-trainable params: 0 (0.00 B)

RNN-LSTM Model

In [16]:
```
model_RNN_LSTM = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.SimpleRNN(64, return_sequences=True),
  tf.keras.layers.LSTM(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_RNN_LSTM.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
conv1d_3 (Conv1D)	(None, 7, 64)	256
simple_rnn_2 (SimpleRNN)	(None, 7, 64)	8,256
lstm_2 (LSTM)	(None, 64)	33,024
dense_3 (Dense)	(None, 1)	65
lambda_3 (Lambda)	(None, 1)	0

Total params: 41,601 (162.50 KB)

Trainable params: 41,601 (162.50 KB)

RNN-GRU Model

In [17]:
```
model_RNN_GRU = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.SimpleRNN(64, return_sequences=True),
  tf.keras.layers.GRU(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_RNN_GRU.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv1d_4 (Conv1D)	(None, 7, 64)	256
simple_rnn_3 (SimpleRNN)	(None, 7, 64)	8,256
gru_2 (GRU)	(None, 64)	24,960
dense_4 (Dense)	(None, 1)	65
lambda_4 (Lambda)	(None, 1)	0

Total params: 33,537 (131.00 KB)

Trainable params: 33,537 (131.00 KB)

Non-trainable params: 0 (0.00 B)

LSTM-RNN

In [18]:
```
model_LSTM_RNN = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.LSTM(64, return_sequences=True),
  tf.keras.layers.SimpleRNN(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
```

```
])
model_LSTM_RNN.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv1d_5 (Conv1D)	(None, 7, 64)	256
lstm_3 (LSTM)	(None, 7, 64)	33,024
simple_rnn_4 (SimpleRNN)	(None, 64)	8,256
dense_5 (Dense)	(None, 1)	65
lambda_5 (Lambda)	(None, 1)	0

Total params: 41,601 (162.50 KB)

Trainable params: 41,601 (162.50 KB)

Non-trainable params: 0 (0.00 B)

LSTM-GRU Model

In [19]:
```
model_LSTM_GRU = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.LSTM(64, return_sequences=True),
  tf.keras.layers.GRU(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_LSTM_GRU.summary()
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
conv1d_6 (Conv1D)	(None, 7, 64)	256
lstm_4 (LSTM)	(None, 7, 64)	33,024
gru_3 (GRU)	(None, 64)	24,960
dense_6 (Dense)	(None, 1)	65
lambda_6 (Lambda)	(None, 1)	0

Total params: 58,305 (227.75 KB)

Trainable params: 58,305 (227.75 KB)

Non-trainable params: 0 (0.00 B)

GRU-RNN Model

In [20]:
```
model_GRU_RNN = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
```

```
                      input_shape=[window_size, 1]),
  tf.keras.layers.GRU(64, return_sequences=True),
  tf.keras.layers.SimpleRNN(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_GRU_RNN.summary()
```

Model: "sequential_7"

Layer (type)	Output Shape	Param #
conv1d_7 (Conv1D)	(None, 7, 64)	256
gru_4 (GRU)	(None, 7, 64)	24,960
simple_rnn_5 (SimpleRNN)	(None, 64)	8,256
dense_7 (Dense)	(None, 1)	65
lambda_7 (Lambda)	(None, 1)	0

Total params: 33,537 (131.00 KB)

Trainable params: 33,537 (131.00 KB)

Non-trainable params: 0 (0.00 B)

GRU-LSTM Model

In [21]:
```
model_GRU_LSTM = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.GRU(64, return_sequences=True),
  tf.keras.layers.LSTM(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_GRU_LSTM  .summary()
```

Model: "sequential_8"

Layer (type)	Output Shape	Param #
conv1d_8 (Conv1D)	(None, 7, 64)	256
gru_5 (GRU)	(None, 7, 64)	24,960
lstm_5 (LSTM)	(None, 64)	33,024
dense_8 (Dense)	(None, 1)	65
lambda_8 (Lambda)	(None, 1)	0

Total params: 58,305 (227.75 KB)

Trainable params: 58,305 (227.75 KB)

Non-trainable params: 0 (0.00 B)

5. Model Training

In [22]:
```
tf.keras.backend.clear_session()
learning_rate = 8e-7
```

In [ ]:
```
optimizer_RNN = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_RNN.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_RNN,
              metrics=["mae", "mse", "mape"])
history_RNN = model_RNN.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_LSTM = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_LSTM.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_LSTM,
              metrics=["mae", "mse", "mape"])
history_LSTM = model_LSTM.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_GRU= tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_GRU.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_GRU,
              metrics=["mae", "mse", "mape"])
history_GRU = model_GRU.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_RNN_LSTM = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_RNN_LSTM.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_RNN_LSTM,
              metrics=["mae", "mse", "mape"])
history_RNN_LSTM = model_RNN_LSTM.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_RNN_GRU = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_RNN_GRU.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_RNN_GRU,
              metrics=["mae", "mse", "mape"])
history_RNN_GRU = model_RNN_GRU.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_LSTM_RNN = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_LSTM_RNN.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_LSTM_RNN,
              metrics=["mae", "mse", "mape"])
history_LSTM_RNN = model_LSTM_RNN.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_LSTM_GRU = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_LSTM_GRU.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_LSTM_GRU,
              metrics=["mae", "mse", "mape"])
history_LSTM_GRU = model_LSTM_GRU.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_GRU_RNN= tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_GRU_RNN.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_GRU_RNN,
              metrics=["mae", "mse", "mape"])
history_GRU_RNN = model_GRU_RNN.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_GRU_LSTM= tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_GRU_LSTM.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_GRU_LSTM,
              metrics=["mae", "mse", "mape"])
history_GRU_LSTM = model_GRU_LSTM.fit(train_set,epochs=100)
```

6. Model Evaluation

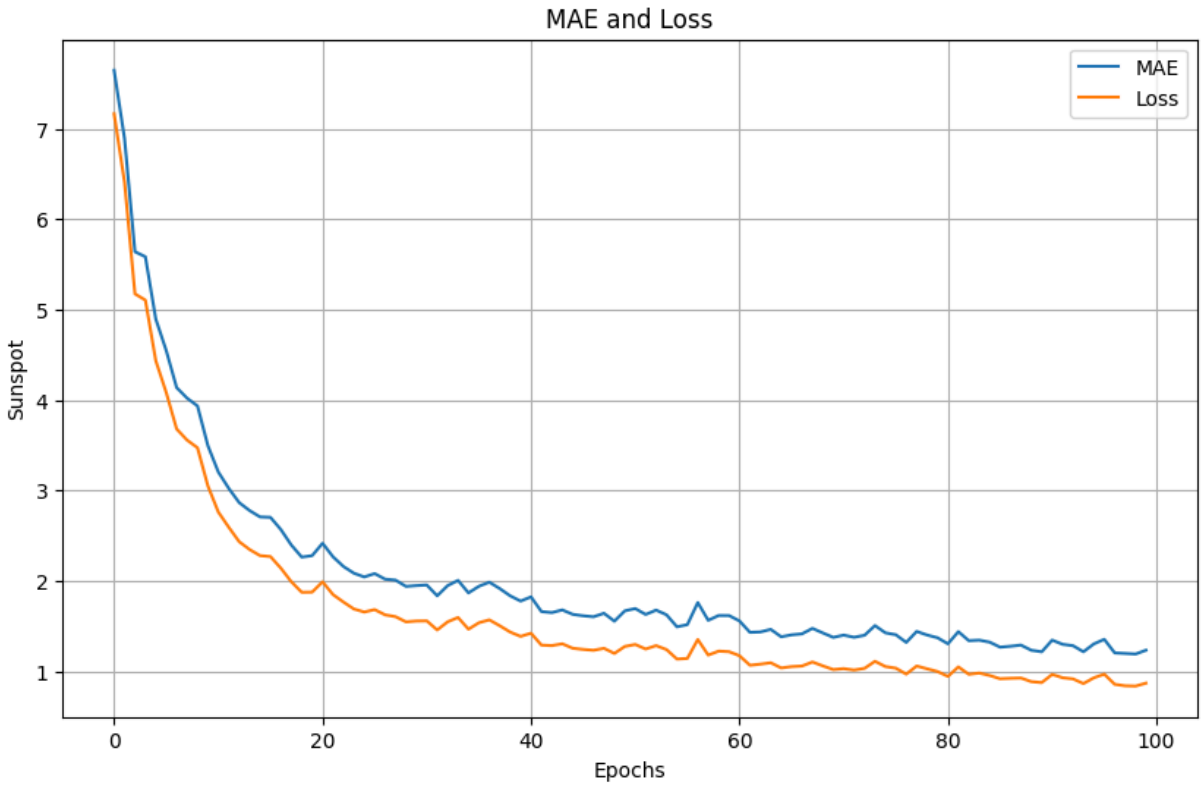
Loss evaluation using Scatter Plot

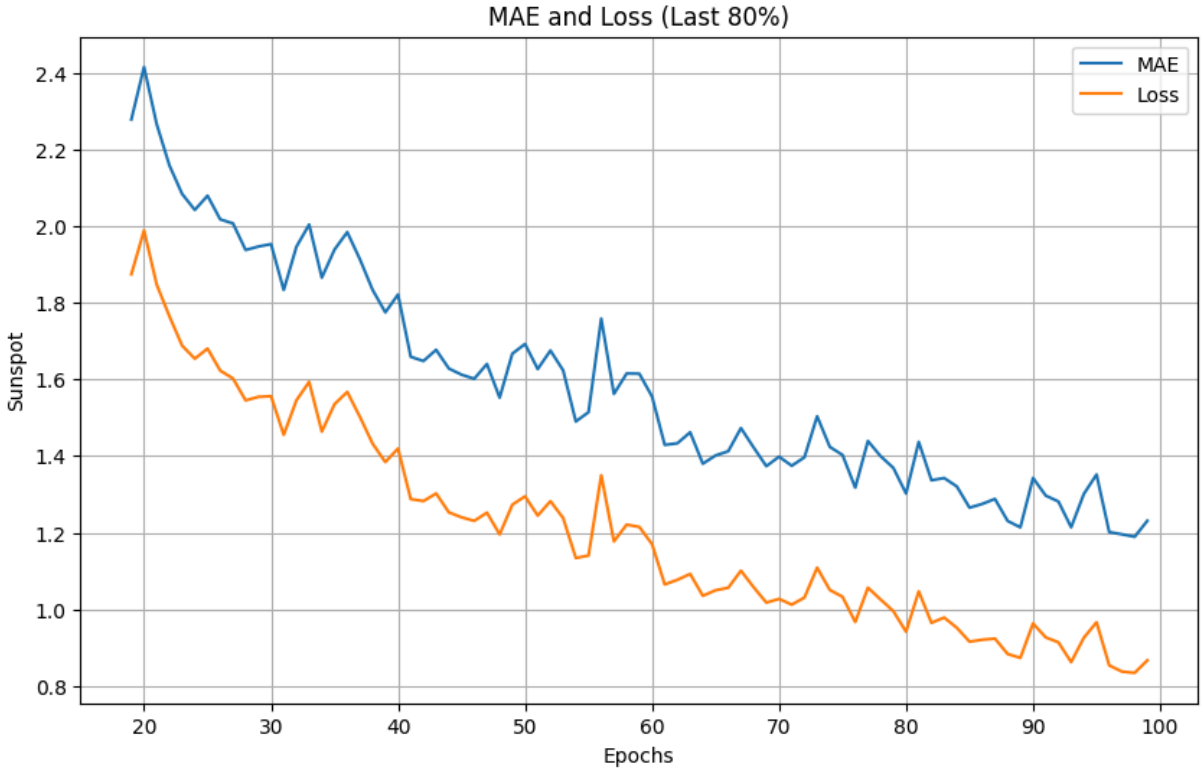
In [32]:
```
# Plot Function
def visualize_evaluation(history):
  mae=history.history['mae']
  loss=history.history['loss']
```

```
epochs=range(len(loss))

plot_series(
    x=epochs,
    y=(mae, loss),
    title='MAE and Loss',
    xlabel='Epochs',
    ylabel='Sunspot',
    legend=['MAE', 'Loss'])

zoom_split = int(epochs[-1] * 0.2)
epochs_zoom = epochs[zoom_split:]
mae_zoom = mae[zoom_split:]
loss_zoom = loss[zoom_split:]

plot_series(
    x=epochs_zoom,
    y=(mae_zoom, loss_zoom),
    title='MAE and Loss (Last 80%)',
    xlabel='Epochs',
    ylabel='Sunspot',
    legend=['MAE', 'Loss'])
```

RNN Evaluation

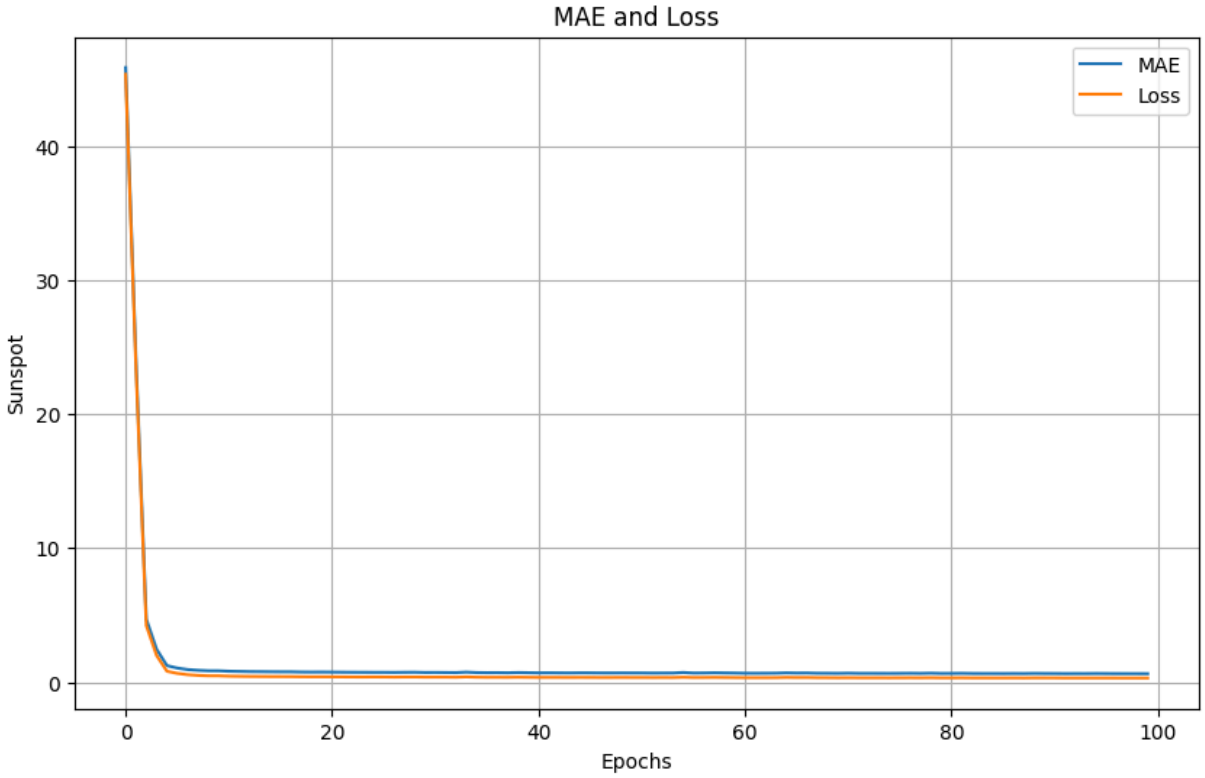
In [33]:
```
visualize_evaluation(history_RNN)
```

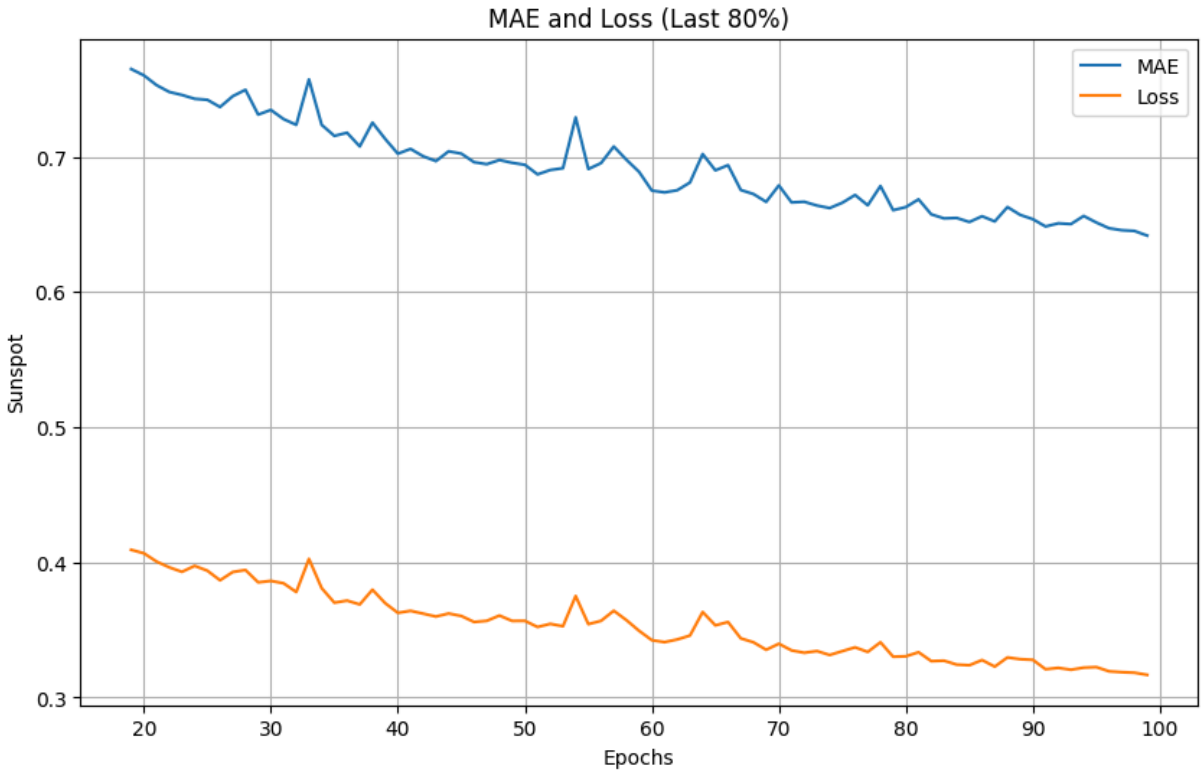




LSTM Evaluation

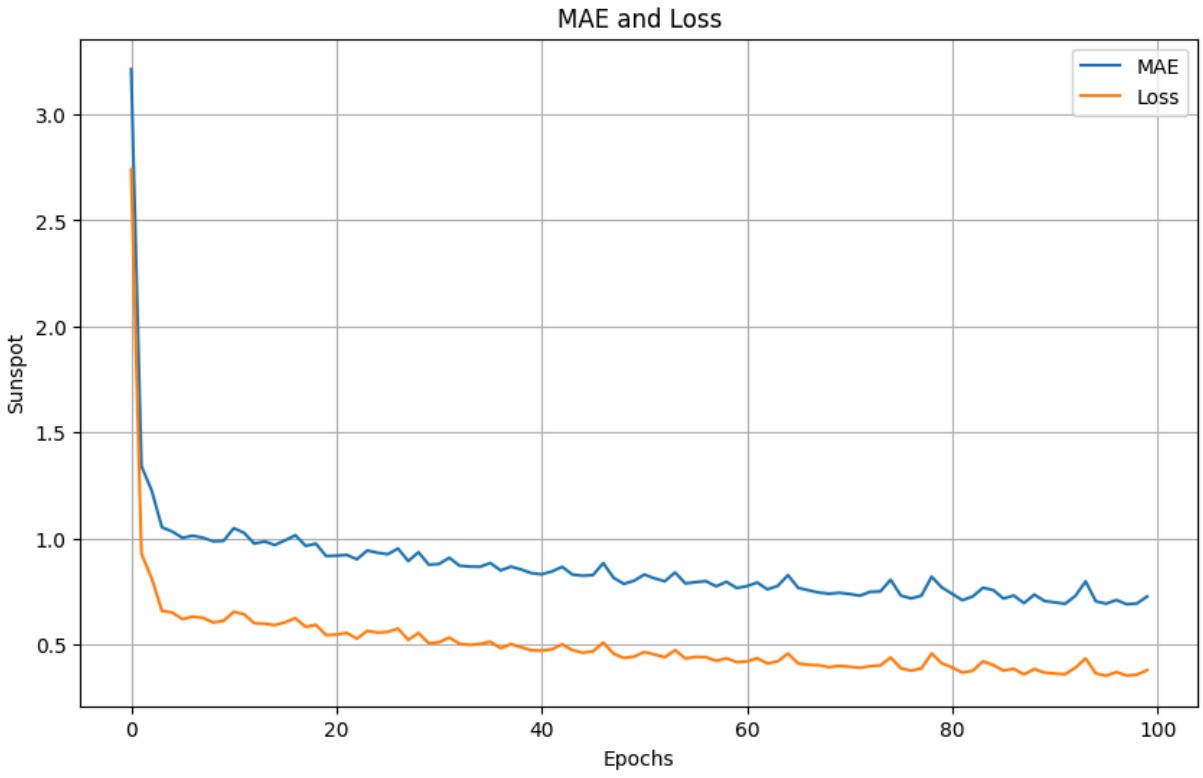
In [34]:
```
visualize_evaluation(history_LSTM)
```

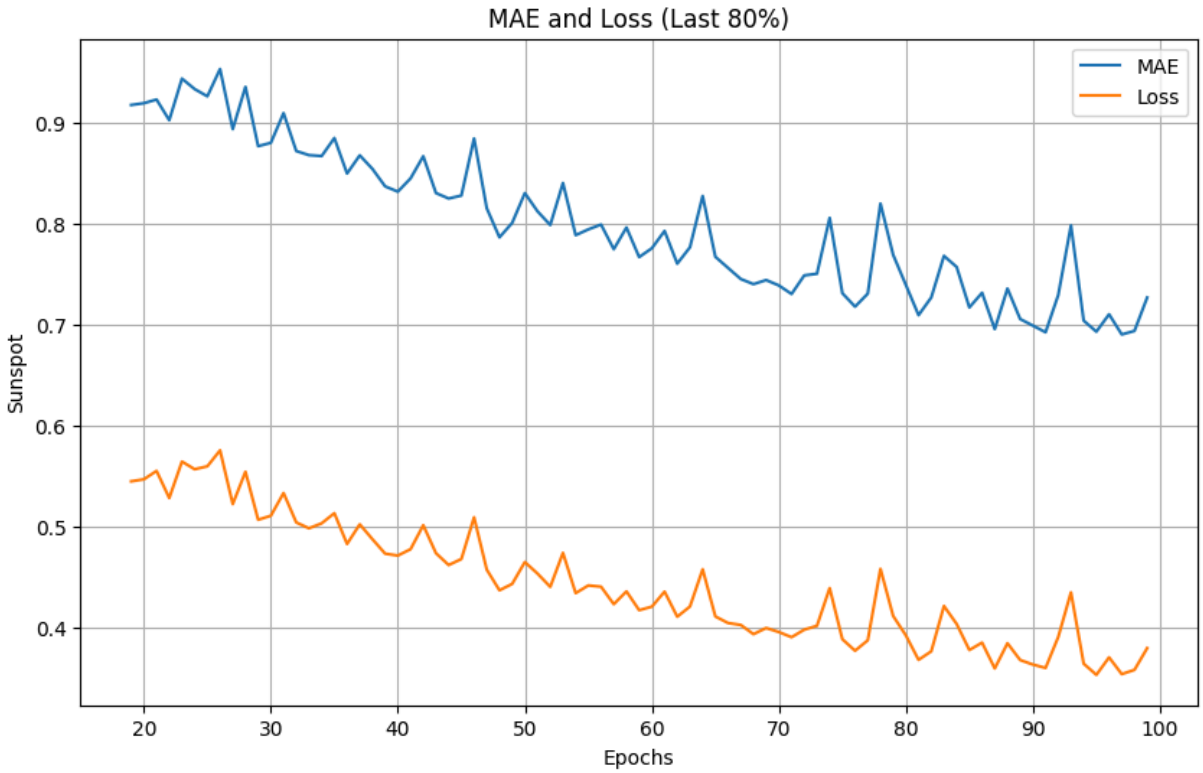




GRU Evaluation

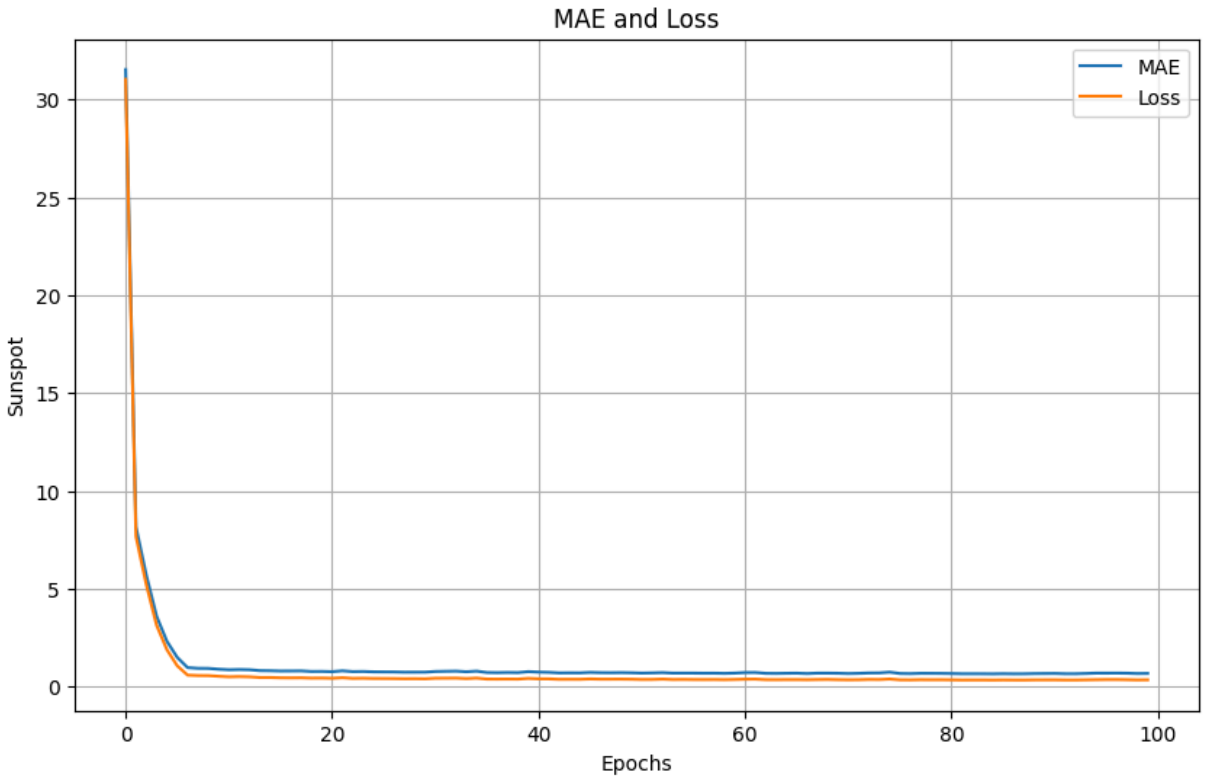
In [35]:
```
visualize_evaluation(history_GRU)
```

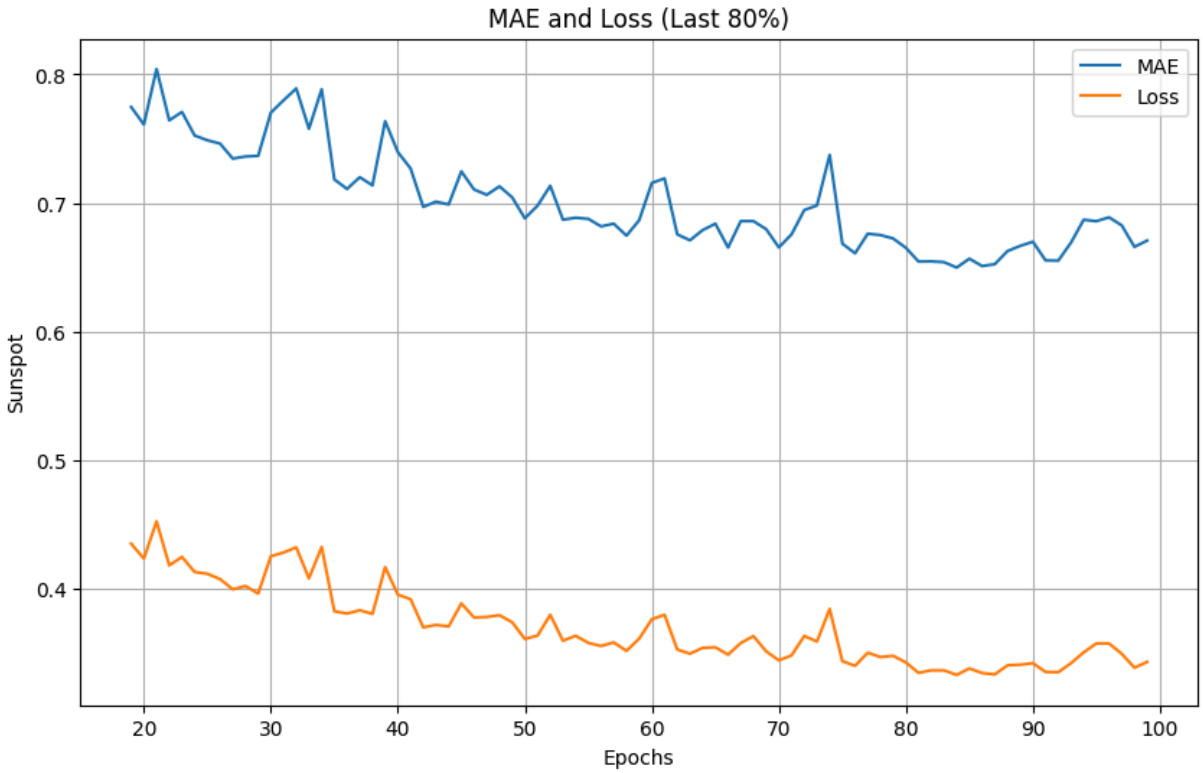




RNN-LSTM Evaluation

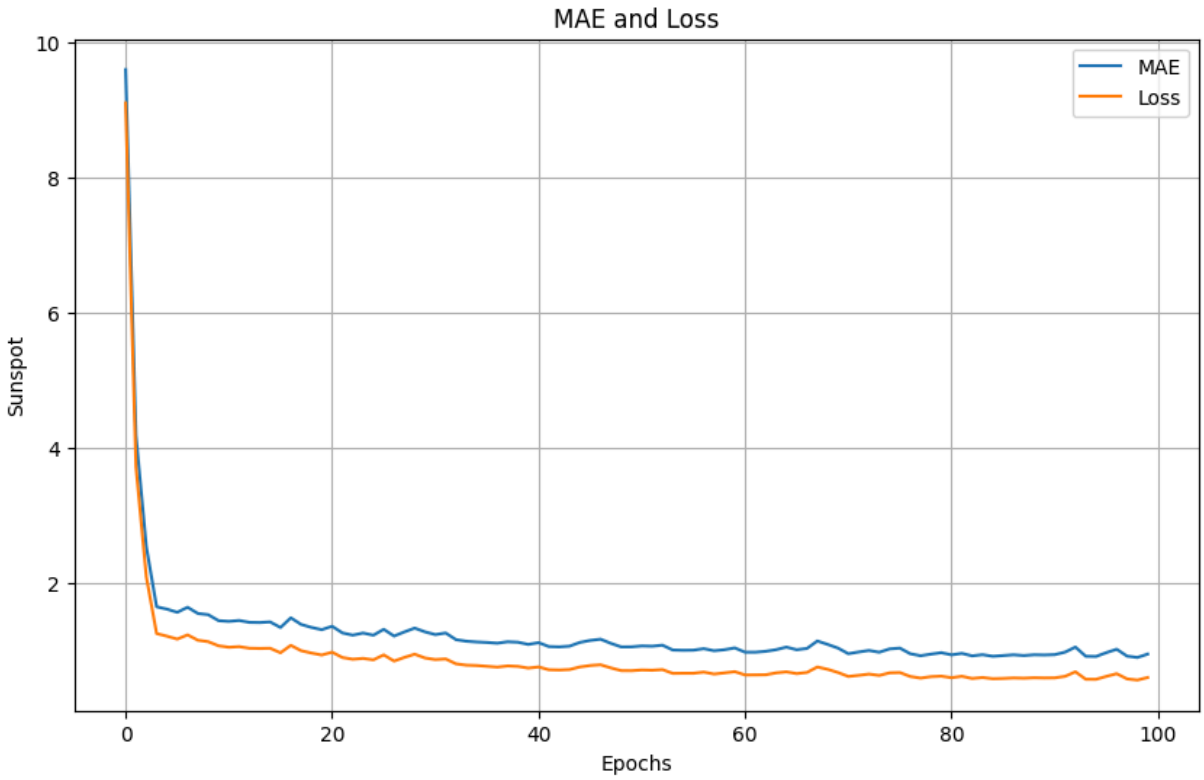
In [36]:
```
visualize_evaluation(history_RNN_LSTM)
```

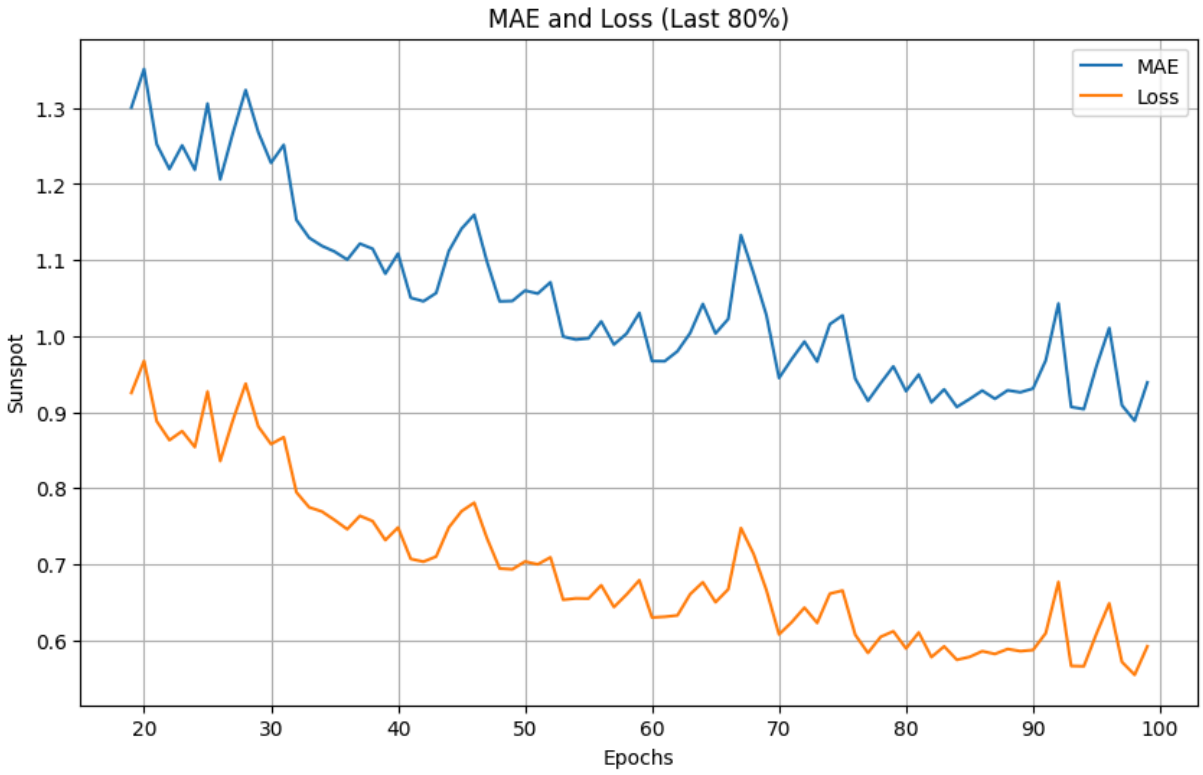




RNN-GRU Evaluation

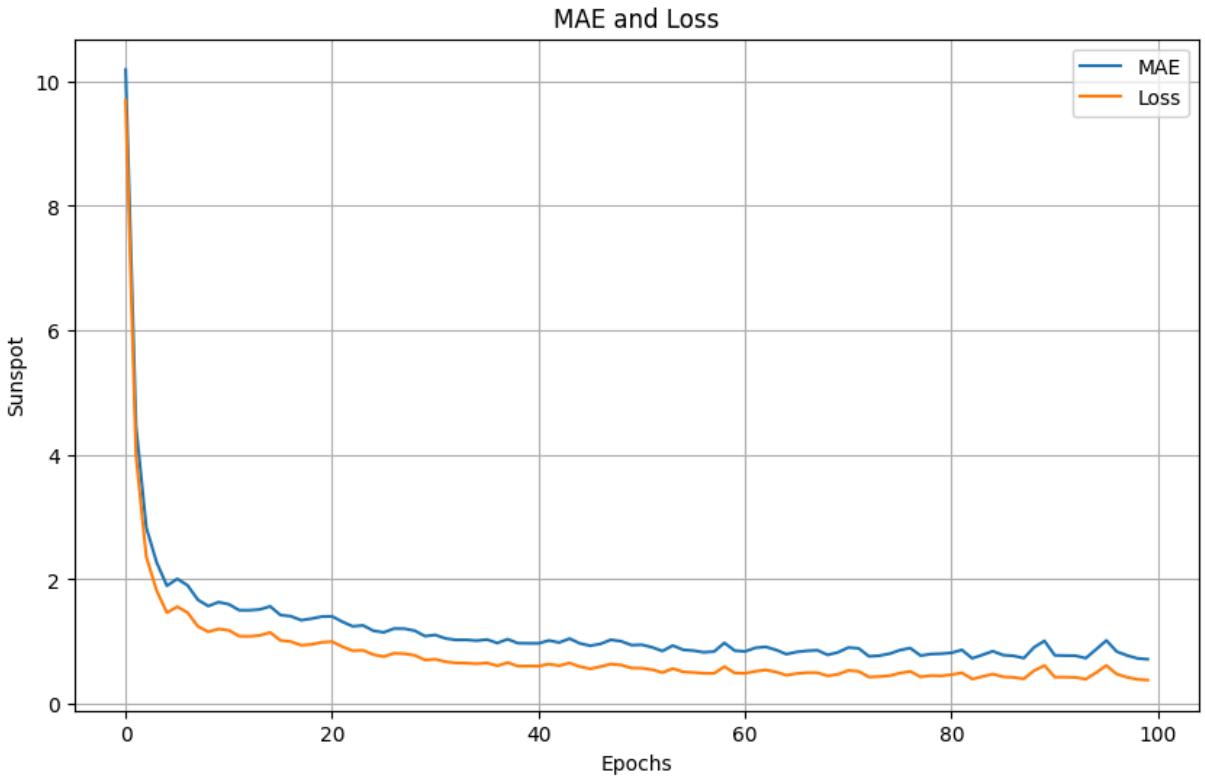
In [37]:
```
visualize_evaluation(history_RNN_GRU)
```

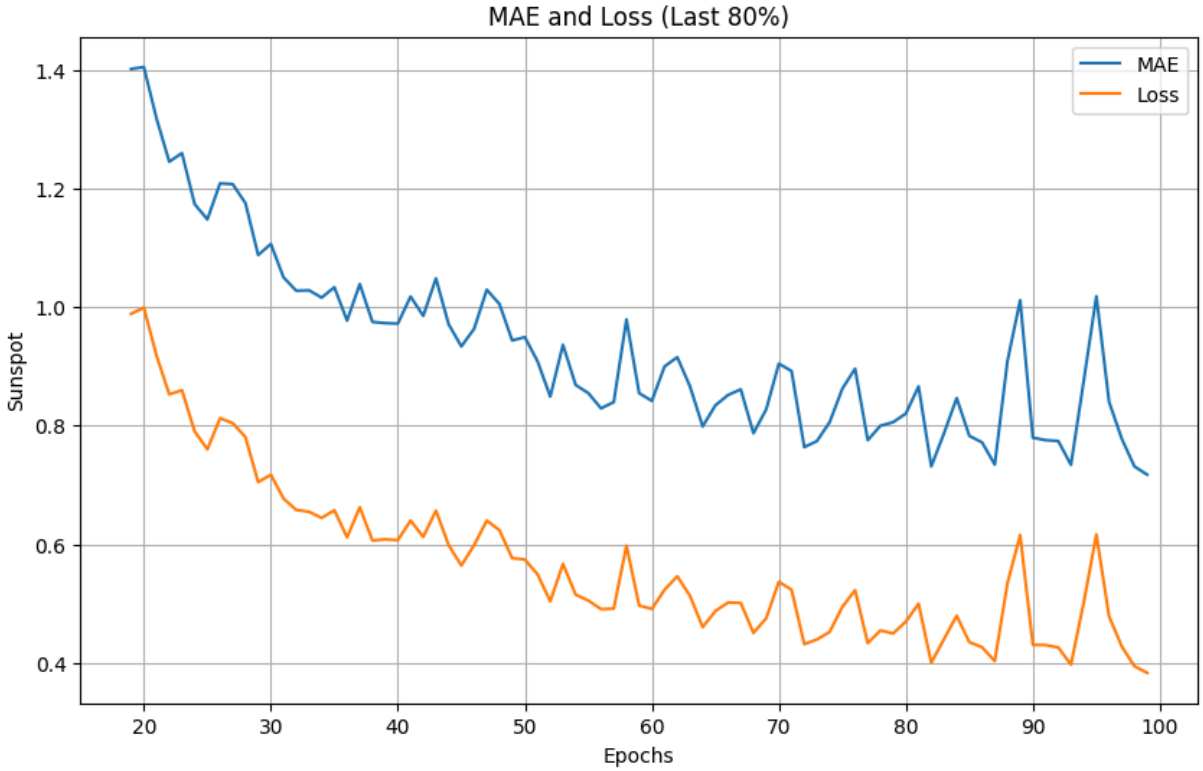




LSTM-RNN Evaluation

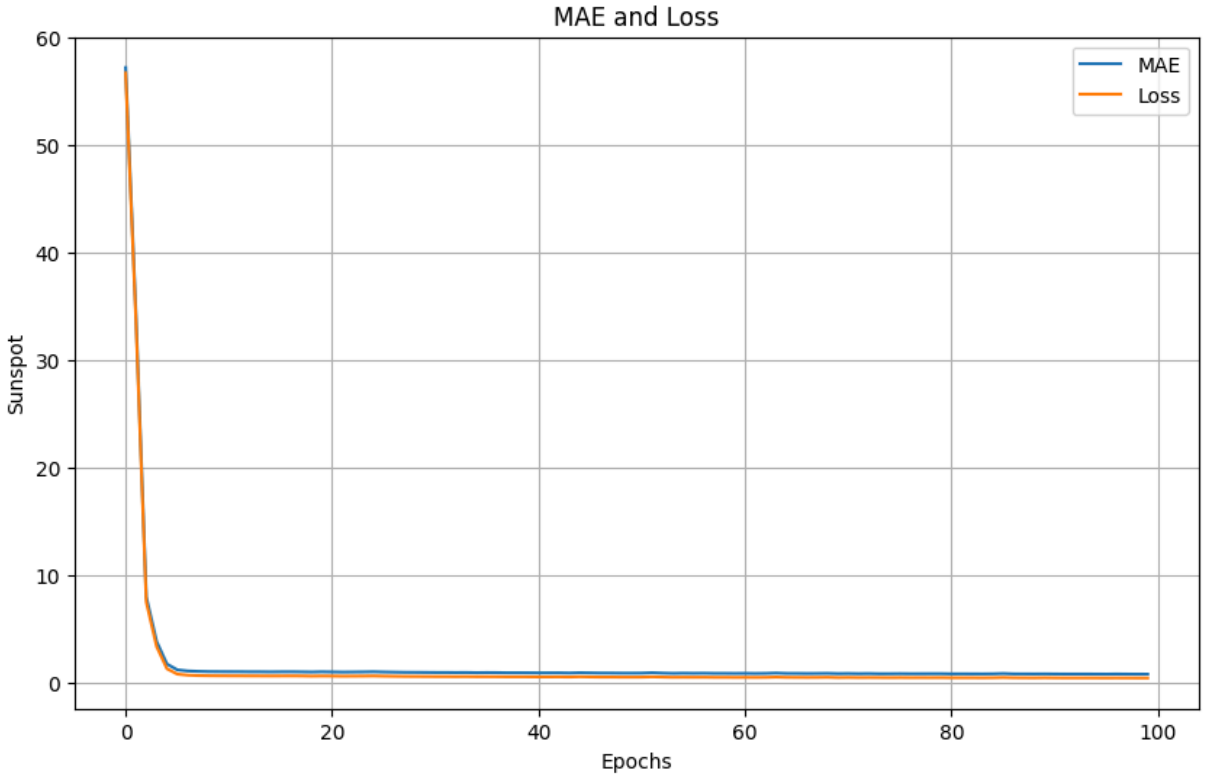
In [38]:
```
visualize_evaluation(history_LSTM_RNN)
```

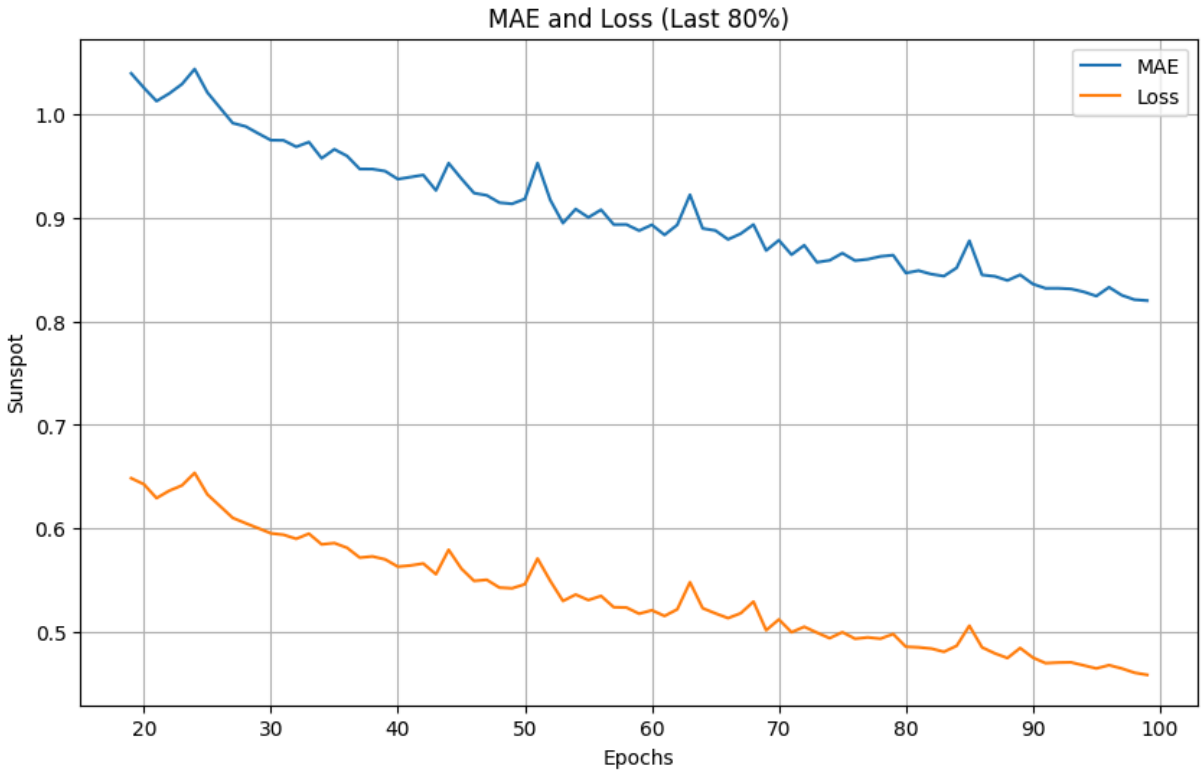




LSTM-GRU Evaluation

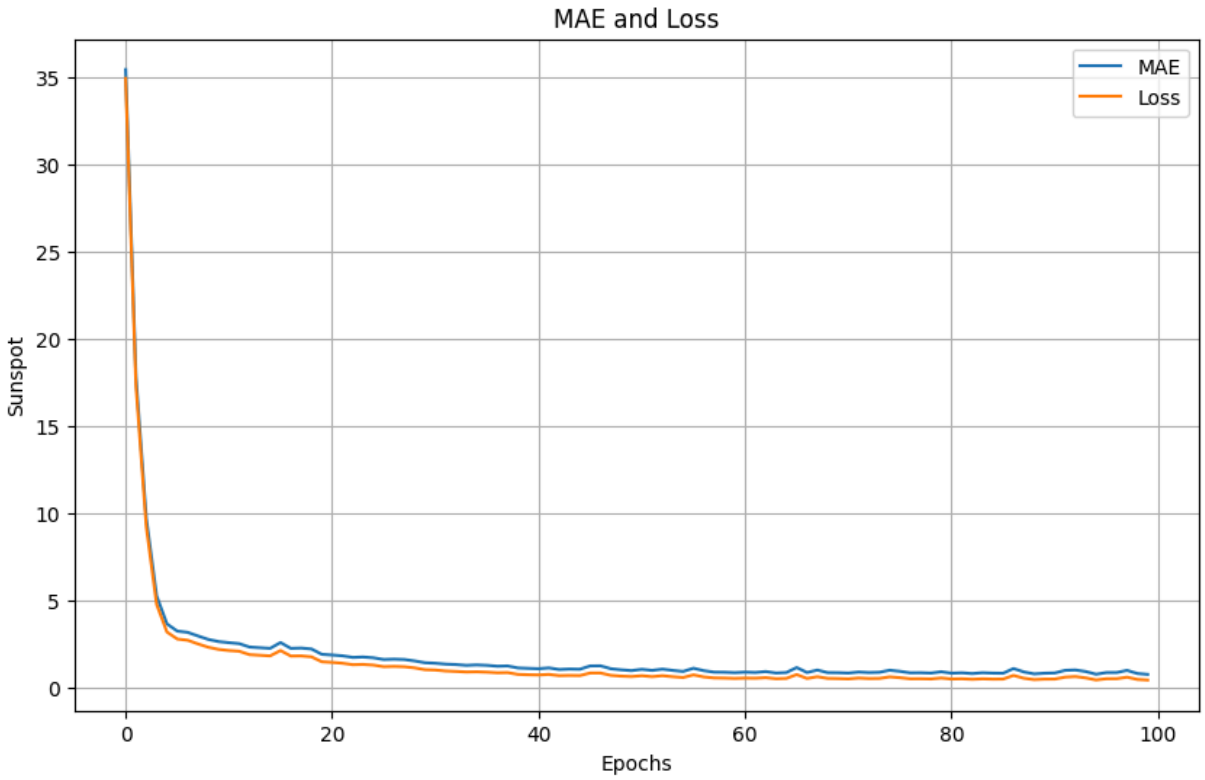
In [39]:
```
visualize_evaluation(history_LSTM_GRU)
```

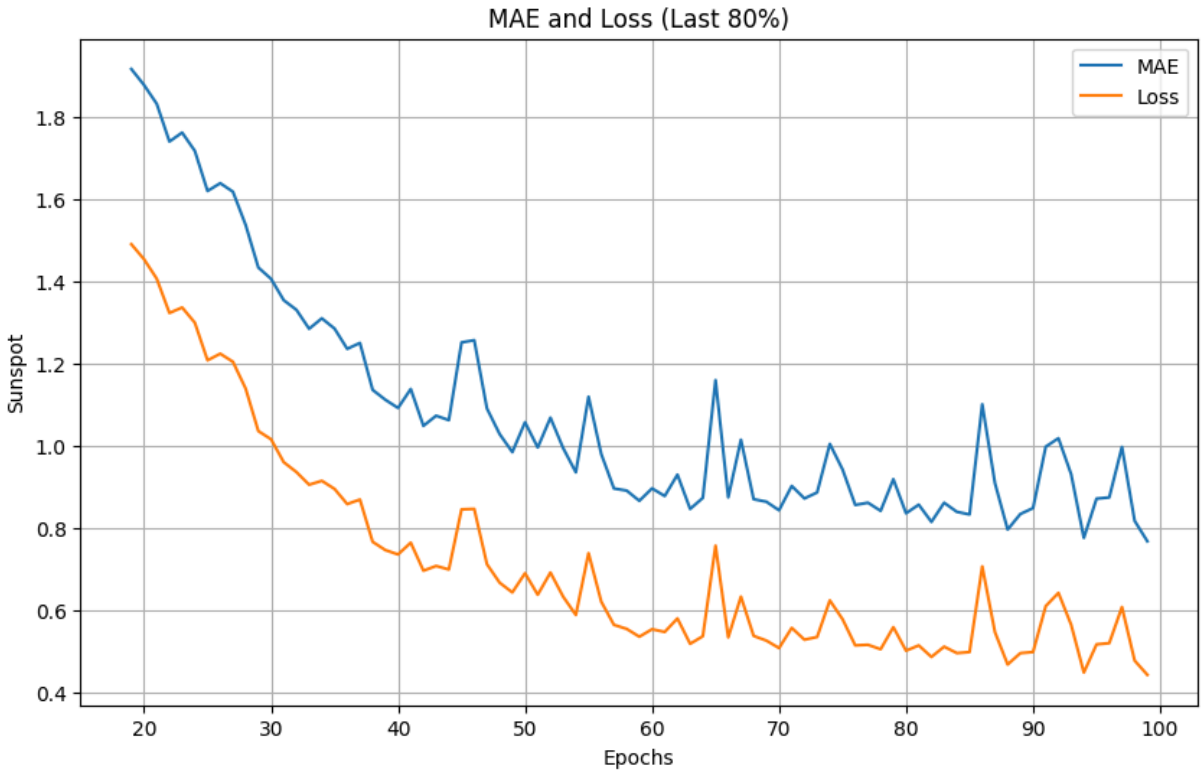




GRU-RNN Evaluation

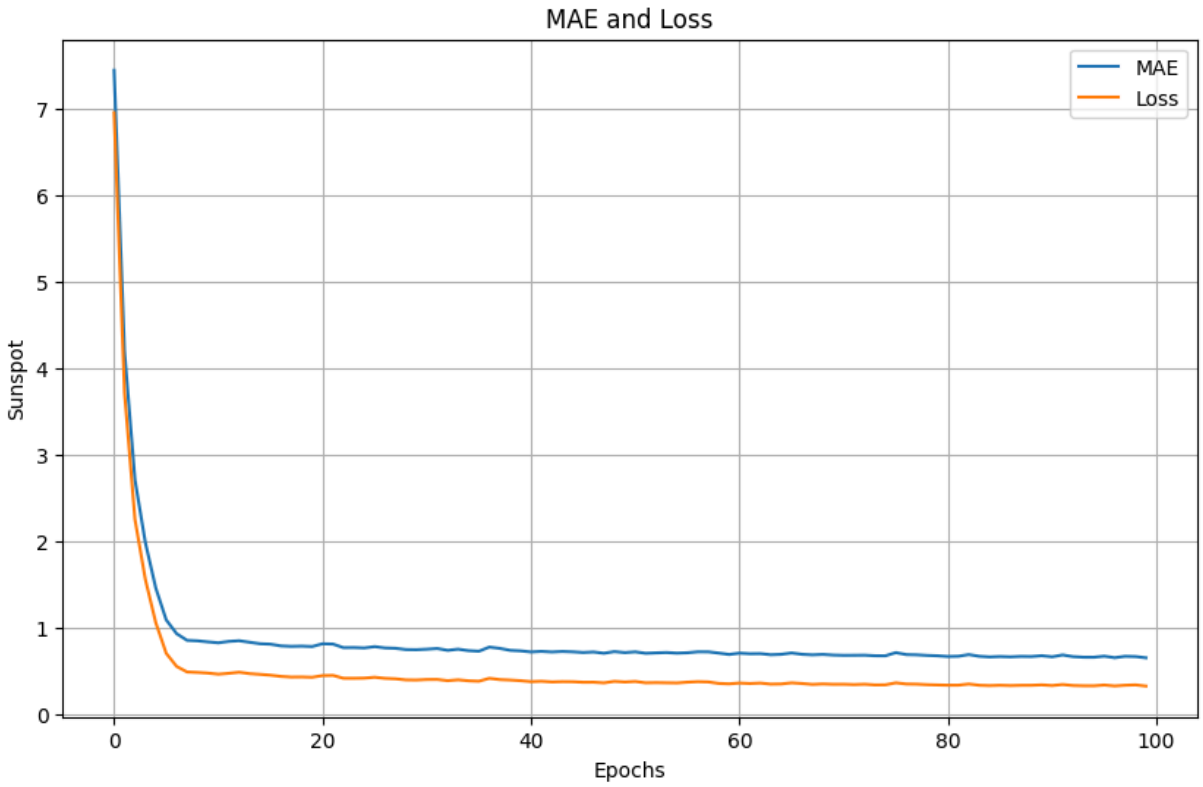
In [40]:
```
visualize_evaluation(history_GRU_RNN)
```

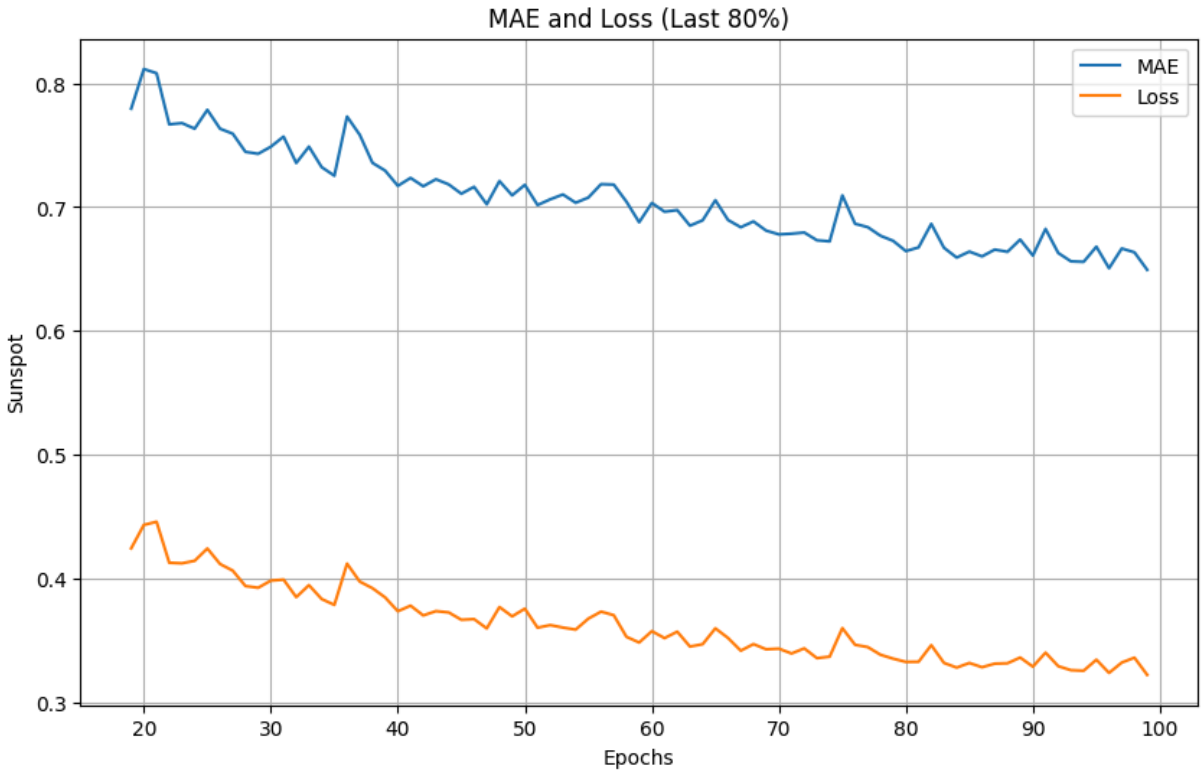




GRU-LSTM Evaluation

In [41]:
```
visualize_evaluation(history_GRU_LSTM)
```





7. Model Prediction

Analysis outcome of clustering for whale transaction characteristic

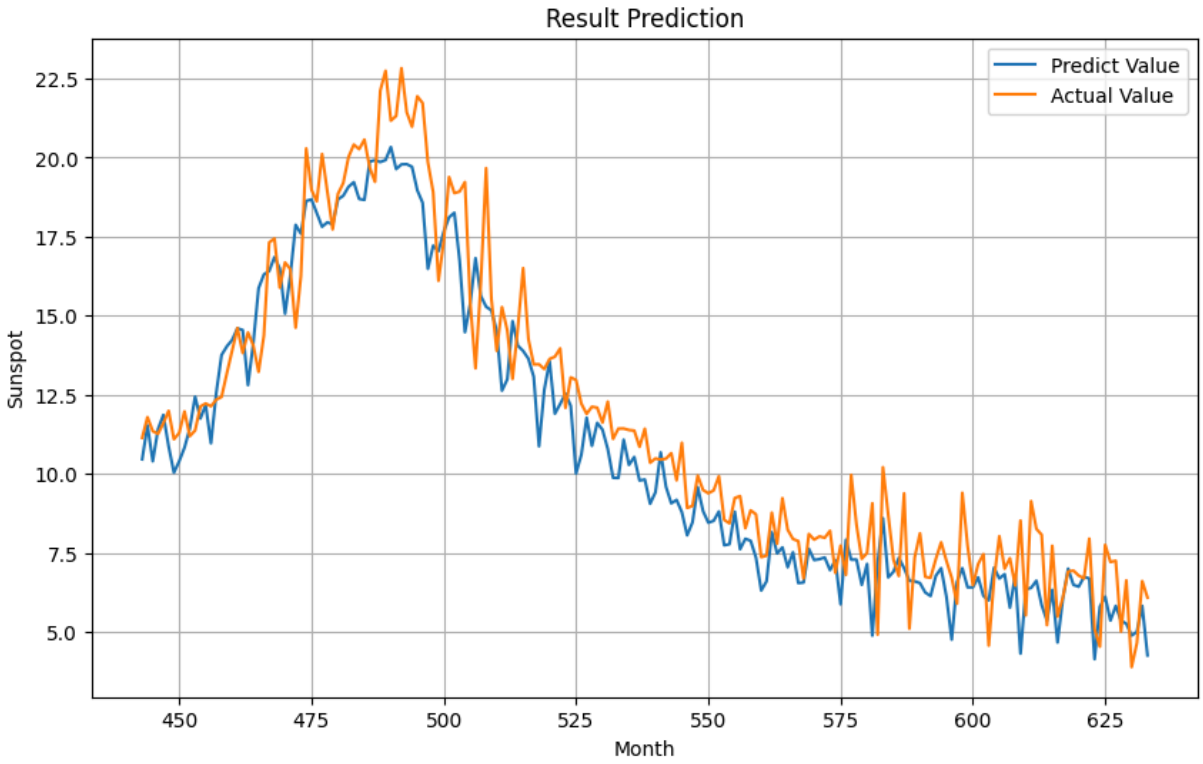
In [42]:
```
def model_forecast(model, series, window_size, batch_size):
    dataset = tf.data.Dataset.from_tensor_slices(series)
    dataset = dataset.window(window_size, shift=1, drop_remainder=True)
    dataset = dataset.flat_map(lambda w: w.batch(window_size))
    dataset = dataset.batch(batch_size).prefetch(1)
    forecast = model.predict(dataset)
    return forecast
```

In [43]:
```
def predict(model):
  forecast_series = series[split_time-window_size:-1]
  forecast = model_forecast(model, forecast_series, window_size, batch_size)
  results = forecast.squeeze()
  plot_series(time_valid, (x_valid, results, ), title='Result Prediction',
  xlabel='Month',
  ylabel='Sunspot',
  legend=['Predict Value', 'Actual Value'])
```

RNN Prediction

In [44]:
```
predict(model_RNN)
```

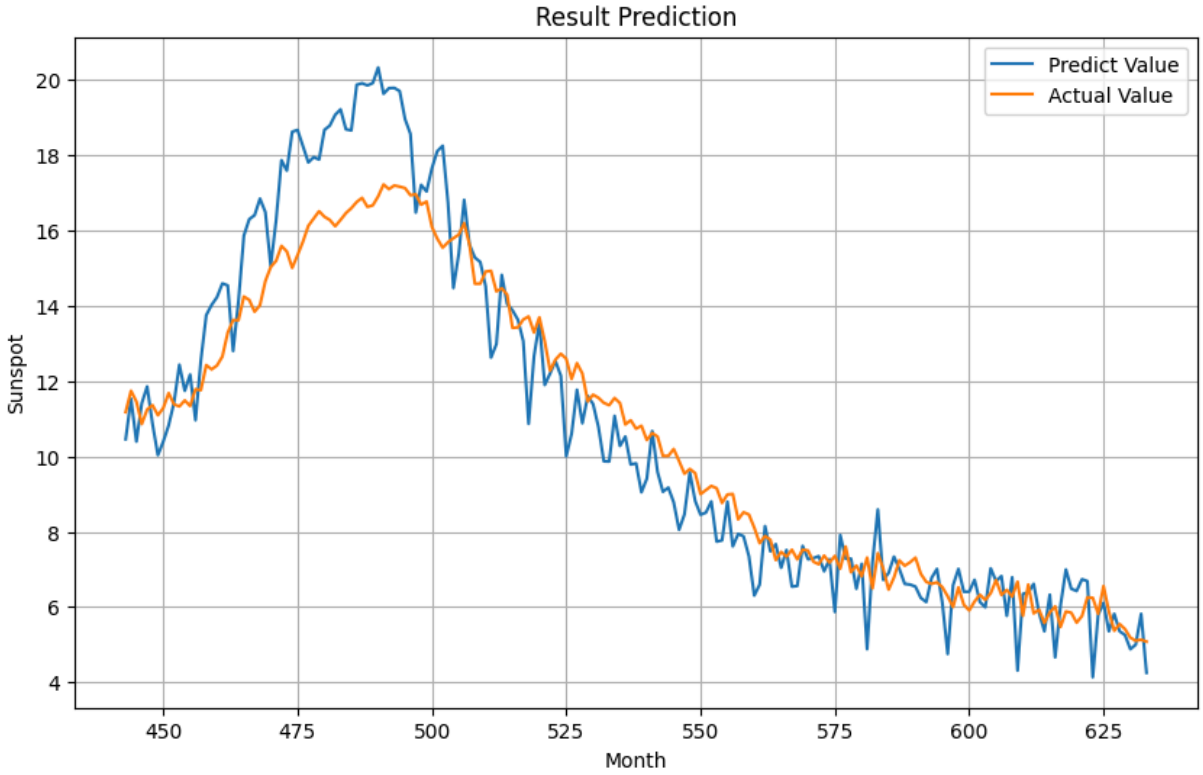
```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 51ms/step
```



LSTM Prediction

In [45]:
```
predict(model_LSTM)
```

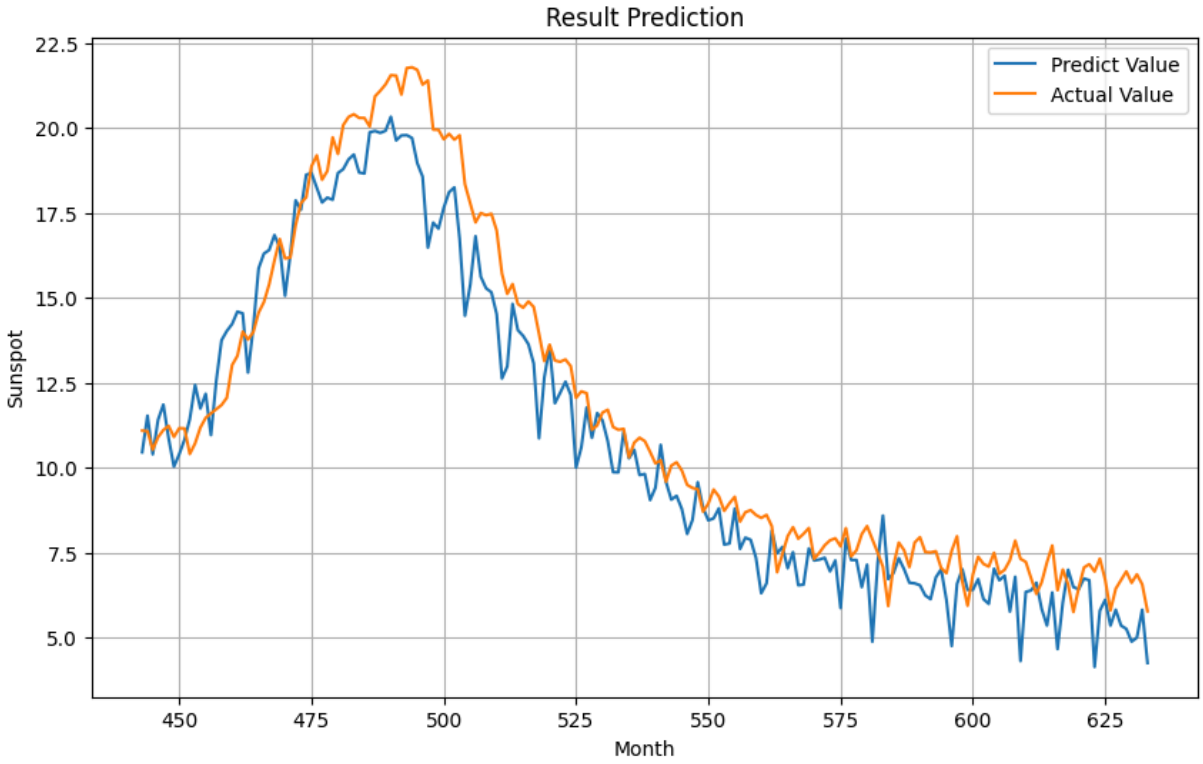
```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 61ms/step
```



GRU Prediction

In [46]:
```
predict(model_GRU)
```

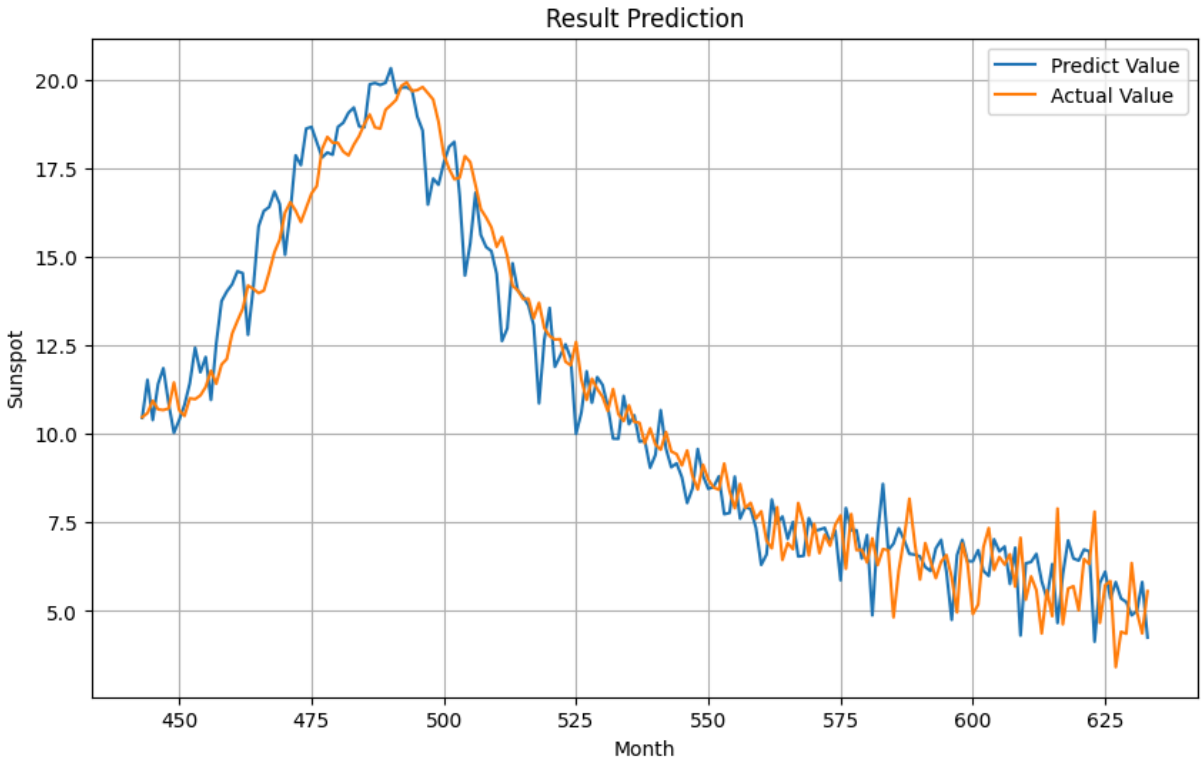
```
WARNING:tensorflow:5 out of the last 13 calls to <function TensorFlowTrainer.make_predict_funct
ion.<locals>.one_step_on_data_distributed at 0x7bdd492005e0> triggered tf.function retracing. T
racing is expensive and the excessive number of tracings could be due to (1) creating @tf.funct
ion repeatedly 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.tensor
flow.org/api_docs/python/tf/function for  more details.
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 73ms/step
```



RNN-LSTM Prediction

In [47]:
```
predict(model_RNN_LSTM)
```

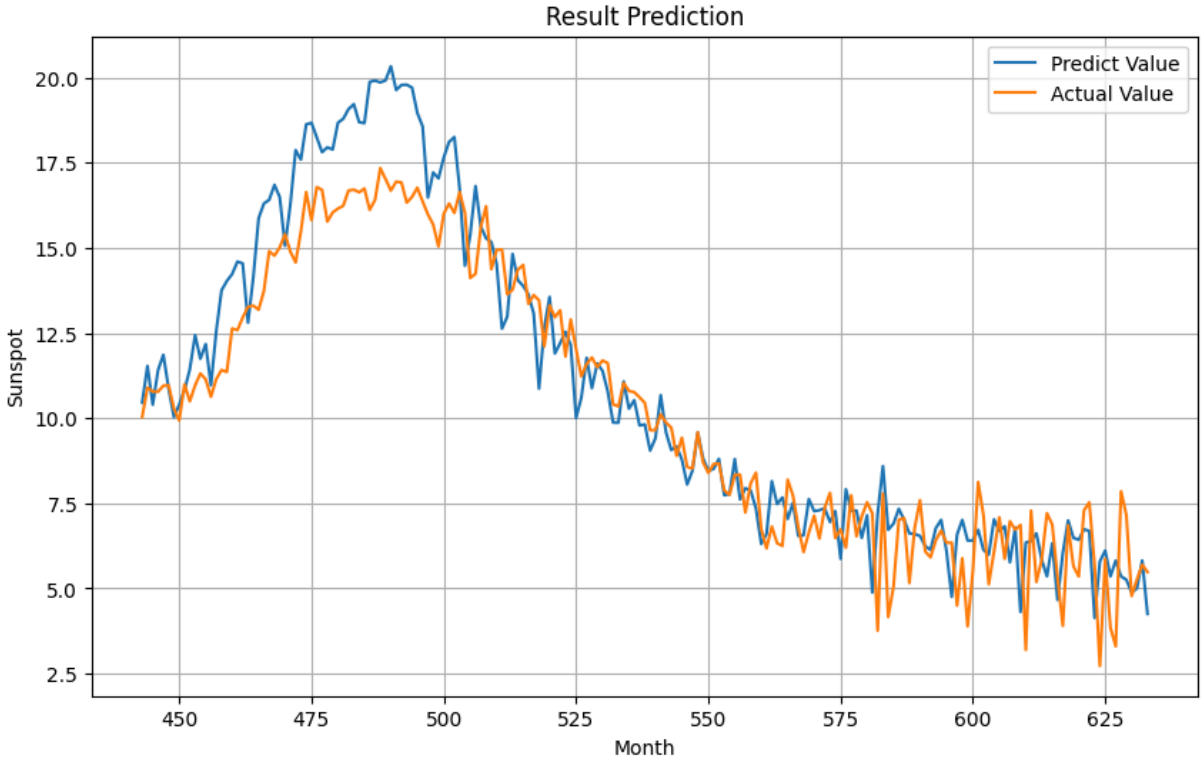
```
WARNING:tensorflow:5 out of the last 13 calls to <function TensorFlowTrainer.make_predict_funct
ion.<locals>.one_step_on_data_distributed at 0x7bdd49171c60> triggered tf.function retracing. T
racing is expensive and the excessive number of tracings could be due to (1) creating @tf.funct
ion repeatedly 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.tensor
flow.org/api_docs/python/tf/function for  more details.
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 57ms/step
```



RNN-GRU Prediction

In [48]:
```
predict(model_RNN_GRU)
```

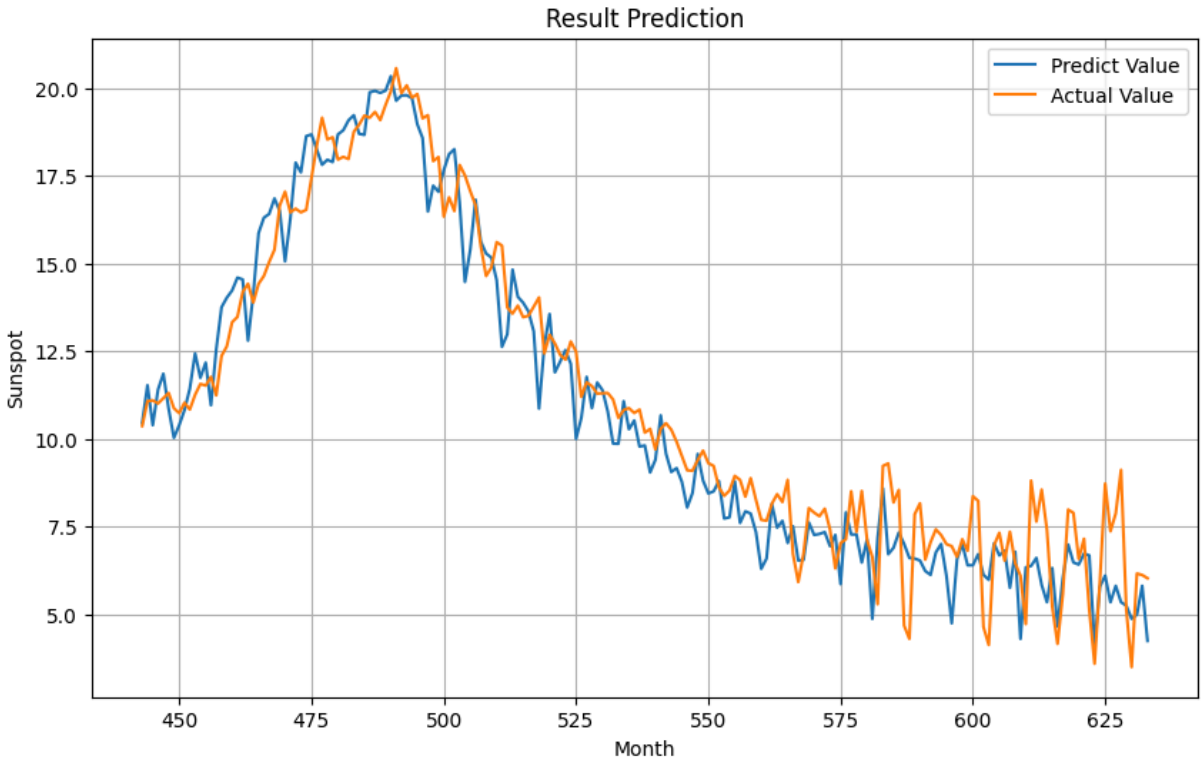
```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 66ms/step
```



LSTM-RNN Prediction

In [49]:
```
predict(model_LSTM_RNN)
```

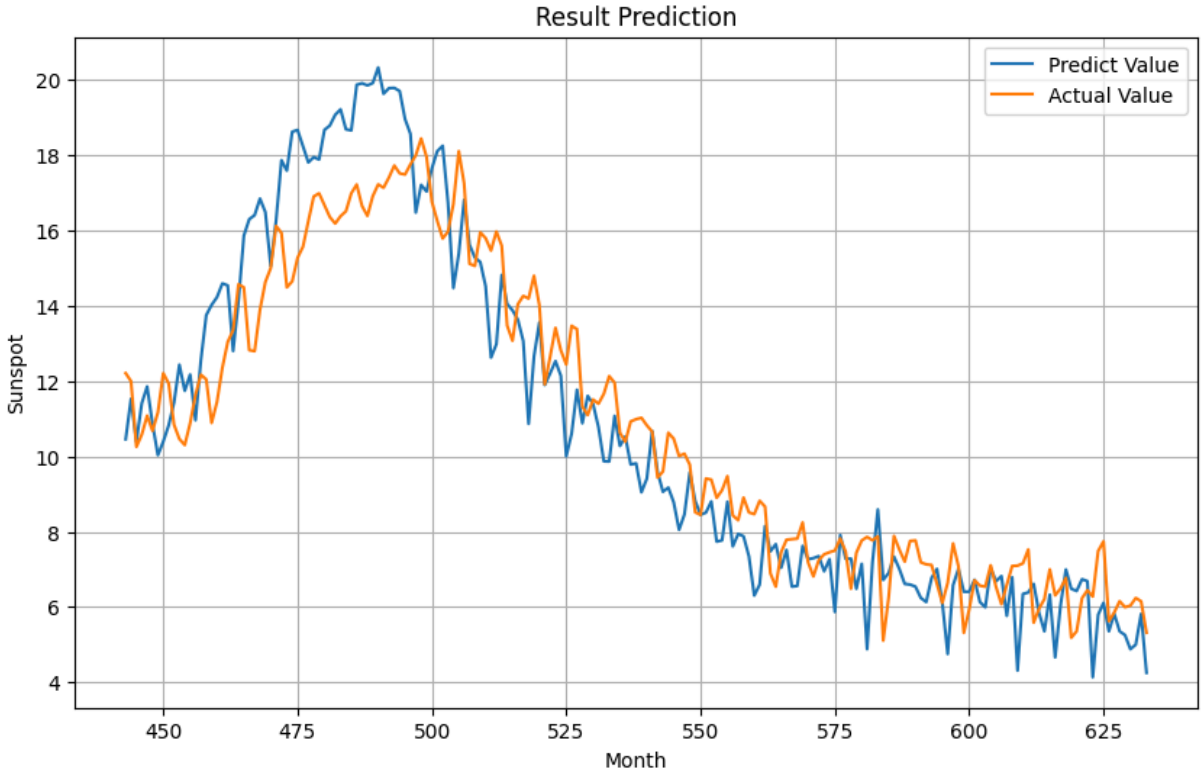
```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 91ms/step
```



LSTM-GRU Prediction

In [50]:
```
predict(model_LSTM_GRU)
```

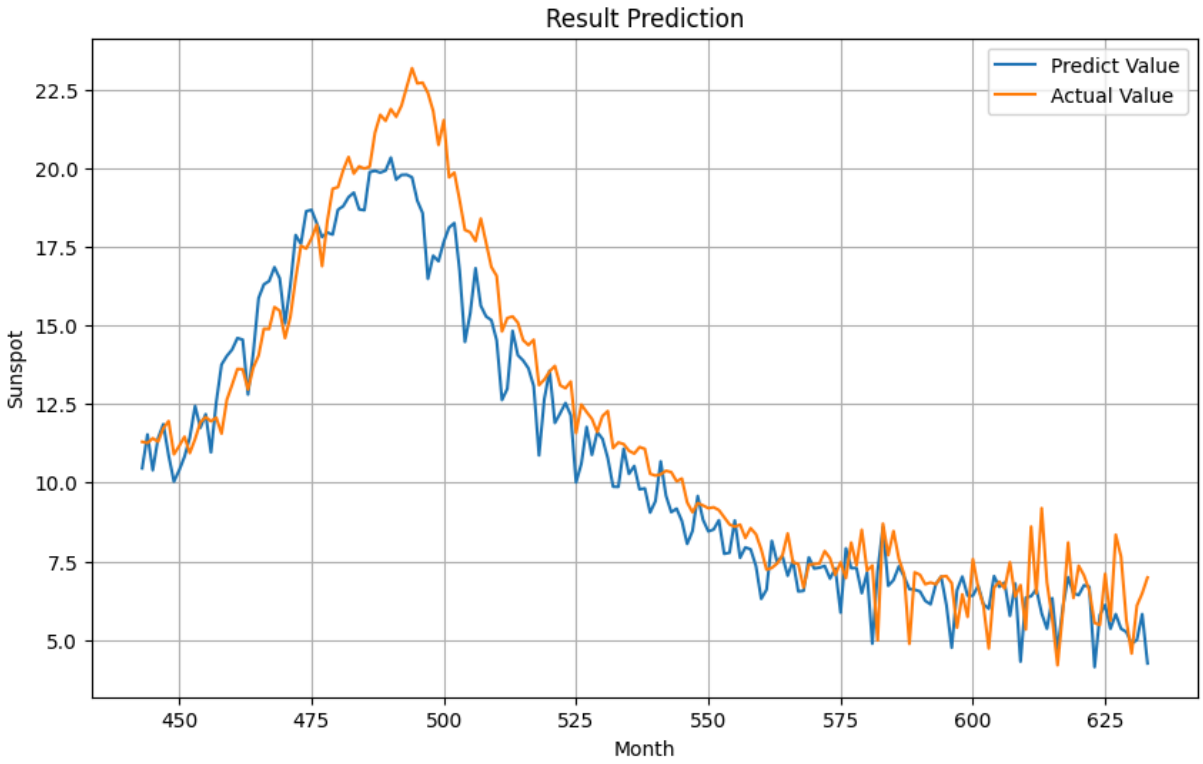
```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 106ms/step
```



GRU-RNN Prediction

In [51]:
```
predict(model_GRU_RNN)
```

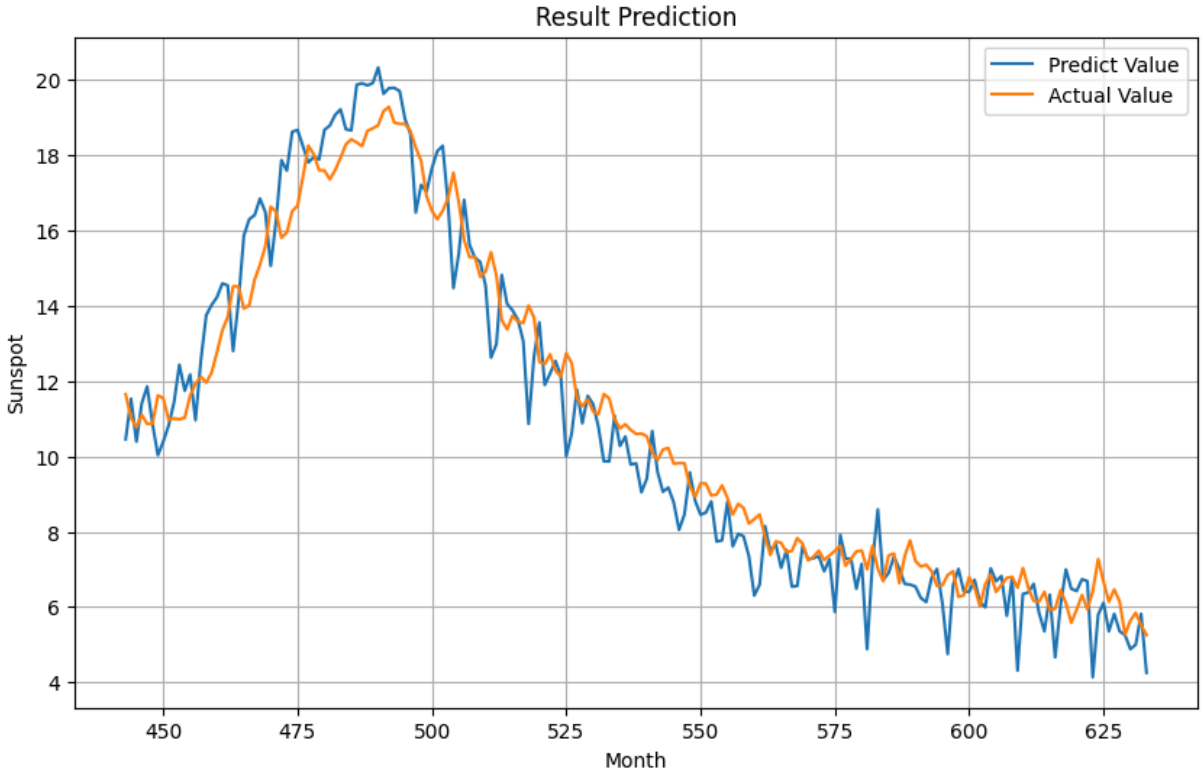
```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 65ms/step
```



GRU-LSTM Prediction

In [52]:
```
predict(model_GRU_LSTM)
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 74ms/step
```



Confident Interval

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import files
import time
```

Donwload Data

In [ ]:
```
!wget https://github.com/kkms51/data/raw/main/GRU_LSTM_TIME.xlsx
!wget https://github.com/kkms51/data/raw/main/GRU_RNN_TIME.xlsx
!wget https://github.com/kkms51/data/raw/main/GRU_TIME.xlsx
!wget https://github.com/kkms51/data/raw/main/LSTM_GRU_TIME.xlsx
!wget https://github.com/kkms51/data/raw/main/LSTM_RNN_TIME.xlsx
!wget https://github.com/kkms51/data/raw/main/RNN_LSTM_TIME.xlsx
!wget https://github.com/kkms51/data/raw/main/RNN_GRU_TIME.xlsx
```

In [ ]:
```
!gdown 1OusiKKuYGBZxP41JqALwjS5fiZ5bVET8
!gdown 17Z12L9mQh91d7wz5tu2V4ywzrVJ91hRj
!gdown 1sgrbiaGJrwF-AEXEr8R5x2Ulk95dq56K
!gdown 11dDMmQ8RWVDHcZuNyEeWlC-k0nHx5pv4
!gdown 1RCRBAGpTxkxruxc-XBDxBUq5A-eIS7RB
!gdown 1jzDhLE81rWPZffIwBg-MvuMqVPpg-bY-
!gdown 1ar8H4y9QWquY6zM_cxpk3vp_aDy6gcjU
!gdown 1Lmaa9hUtdTD_OFdC4aRwfYxtMjjLWU7i
!gdown 1ar8H4y9QWquY6zM_cxpk3vp_aDy6gcjU
!gdown 1Lmaa9hUtdTD_OFdC4aRwfYxtMjjLWU7i
!gdown 1Fg9-g0HfM6OPAIBetFllDdiHOQDU7_Pe
!gdown 1uHwTBW5IhPG9cnnBN3P5vGAW0HlJEUfG
!gdown 1xOn5Jvk_5hzaLVbmCWMSulcEqPzJNm29
!gdown 1RkZQ50WhKxoCRswyMTEDp-Jpfbwm5six
!gdown 1-uCIfgqEUmM2EOiFb9v7iBVRL1kMMXj1
!gdown 18hpQAoeUicSeYaJb0SKuHj-Op6LAHXrG
!gdown 1gXJIGhIKKkPERaecvST5rX16lrnqGZ1j
!gdown 1MGNVSDpfEerjj9fOlZI3LYkLxN6YHGiS
```

Viz

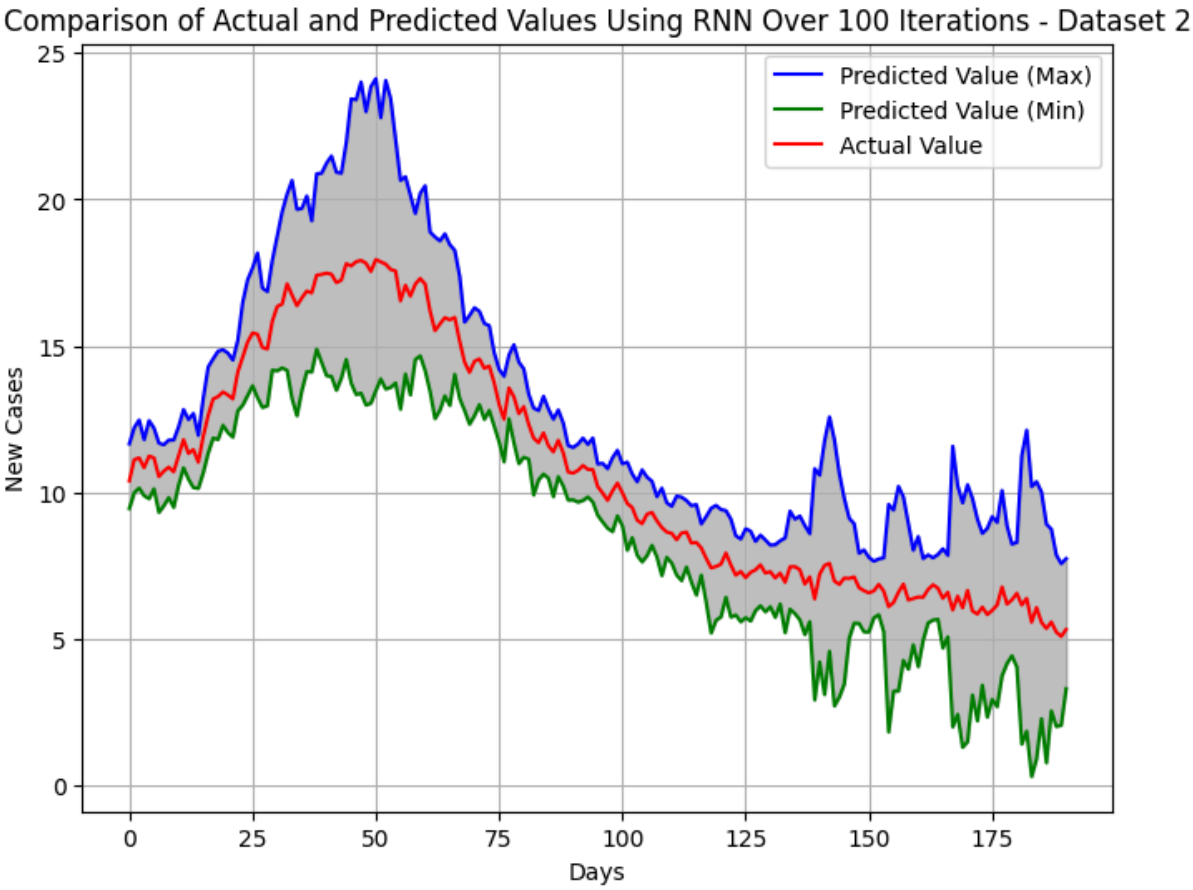
In [4]:
```
from re import X
def shade_plot(temp, x_valid='0', line='MAE', predict=''):
  import matplotlib.pyplot as plt

  if predict == '':
    redline = f'Mean {line}'
    axis = 'Epochs'
  else:
    redline = 'Actual Value'
    axis = 'Days'

  #SORT
  temp = temp.apply(lambda x: x.sort_values().reset_index(drop=True))

  #CUT 2.5%
  n = int(len(temp) * 0.025)
  temp = temp.iloc[n:-n]

  batas_atas = temp.max().tolist()
  batas_bawah = temp.min().tolist()
  rata = temp.mean().tolist()

  # Replace these lists with your actual data
  # Dataset 1
  x1 = [i for i in range(0,len(batas_atas))]
```

```
  y1 = batas_atas

  # Dataset 2
  x2 = [i for i in range(0,len(batas_bawah))]
  y2 = batas_bawah

  if(x_valid=='0'):
    # Dataset 3
    x3 = [i for i in range(0,len(rata))]
    y3 = rata
  else:
    x3 = [i for i in range(0,len(x_valid))]
    y3 = x_valid

  # Create the plot
  plt.figure(figsize=(8, 6))

  # Plot the first linear dataset
  plt.plot(x1, y1, label=f'Predicted Value (Max)', color='blue')

  # Plot the second linear dataset
  plt.plot(x2, y2, label=f'Predicted Value (Min)', color='green')

  plt.plot(x3, y3, label=f'{redline}', color='red')

  # Create a mask for the shaded area where y1 >= y2
  mask = [y1_val >= y2_val for y1_val, y2_val in zip(y1, y2)]

  # Shade the area between the two datasets
  plt.fill_between(x1, y1, y2, where=mask, interpolate=True, color='gray', alpha=0.5)

  # Add labels and legend
  plt.xlabel(f'{axis}')
  plt.ylabel('New Cases')
  plt.title(f'Comparison of Actual and Predicted Values Using {line} Over 100 Iterations - Data
  plt.legend()
  plt.savefig(f"Predicted_Actual_Value_Dataset2_{line}.pdf", dpi=300)
  files.download(f"Predicted_Actual_Value_Dataset2_{line}.pdf")
  # Show the plot
  plt.grid(True)
  plt.show()
```

In [ ]:
```
!wget https://raw.githubusercontent.com/MhdIqbalPratama/ware-house/main/Data%20COVID-19%20Indon
```

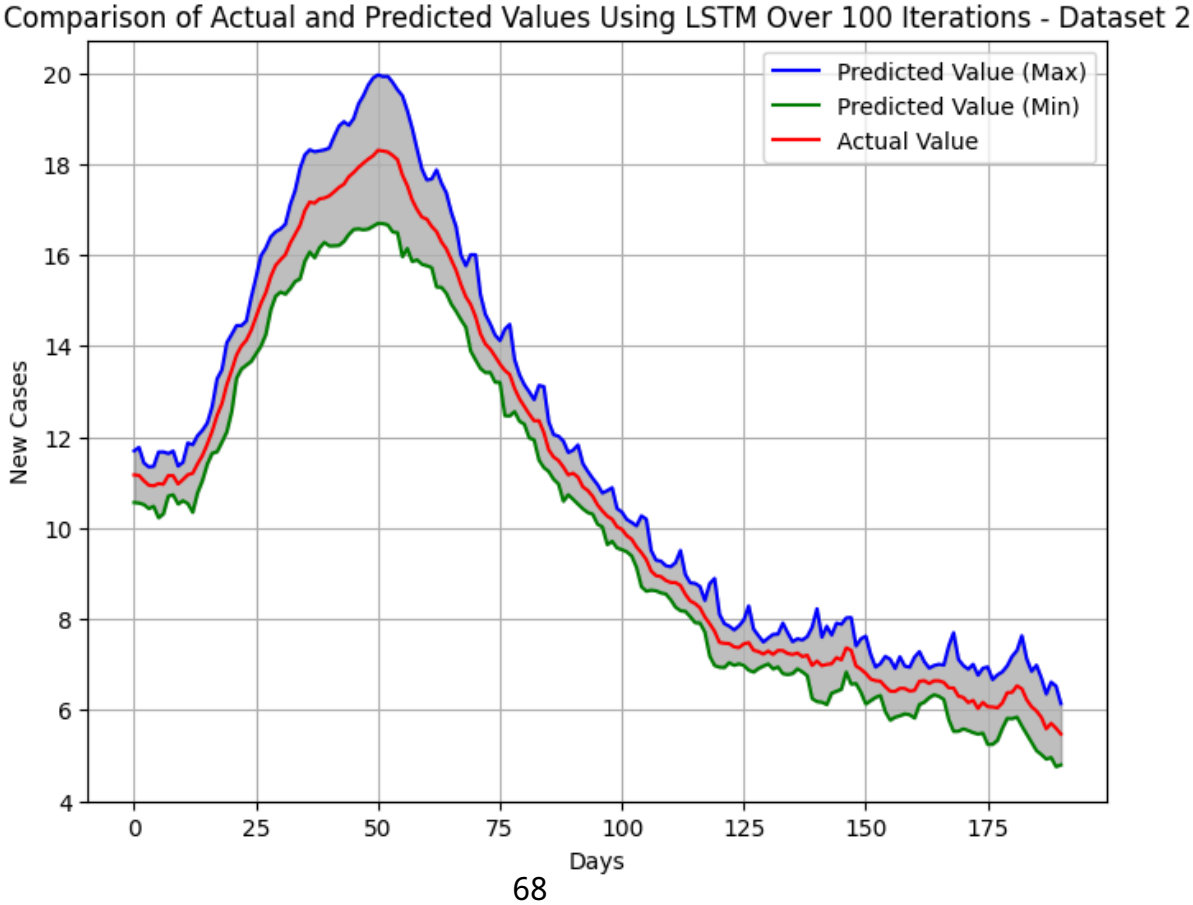
RNN

In [13]:
```
temp = pd.read_excel('RNN_PREDICT.xlsx')
shade_plot(temp, line='RNN', predict='YES')
```



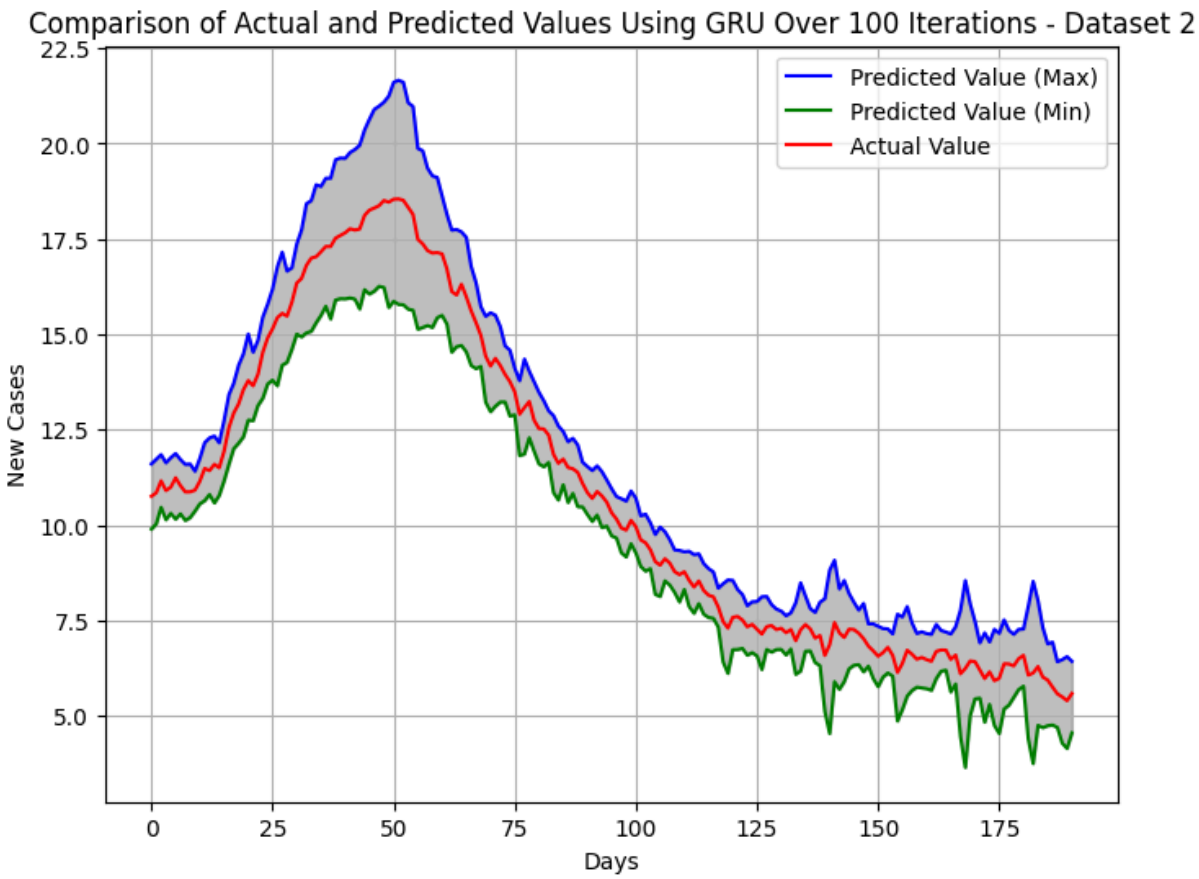
LSTM

In [18]:
```
temp = pd.read_excel('LSTM_PREDICT.xlsx')
shade_plot(temp, line='LSTM', predict='YES')
```



GRU

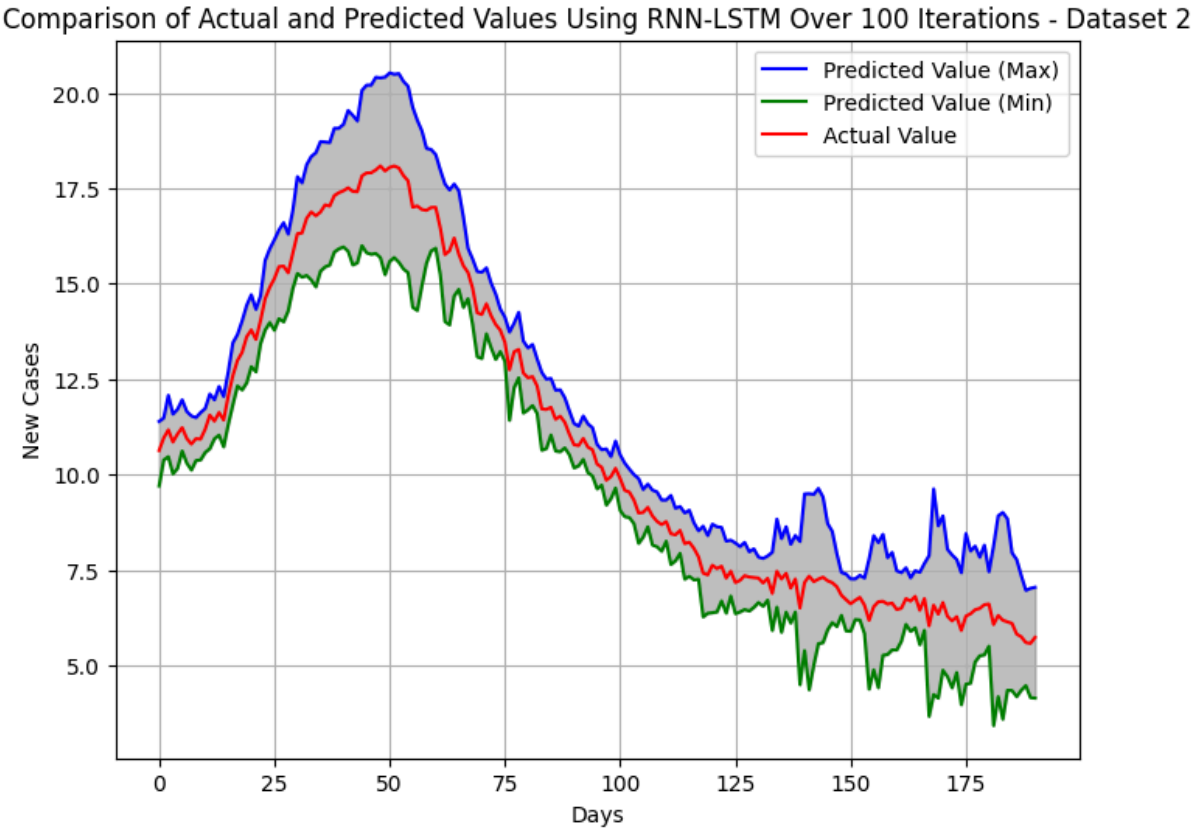
In [23]:
```
temp = pd.read_excel('GRU_PREDICT.xlsx')
shade_plot(temp, line='GRU', predict='YES')
```



In [ ]:
```
!gdown 1Jcj7_vtMQ2foct0YPmWC6nO9q4T_x3bl
!gdown 1d-M7kCjRcggRBII-8o9WUhbWPaFxcPRg
```

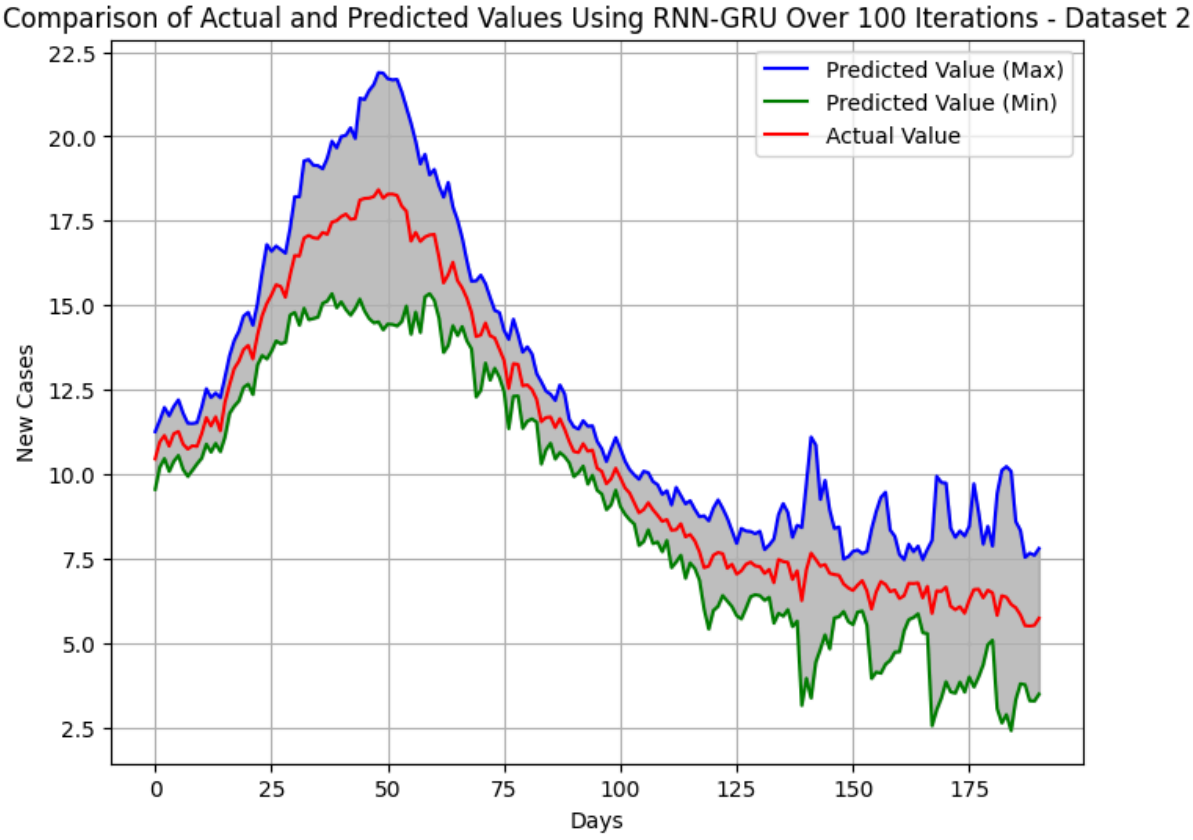
RNN-LSTM

In [29]:
```
temp = pd.read_excel('RNN_LSTM_PREDICT.xlsx')
shade_plot(temp, line='RNN-LSTM', predict='YES')
```



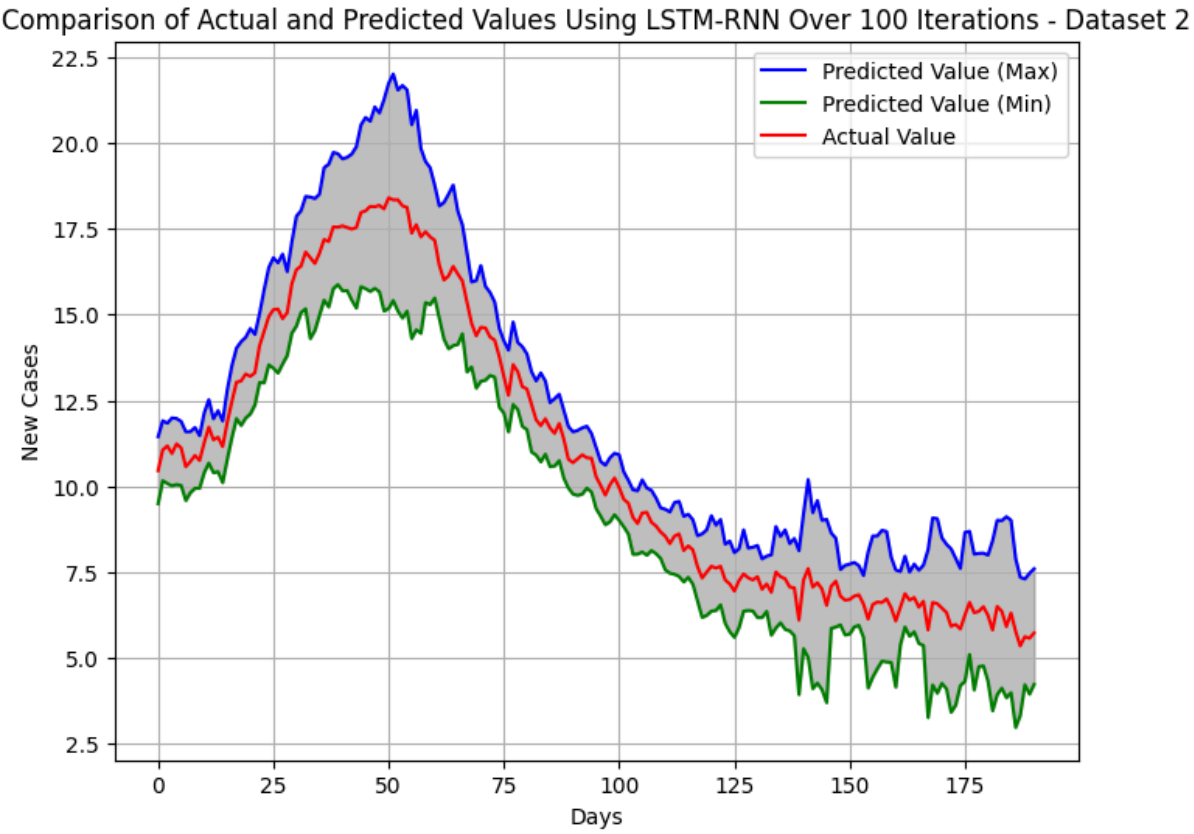
RNN-GRU

In [34]:
```
temp = pd.read_excel('RNN_GRU_PREDICT.xlsx')
shade_plot(temp, line='RNN-GRU', predict='YES')
```



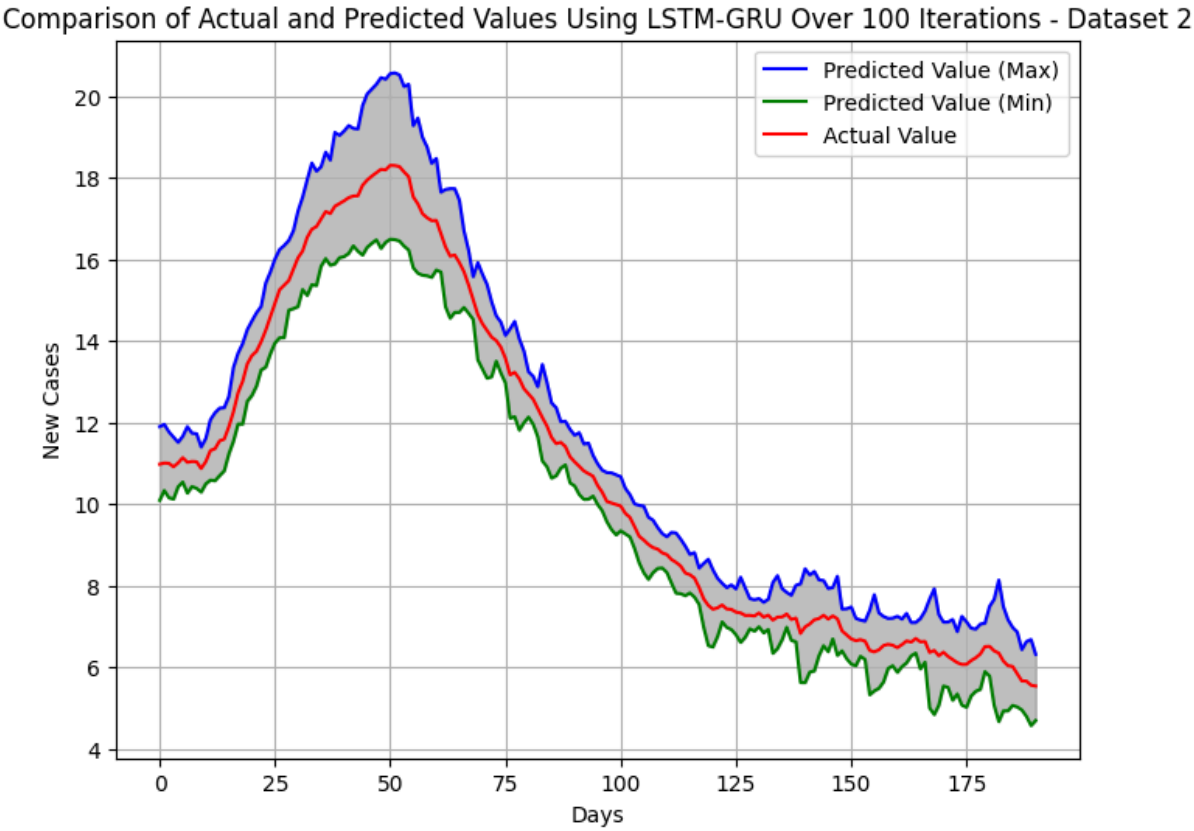
LSTM-RNN

In [39]:
```
temp = pd.read_excel('LSTM_RNN_PREDICT.xlsx')
shade_plot(temp, line='LSTM-RNN', predict='YES')
```



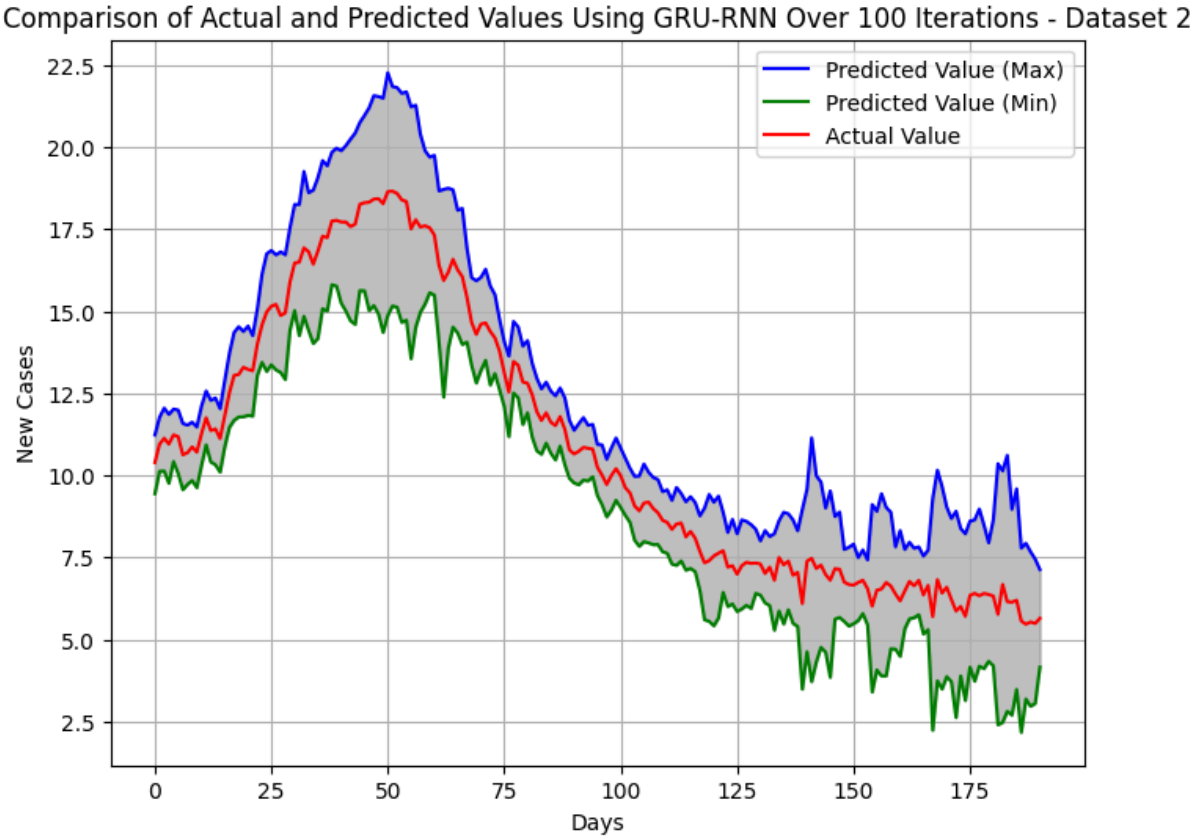
LSTM-GRU

In [44]:
```
temp = pd.read_excel('LSTM_GRU_PREDICT.xlsx')
shade_plot(temp, line='LSTM-GRU', predict='YES')
```



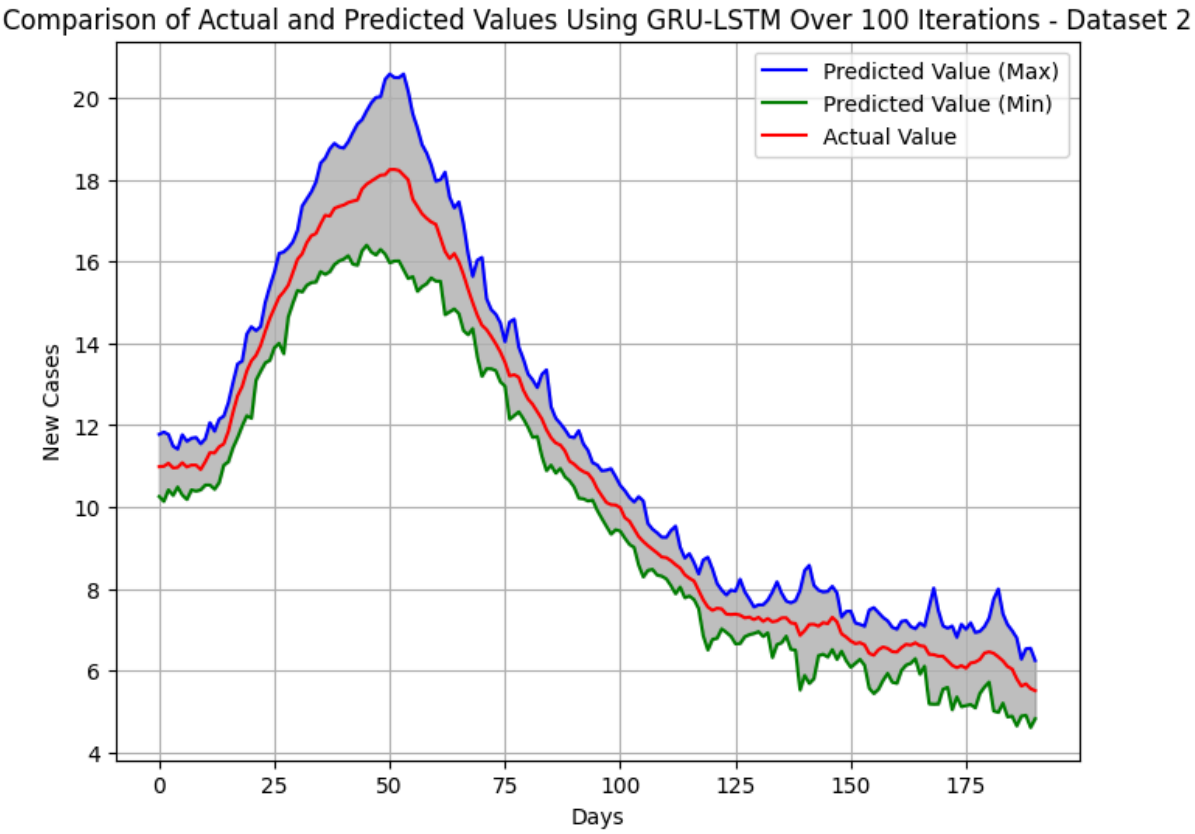
GRU-RNN

In [49]:
```
temp = pd.read_excel('GRU_RNN_PREDICT.xlsx')
shade_plot(temp, line='GRU-RNN', predict='YES')
```



GRU-LSTM

In [54]:
```
temp = pd.read_excel('GRU_LSTM_PREDICT.xlsx')
shade_plot(temp, line='GRU-LSTM', predict='YES')
```



DONWLOAD DATA

In [ ]:
```
!gdown 1_Xk_aBt72cg0IhtrDHByatBuGuLi-svr
!gdown 1ZrtG6EfZxXeV19WMzla_qniBb4E0vHGp
!gdown 1YCs0hRgt-wpSVI7EbtLit5HvjM7brmtB
!gdown 194--ZfpP3lr5eg8jfjbDLSWDSvWVVx18
!gdown 1mrYem8IETC1Bvv4XLfkuFc_Yxs0L-1M5
!gdown 11ElHC2LM013wujQwqW12SD6gDrv60mOl
!gdown 1f62wFr9ML2AAO39aeU2dbKsmh3idLyOi
!gdown 1EImqlbcinVzjSxp5wM27YfCo9Nf_YBn0
```

In [ ]:
```
!gdown 1NyWC6xVK2tlvtjcx0xv8I4O_bI0KebdS
!gdown 1UFgEoC6-313M_dpjq7mW9LICaUvbkoNa
!gdown 1vuERyAz3ckNgg_vAAcjznPa7jpNJN9Rt
!gdown 1ZumVvaJpYdkWhSKZNlqbrHzi--A3iwtx
!gdown 1z0qcyj5D7XoZ4bTMDZ3yaOuHaFaqmXSZ
!gdown 16dF5YhHT4R_g5HbdAsO_cEXejJQ87Pg2
!gdown 1DLTaT7OQxd_R71nSjjj7r7NSJfkG0X8X
!gdown 1A1ARznJ4X2xQM5AL05yfhZo6KIQ21rxZ
!gdown 1fvzFbPqCzqdoLujlHxqIqNlnuCRPddTV
!gdown 1avI3Q59EZV92abBlLrSjNYG05ndLcOJ9
!gdown 16ZR-PaPNwqSyzFj-0SS8AqB7xIJ4OrYe
!gdown 1SgjgWPVq-QTgva1OFAZNKrVzQr0aJwRr
!gdown 1b1zT-srRQd1PEmXi2MyhojUFTGhPTHBM
!gdown 1zsmjBebdjFhh-tm8V4zPF9rQDKs76Vyv
!gdown 1raNErRqrAcr5qFCXH2T1G4bqhbu6l-m5
!gdown 1MHL7n1sIjWsouMWbYfgvDLud-Ba6wWM1
!gdown 1FblK2jeAC9kkZsRp9I6o-64Uqtpql-XI
!gdown 1n718TN1i5kwMEIm0Q6NTcz94D34YXgpA
!gdown 1oy-KECRHSE07R7-78D1tBdiJNbEoxI8E
!gdown 19--phk8Mf1z4QX464ZV_wVL4hfyQmSW1
!gdown 1-JzfQA2dQJe-mXrEK7fdNY1HluF_wSHQ
!gdown 16NiUOKZgspf09ztmREbffpmBKV9zBRhX
!gdown 1mb0yBP7A5seQN2naL8Sgqy54pZ5lYZAZ
!gdown 1CUxws0PZc8T_LWIKyifATBfOzFGMXBi9
!gdown 1ajESJp2rNjlmdWa31-2iIvE8lyvkGKgS
!gdown 14M9gs549r7PLS2CAjEbLoQOiaRfey6X8
!gdown 1j7YuYNeVF4Jt3F3tqG1oH4qgpGwF99jC
!gdown 1Z61vMm0J5Vjn2sNQq87FgaLbAAt8P4or
```

Metrik Evaluation

MAE

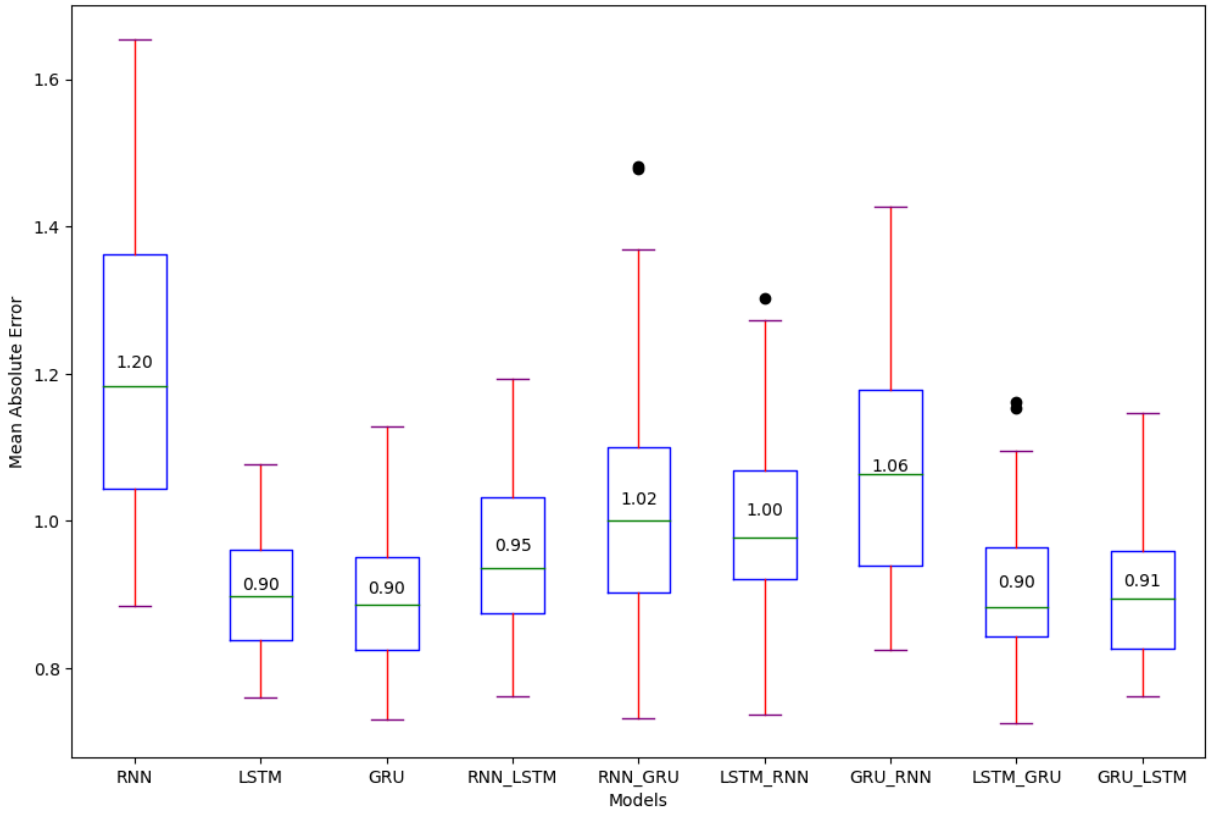
In [ ]:
```
df1 =  pd.read_excel('/content/RNN_FORECASTMae.xlsx')
df2 =  pd.read_excel('/content/LSTM_FORECASTMae.xlsx')
df3 =  pd.read_excel('/content/GRU_FORECASTMae.xlsx')
df4 =  pd.read_excel('/content/RNN_LSTM_FORECASTMae.xlsx')
df5 =  pd.read_excel('/content/RNN_GRU_FORECASTMae.xlsx')
df6 =  pd.read_excel('/content/LSTM_RNN_FORECASTMae.xlsx')
df7 =  pd.read_excel('/content/GRU_RNN_FORECASTMae.xlsx')
df8 =  pd.read_excel('/content/LSTM_GRU_FORECASTMae.xlsx')
df9 =  pd.read_excel('/content/GRU_LSTM_FORECASTMae.xlsx')
```

In [ ]:
```
df = pd.DataFrame()
df['RNN'] =  df1[0]
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]
```

```
# n = int(len(df) * (20 / 100))
n = int(len(df) * (2.5 / 100))
df = df.iloc[n:-n]
```

In [ ]:

```
df = pd.DataFrame()
df['RNN'] =  sorted(df1[0])
df['LSTM'] =  sorted(df2[0])
df['GRU'] =  sorted(df3[0])
df['RNN_LSTM'] =  sorted(df4[0])
df['RNN_GRU'] =  sorted(df5[0])
df['LSTM_RNN'] = sorted(df6[0])
df['GRU_RNN'] =  sorted(df7[0])
df['LSTM_GRU'] = sorted(df8[0])
df['GRU_LSTM'] = sorted(df9[0])


# n = int(len(df)*0.15)
n = int(len(df) * 0.025)
df = df[:].iloc[n:-n]
data = df[:]

box_color = 'blue'
whisker_color = 'red'
median_color = 'green'
flier_color = 'black'
cap_color = 'purple'

fig, ax = plt.subplots(figsize=(12, 8))

plt.boxplot(data.values, labels=data.columns,
            boxprops=dict(color=box_color),
            whiskerprops=dict(color=whisker_color),
            capprops=dict(color=cap_color),
            flierprops=dict(markerfacecolor=flier_color, marker='o', markersize=6),
            medianprops=dict(color=median_color))

for i, column in enumerate(data.columns):
    mean = np.mean(data[column])
    plt.text(i + 1, mean, f'{mean:.2f}', ha='center', va='bottom', color='black')

# plt.title('Predict with Boxplot')
plt.xlabel('Models')
plt.ylabel('Mean Absolute Error')
plt.savefig("Comparison_MAE_Dataset2.pdf", dpi=300)
files.download("Comparison_MAE_Dataset2.pdf")

plt.show()
```

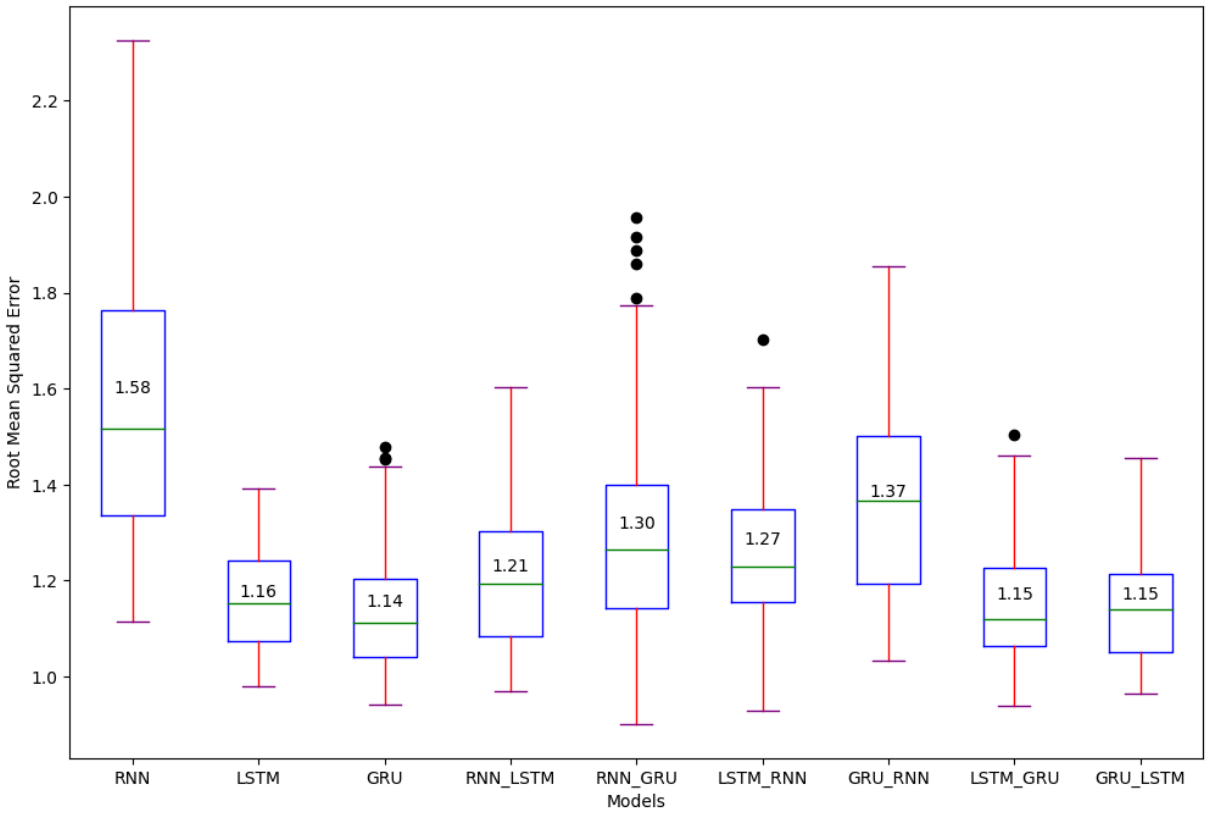


RMSE

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_FORECASTRMse.xlsx')
df2 =  pd.read_excel('/content/LSTM_FORECASTRMse.xlsx')
df3 =  pd.read_excel('/content/GRU_FORECASTRMse.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_FORECASTRMse.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_FORECASTRMse.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_FORECASTRMse.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_FORECASTRMse.xlsx')
df8 =  pd.read_excel('/content/LSTM-GRU_FORECASTRMse.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_FORECASTRMse.xlsx')
df = pd.DataFrame()
df['RNN'] =  df1['RMSE']
df['LSTM'] =  df2['RMSE']
df['GRU'] =  df3['RMSE']
df['RNN_LSTM'] =  df4['RMSE']
df['RNN_GRU'] =  df5['RMSE']
df['LSTM_RNN'] =  df6['RMSE']
df['GRU_RNN'] =  df7['RMSE']
df['LSTM_GRU'] =  df8['RMSE']
df['GRU_LSTM'] =  df9['RMSE']

# n = int(len(df) * (20 / 100))
n = int(len(df) * (2.5 / 100))
df = df.iloc[n:-n]
```

In [ ]:
```
df = pd.DataFrame()
df['RNN'] =  sorted(df1['RMSE'])
df['LSTM'] =  sorted(df2['RMSE'])
df['GRU'] =  sorted(df3['RMSE'])
df['RNN_LSTM'] =  sorted(df4['RMSE'])
df['RNN_GRU'] =  sorted(df5['RMSE'])
df['LSTM_RNN'] = sorted(df6['RMSE'])
df['GRU_RNN'] =  sorted(df7['RMSE'])
df['LSTM_GRU'] = sorted(df8['RMSE'])
df['GRU_LSTM'] = sorted(df9['RMSE'])


# n = int(len(df)*0.15)
n = int(len(df) * 0.025)
```

```
df = df[:].iloc[n:-n]
data = df[:]

box_color = 'blue'
whisker_color = 'red'
median_color = 'green'
flier_color = 'black'
cap_color = 'purple'

fig, ax = plt.subplots(figsize=(12, 8))

plt.boxplot(data.values, labels=data.columns,
            boxprops=dict(color=box_color),
            whiskerprops=dict(color=whisker_color),
            capprops=dict(color=cap_color),
            flierprops=dict(markerfacecolor=flier_color, marker='o', markersize=6),
            medianprops=dict(color=median_color))

for i, column in enumerate(data.columns):
    mean = np.mean(data[column])
    plt.text(i + 1, mean, f'{mean:.2f}', ha='center', va='bottom', color='black')

# plt.title('Predict with Boxplot')
plt.xlabel('Models')
plt.ylabel('Root Mean Squared Error')
plt.savefig("Comparison_RMSE_Dataset2.pdf", dpi=300)
files.download("Comparison_RMSE_Dataset2.pdf")

plt.show()
```



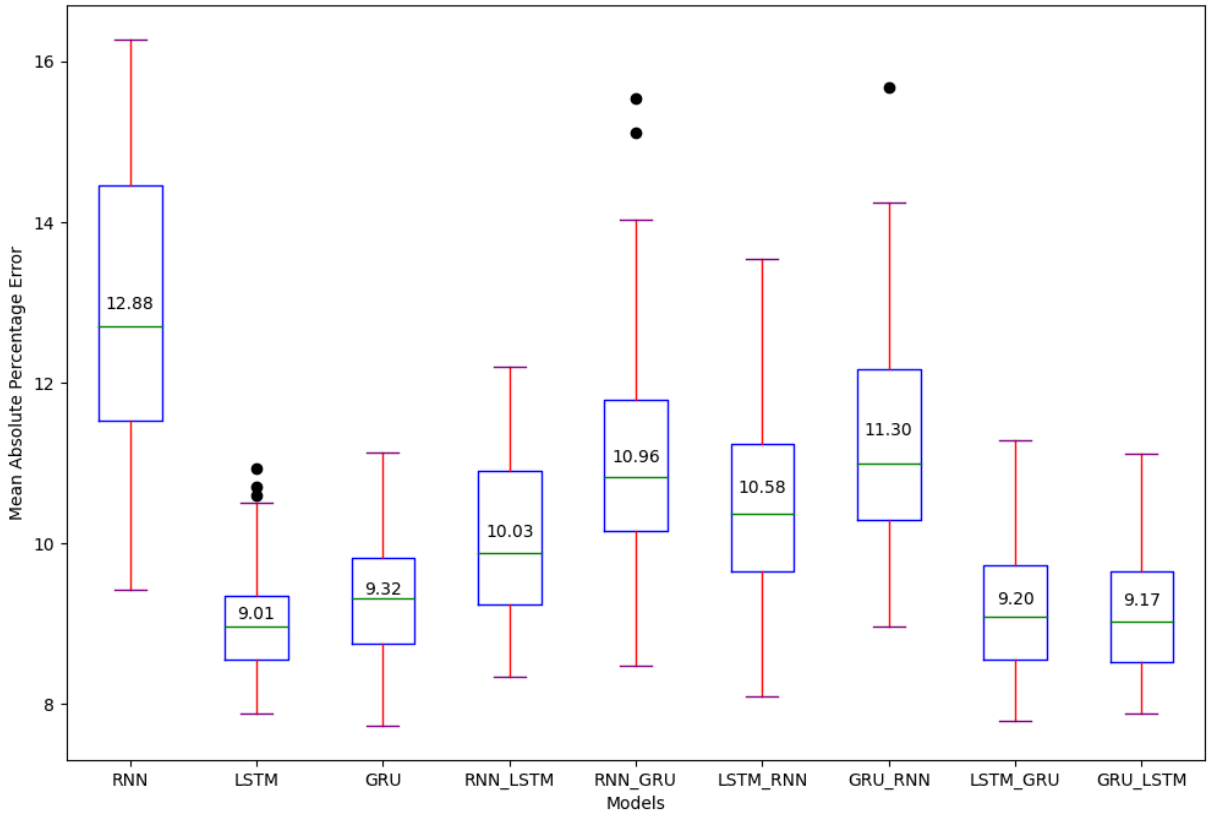
MAPE

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_FORECASTMpe.xlsx')
df2 =  pd.read_excel('/content/LSTM_FORECASTMpe.xlsx')
df3 =  pd.read_excel('/content/GRU_FORECASTMpe.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_FORECASTMpe.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_FORECASTMpe.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_FORECASTMpe.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_FORECASTMpe.xlsx')
```

```
df8 =  pd.read_excel('/content/LSTM-GRU_FORECASTMpe.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_FORECASTMpe.xlsx')
df = pd.DataFrame()
df['RNN'] =  df1['MAPE']
df['LSTM'] =  df2['MAPE']
df['GRU'] =  df3['MAPE']
df['RNN_LSTM'] =  df4['MAPE']
df['RNN_GRU'] =  df5['MAPE']
df['LSTM_RNN'] =  df6['MAPE']
df['GRU_RNN'] =  df7['MAPE']
df['LSTM_GRU'] =  df8['MAPE']
df['GRU_LSTM'] =  df9['MAPE']

# n = int(len(df) * (20 / 100))
n = int(len(df) * (2.5 / 100))
df = df.iloc[n:-n]
```

In [ ]:

```
df = pd.DataFrame()
df['RNN'] =  sorted(df1['MAPE'])
df['LSTM'] =  sorted(df2['MAPE'])
df['GRU'] =  sorted(df3['MAPE'])
df['RNN_LSTM'] =  sorted(df4['MAPE'])
df['RNN_GRU'] =  sorted(df5['MAPE'])
df['LSTM_RNN'] = sorted(df6['MAPE'])
df['GRU_RNN'] =  sorted(df7['MAPE'])
df['LSTM_GRU'] = sorted(df8['MAPE'])
df['GRU_LSTM'] = sorted(df9['MAPE'])


# n = int(len(df)*0.15)
n = int(len(df) * 0.025)
df = df[:].iloc[n:-n]
data = df[:]

box_color = 'blue'
whisker_color = 'red'
median_color = 'green'
flier_color = 'black'
cap_color = 'purple'

fig, ax = plt.subplots(figsize=(12, 8))

plt.boxplot(data.values, labels=data.columns,
            boxprops=dict(color=box_color),
            whiskerprops=dict(color=whisker_color),
            capprops=dict(color=cap_color),
            flierprops=dict(markerfacecolor=flier_color, marker='o', markersize=6),
            medianprops=dict(color=median_color))

for i, column in enumerate(data.columns):
    mean = np.mean(data[column])
    plt.text(i + 1, mean, f'{mean:.2f}', ha='center', va='bottom', color='black')

# plt.title('Predict with Boxplot')
plt.xlabel('Models')
plt.ylabel('Mean Absolute Percentage Error')
plt.savefig("Comparison_MAPE_Dataset2.pdf", dpi=300)
files.download("Comparison_MAPE_Dataset2.pdf")

plt.show()
```

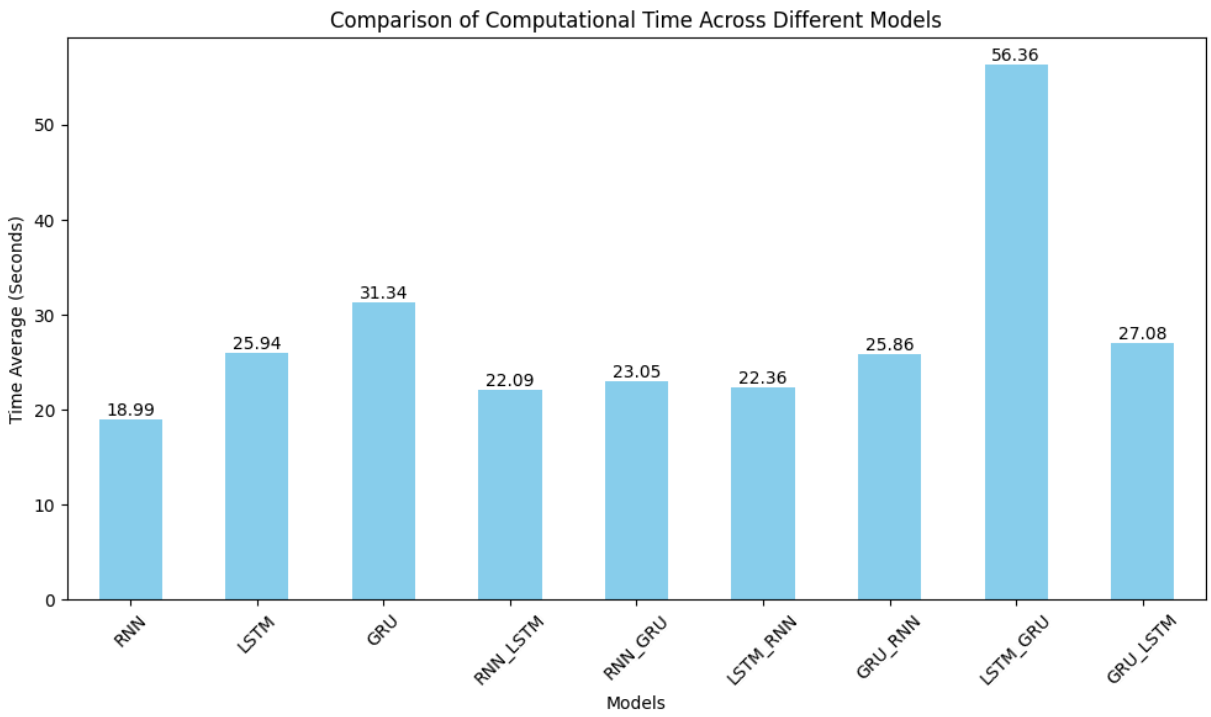


Time Comparison

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_TIME.xlsx')
df2 =  pd.read_excel('/content/LSTM_TIME.xlsx')
df3 =  pd.read_excel('/content/GRU_TIME.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_TIME.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_TIME.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_TIME.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_TIME.xlsx')
df8 =  pd.read_excel('/content/LSTM-GRU_TIME.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_TIME.xlsx')
df = pd.DataFrame()
df['RNN'] =  df1[0]
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]
```

In [ ]:
```
# Calculate the average time for each model
average_times = df.mean()

# Create a bar chart
plt.figure(figsize=(10, 6))
average_times.plot(kind='bar', color='skyblue')
plt.title('Comparison of Computational Time Across Different Models')
plt.xlabel('Models')
plt.ylabel('Time Average (Seconds)')
plt.xticks(rotation=45)
plt.tight_layout()

# Display the average times on top of the bars
for i, v in enumerate(average_times):
    plt.text(i, v, f"{v:.2f}", ha='center', va='bottom')

plt.savefig("Comparison_Time_Dataset2.pdf", dpi=300)
```

```
files.download("Comparison_Time_Dataset2.pdf")
plt.show()
```



1. Import Libraries

List of libraries that will be used.

In [1]:
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import csv
```

Using Utilites of Data Visualization

In [2]:
```
def plot_series(x, y, format="-", start=0, end=None,
                title=None, xlabel=None, ylabel=None, legend=None ):
    plt.figure(figsize=(10, 6))
    if type(y) is tuple:
      for y_curr in y:
        plt.plot(x[start:end], y_curr[start:end], format)
    else:
      plt.plot(x[start:end], y[start:end], format)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    if legend:
      plt.legend(legend)
    plt.title(title)
    plt.grid(True)
    plt.show()
```

2. Get DATA

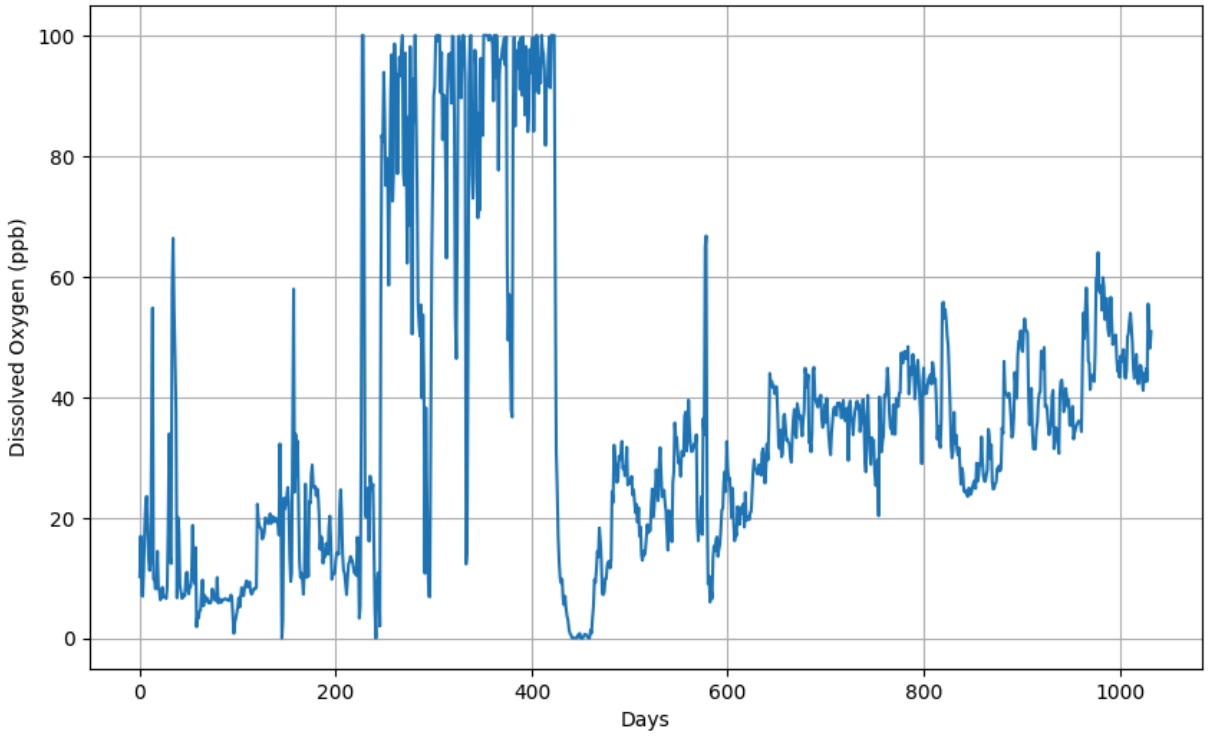
Take Data from Upstream (Local, Gdrive, Github, etc).

In [ ]:
```
!gdown 1tFt9l06v8hl2dRXRx-yMXMv6QRlwkF2p
```

Data Visualize

In [4]:
```
file = pd.read_excel('DissolvedOxygen.xlsx')
def take(file):
  time_step = []
  sunspots = []

  for i in range(len(file)):
    time_step.append(i)
    sunspots.append(file.iloc[i][1])
  time = np.array(time_step)
  series = np.array(sunspots)
  return time, series
time, series = take(file)
plot_series(time, series, xlabel='Days', ylabel='Dissolved Oxygen (ppb)')
```

```
<ipython-input-4-52403bb85ecb>:8: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  sunspots.append(file.iloc[i][1])
```



3. Data Prerocessing

Analysis and Cleaning Data -> Extract, Transform, Load.

Split Data

In [5]:
```
split_time = int(len(time)*0.8)

time_train = time[:split_time]
x_train = series[:split_time]

time_valid = time[split_time:]
x_valid = series[split_time:]
```

Prepare Features and Labels

In [6]:
```
def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
    dataset = tf.data.Dataset.from_tensor_slices(series)
    dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
    dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
    dataset = dataset.map(lambda window: (window[:-1], window[-1]))
    dataset = dataset.shuffle(shuffle_buffer)
    dataset = dataset.batch(batch_size).prefetch(1)
    return dataset

window_size = 30
batch_size = 32
shuffle_buffer_size = 1000

train_set = windowed_dataset(x_train, window_size, batch_size, shuffle_buffer_size)
```

4. Model Architechture

Using library from Scikit-learn, Tensorflow(?).

RNN Model

In [7]:
```
model_RNN = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.SimpleRNN(64, return_sequences=True),
  tf.keras.layers.SimpleRNN(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_RNN.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 30, 64)	256
simple_rnn (SimpleRNN)	(None, 30, 64)	8,256
simple_rnn_1 (SimpleRNN)	(None, 64)	8,256
dense (Dense)	(None, 1)	65
lambda (Lambda)	(None, 1)	0

Total params: 16,833 (65.75 KB)

Trainable params: 16,833 (65.75 KB)

Non-trainable params: 0 (0.00 B)

LSTM Model

In [8]:
```
model_LSTM = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.LSTM(64, return_sequences=True),
  tf.keras.layers.LSTM(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_LSTM.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D)	(None, 30, 64)	256
lstm (LSTM)	(None, 30, 64)	33,024
lstm_1 (LSTM)	(None, 64)	33,024
dense_1 (Dense)	(None, 1)	65
lambda_1 (Lambda)	(None, 1)	0

Total params: 66,369 (259.25 KB)

Trainable params: 66,369 (259.25 KB)

GRU Model

In [9]:
```
model_GRU = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.GRU(64, return_sequences=True),
  tf.keras.layers.GRU(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_GRU.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv1d_2 (Conv1D)	(None, 30, 64)	256
gru (GRU)	(None, 30, 64)	24,960
gru_1 (GRU)	(None, 64)	24,960
dense_2 (Dense)	(None, 1)	65
lambda_2 (Lambda)	(None, 1)	0

Total params: 50,241 (196.25 KB)

Trainable params: 50,241 (196.25 KB)

Non-trainable params: 0 (0.00 B)

RNN-LSTM Model

In [10]:
```
model_RNN_LSTM = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.SimpleRNN(64, return_sequences=True),
  tf.keras.layers.LSTM(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_RNN_LSTM.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
conv1d_3 (Conv1D)	(None, 30, 64)	256
simple_rnn_2 (SimpleRNN)	(None, 30, 64)	8,256
lstm_2 (LSTM)	(None, 64)	33,024
dense_3 (Dense)	(None, 1)	65
lambda_3 (Lambda)	(None, 1)	0

Total params: 41,601 (162.50 KB)

Trainable params: 41,601 (162.50 KB)

RNN-GRU Model

In [11]:
```
model_RNN_GRU = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.SimpleRNN(64, return_sequences=True),
  tf.keras.layers.GRU(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_RNN_GRU.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv1d_4 (Conv1D)	(None, 30, 64)	256
simple_rnn_3 (SimpleRNN)	(None, 30, 64)	8,256
gru_2 (GRU)	(None, 64)	24,960
dense_4 (Dense)	(None, 1)	65
lambda_4 (Lambda)	(None, 1)	0

Total params: 33,537 (131.00 KB)

Trainable params: 33,537 (131.00 KB)

Non-trainable params: 0 (0.00 B)

LSTM-RNN

In [12]:
```
model_LSTM_RNN = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.LSTM(64, return_sequences=True),
  tf.keras.layers.SimpleRNN(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
```

```
])
model_LSTM_RNN.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv1d_5 (Conv1D)	(None, 30, 64)	256
lstm_3 (LSTM)	(None, 30, 64)	33,024
simple_rnn_4 (SimpleRNN)	(None, 64)	8,256
dense_5 (Dense)	(None, 1)	65
lambda_5 (Lambda)	(None, 1)	0

Total params: 41,601 (162.50 KB)

Trainable params: 41,601 (162.50 KB)

Non-trainable params: 0 (0.00 B)

LSTM-GRU Model

In [13]:
```
model_LSTM_GRU = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
                         input_shape=[window_size, 1]),
  tf.keras.layers.LSTM(64, return_sequences=True),
  tf.keras.layers.GRU(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_LSTM_GRU.summary()
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
conv1d_6 (Conv1D)	(None, 30, 64)	256
lstm_4 (LSTM)	(None, 30, 64)	33,024
gru_3 (GRU)	(None, 64)	24,960
dense_6 (Dense)	(None, 1)	65
lambda_6 (Lambda)	(None, 1)	0

Total params: 58,305 (227.75 KB)

Trainable params: 58,305 (227.75 KB)

Non-trainable params: 0 (0.00 B)

GRU-RNN Model

In [14]:
```
model_GRU_RNN = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                         activation="relu",
                         padding='causal',
```

```
                      input_shape=[window_size, 1]),
  tf.keras.layers.GRU(64, return_sequences=True),
  tf.keras.layers.SimpleRNN(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_GRU_RNN.summary()
```

Model: "sequential_7"

Layer (type)	Output Shape	Param #
conv1d_7 (Conv1D)	(None, 30, 64)	256
gru_4 (GRU)	(None, 30, 64)	24,960
simple_rnn_5 (SimpleRNN)	(None, 64)	8,256
dense_7 (Dense)	(None, 1)	65
lambda_7 (Lambda)	(None, 1)	0

Total params: 33,537 (131.00 KB)

Trainable params: 33,537 (131.00 KB)

Non-trainable params: 0 (0.00 B)

GRU-LSTM Model

In [15]:
```
model_GRU_LSTM = tf.keras.models.Sequential([
  tf.keras.layers.Conv1D(filters=64, kernel_size=3,
                         strides=1,
                        activation="relu",
                        padding='causal',
                        input_shape=[window_size, 1]),
  tf.keras.layers.GRU(64, return_sequences=True),
  tf.keras.layers.LSTM(64),
  tf.keras.layers.Dense(1),
  tf.keras.layers.Lambda(lambda x: x * 100)
])
model_GRU_LSTM  .summary()
```

Model: "sequential_8"

Layer (type)	Output Shape	Param #
conv1d_8 (Conv1D)	(None, 30, 64)	256
gru_5 (GRU)	(None, 30, 64)	24,960
lstm_5 (LSTM)	(None, 64)	33,024
dense_8 (Dense)	(None, 1)	65
lambda_8 (Lambda)	(None, 1)	0

Total params: 58,305 (227.75 KB)

Trainable params: 58,305 (227.75 KB)

Non-trainable params: 0 (0.00 B)

5. Model Training

In [16]:
```
tf.keras.backend.clear_session()
learning_rate = 8e-7
```

In [ ]:
```
optimizer_RNN = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_RNN.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_RNN,
              metrics=["mae", "mse", "mape"])
history_RNN = model_RNN.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_LSTM = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_LSTM.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_LSTM,
              metrics=["mae", "mse", "mape"])
history_LSTM = model_LSTM.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_GRU= tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_GRU.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_GRU,
              metrics=["mae", "mse", "mape"])
history_GRU = model_GRU.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_RNN_LSTM = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_RNN_LSTM.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_RNN_LSTM,
              metrics=["mae", "mse", "mape"])
history_RNN_LSTM = model_RNN_LSTM.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_RNN_GRU = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_RNN_GRU.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_RNN_GRU,
              metrics=["mae", "mse", "mape"])
history_RNN_GRU = model_RNN_GRU.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_LSTM_RNN = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_LSTM_RNN.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_LSTM_RNN,
              metrics=["mae", "mse", "mape"])
history_LSTM_RNN = model_LSTM_RNN.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_LSTM_GRU = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_LSTM_GRU.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_LSTM_GRU,
              metrics=["mae", "mse", "mape"])
history_LSTM_GRU = model_LSTM_GRU.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_GRU_RNN= tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_GRU_RNN.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_GRU_RNN,
              metrics=["mae", "mse", "mape"])
history_GRU_RNN = model_GRU_RNN.fit(train_set,epochs=100)
```

In [ ]:
```
optimizer_GRU_LSTM= tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model_GRU_LSTM.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer_GRU_LSTM,
              metrics=["mae", "mse", "mape"])
history_GRU_LSTM = model_GRU_LSTM.fit(train_set,epochs=100)
```

6. Model Evaluation

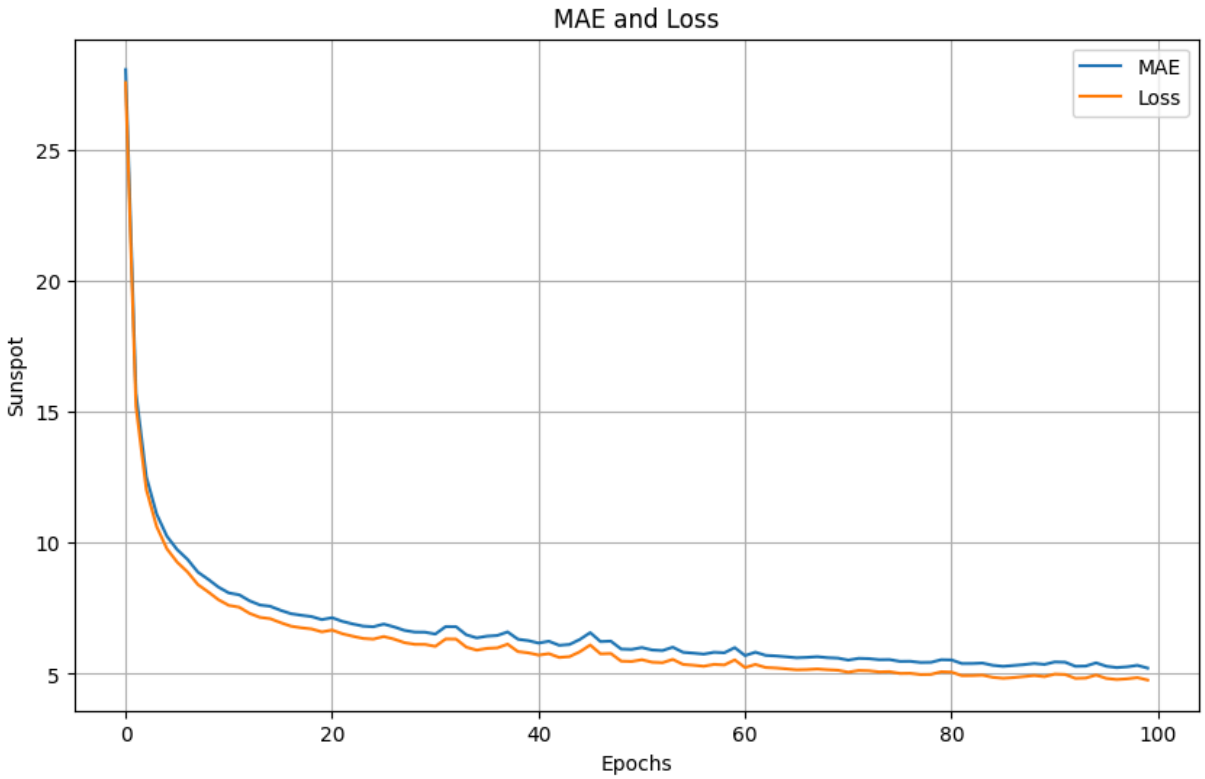
Loss evaluation using Scatter Plot

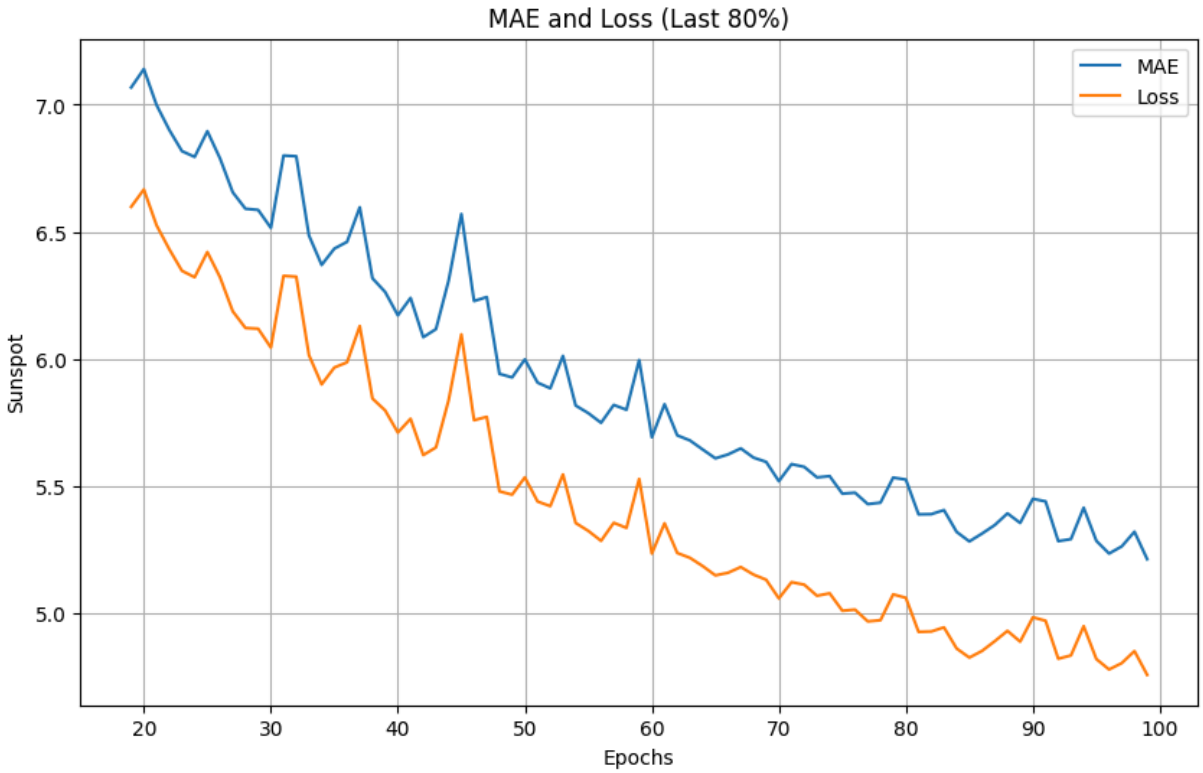
In [26]:
```
# Plot Function
def visualize_evaluation(history):
  mae=history.history['mae']
  loss=history.history['loss']
```

```
epochs=range(len(loss))

plot_series(
    x=epochs,
    y=(mae, loss),
    title='MAE and Loss',
    xlabel='Epochs',
    ylabel='Sunspot',
    legend=['MAE', 'Loss'])

zoom_split = int(epochs[-1] * 0.2)
epochs_zoom = epochs[zoom_split:]
mae_zoom = mae[zoom_split:]
loss_zoom = loss[zoom_split:]

plot_series(
    x=epochs_zoom,
    y=(mae_zoom, loss_zoom),
    title='MAE and Loss (Last 80%)',
    xlabel='Epochs',
    ylabel='Sunspot',
    legend=['MAE', 'Loss'])
```

RNN Evaluation

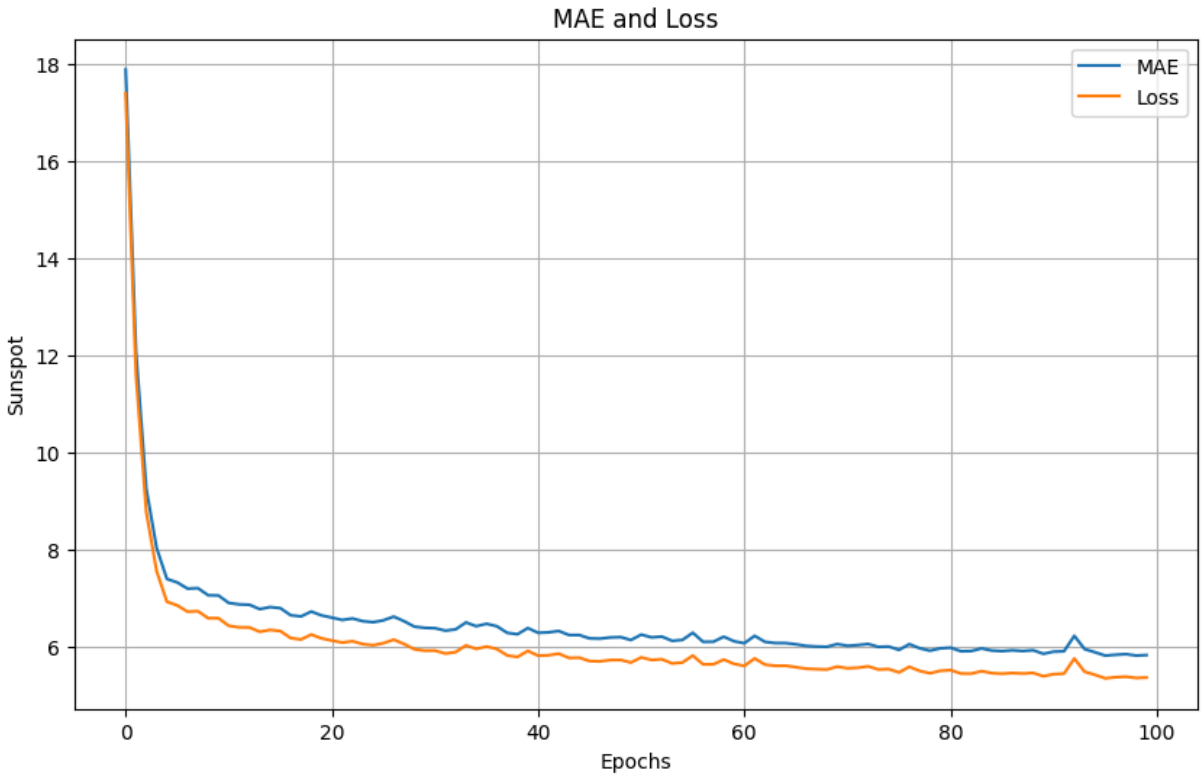
In [27]:
```
visualize_evaluation(history_RNN)
```

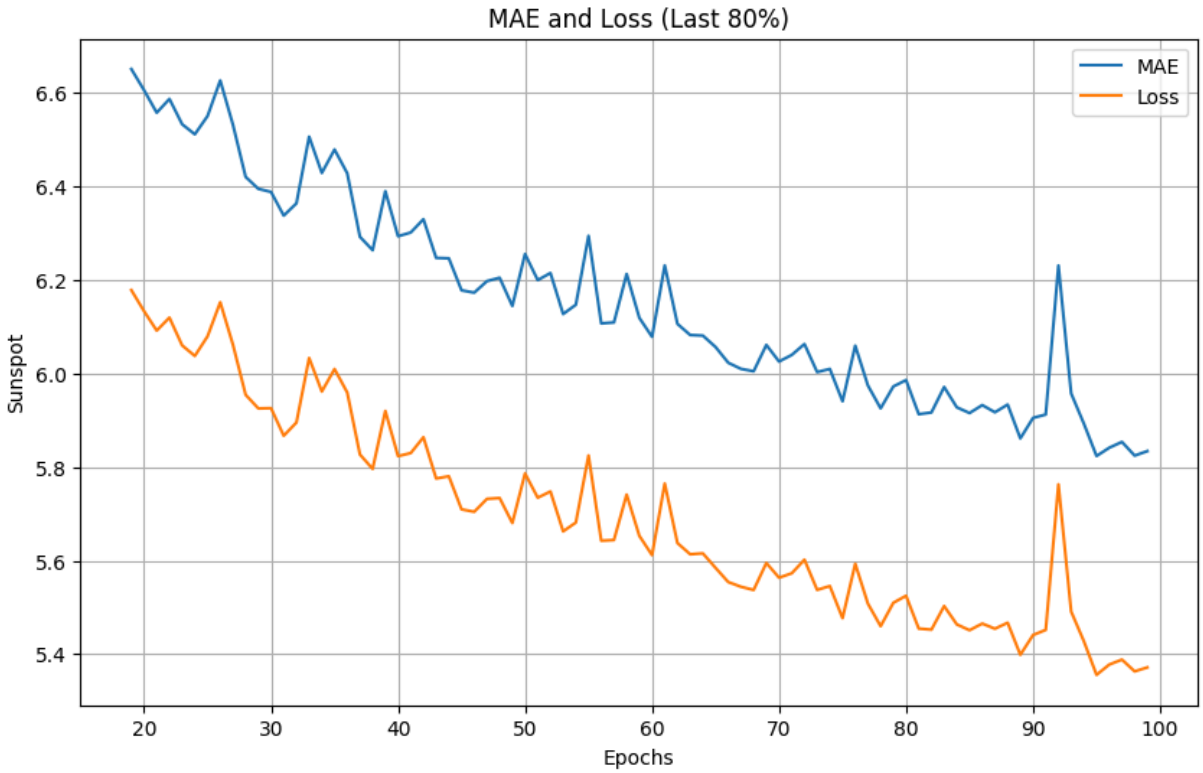




LSTM Evaluation

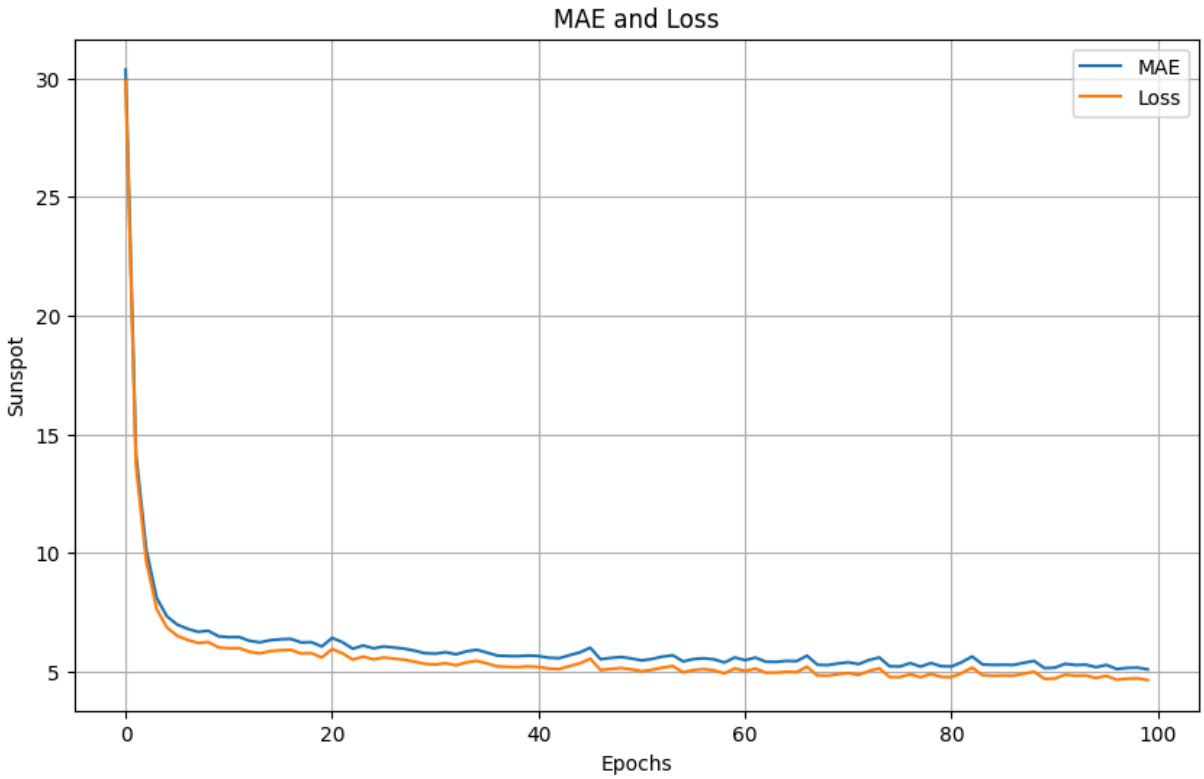
In [28]:
```
visualize_evaluation(history_LSTM)
```

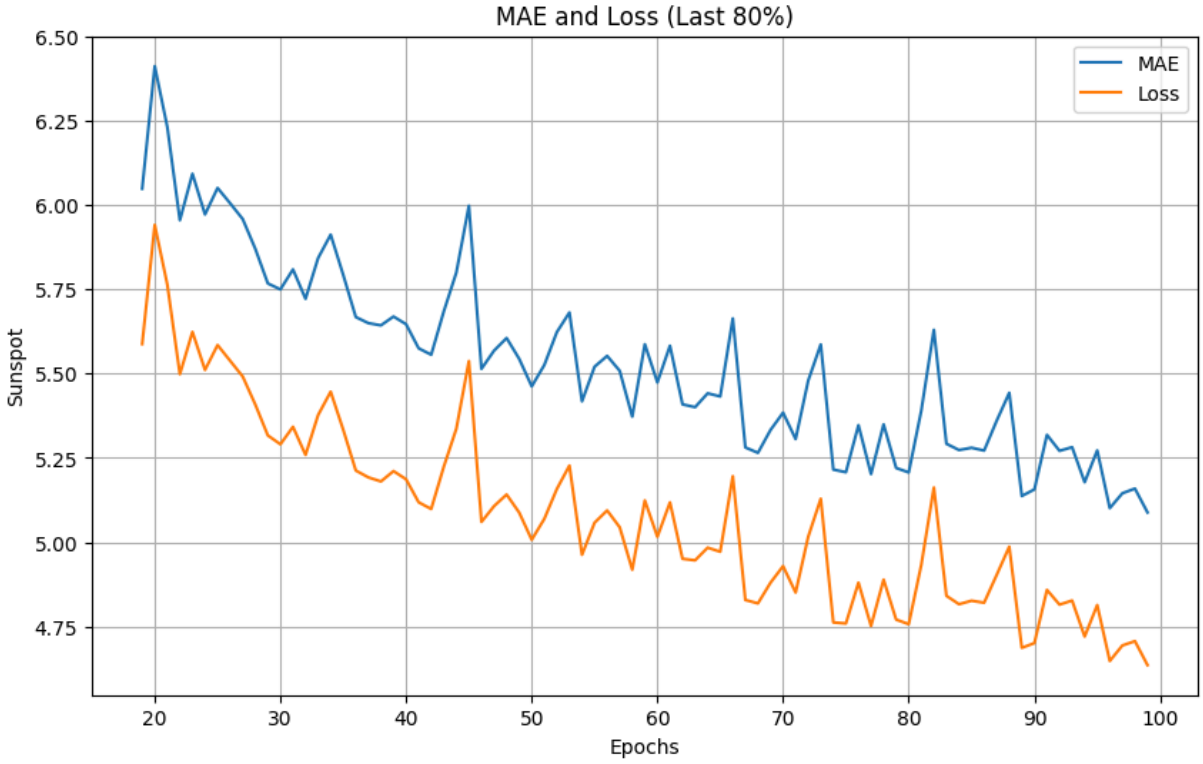




GRU Evaluation

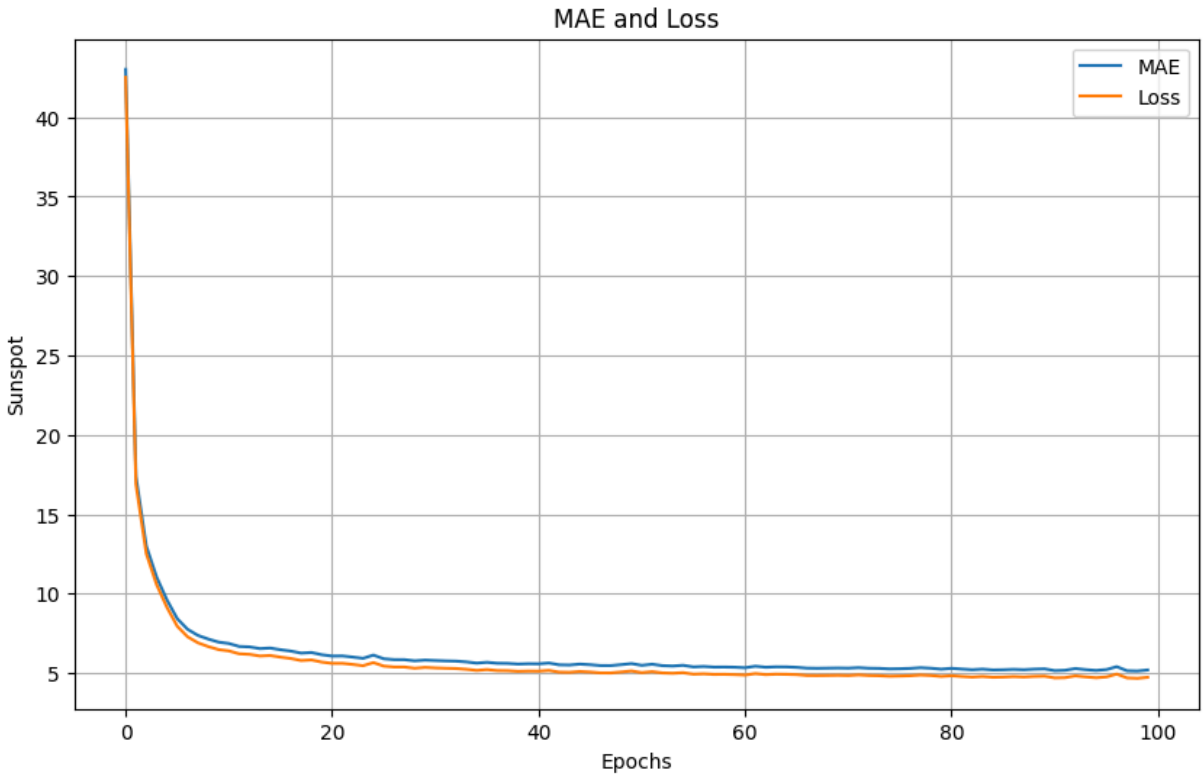
In [29]:
```
visualize_evaluation(history_GRU)
```

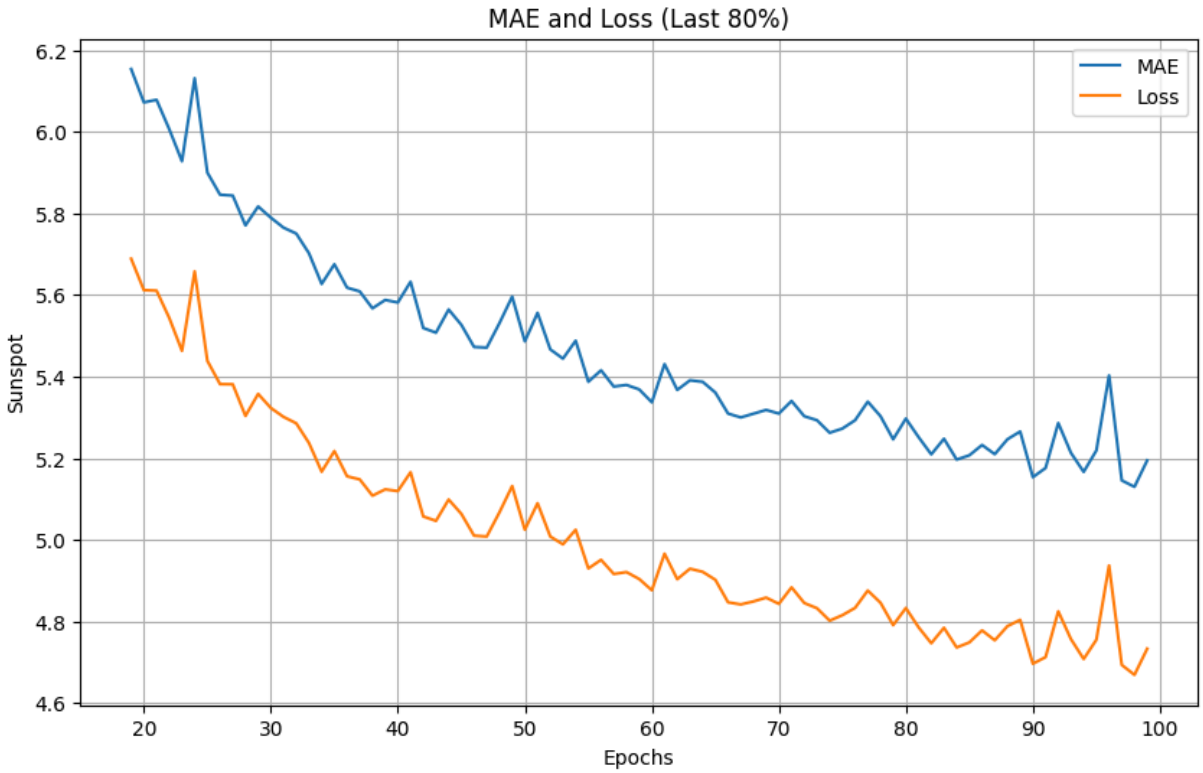




RNN-LSTM Evaluation

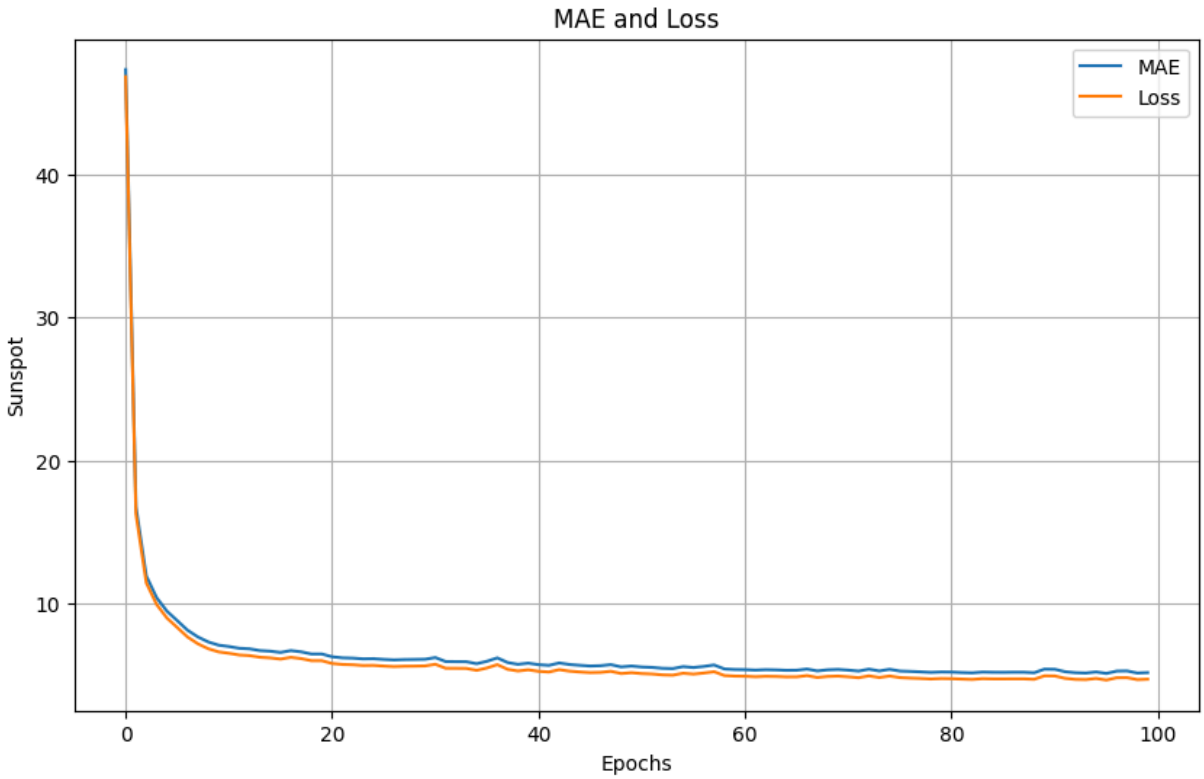
In [30]:
```
visualize_evaluation(history_RNN_LSTM)
```





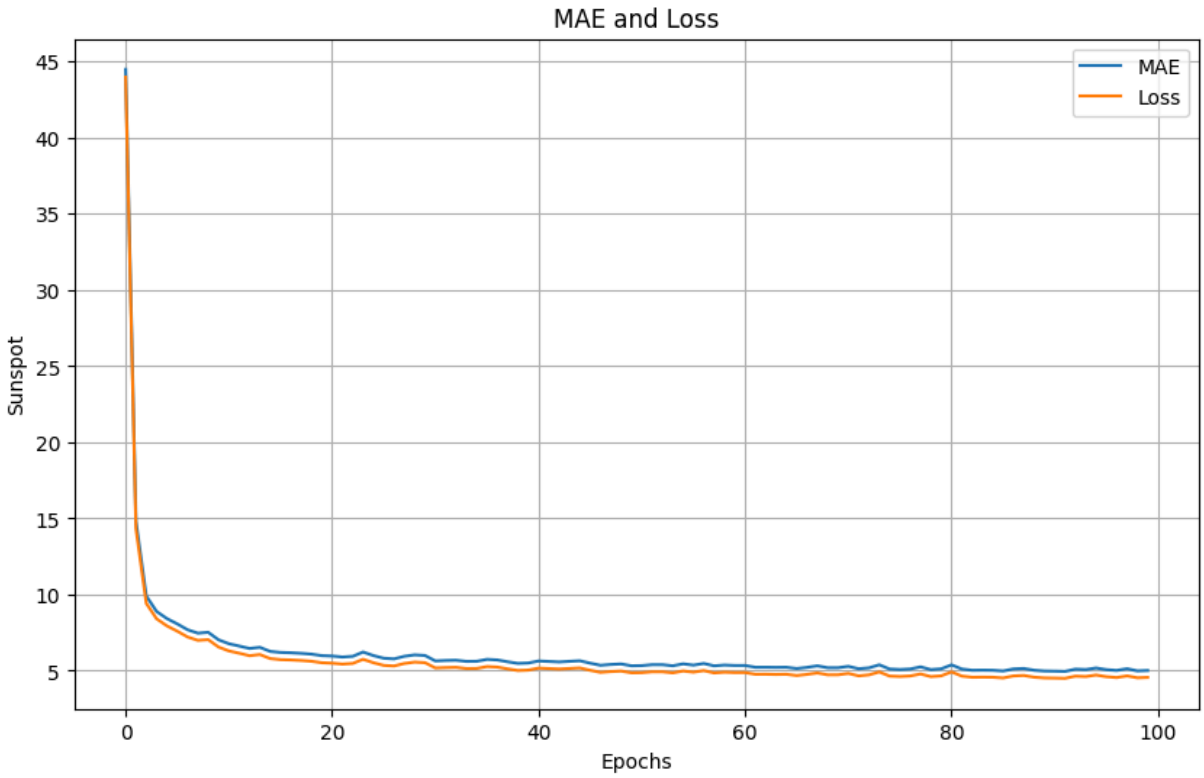
RNN-GRU Evaluation

In [31]:
```
visualize_evaluation(history_RNN_GRU)
```



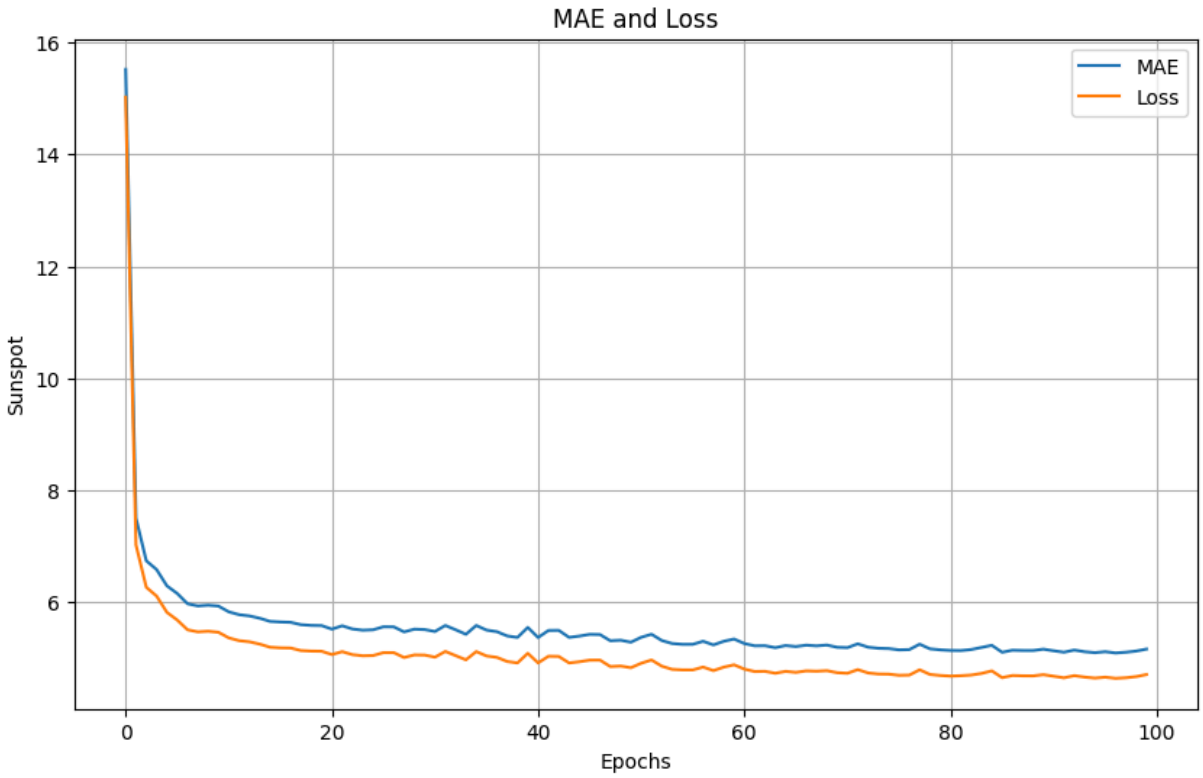
LSTM-RNN Evaluation

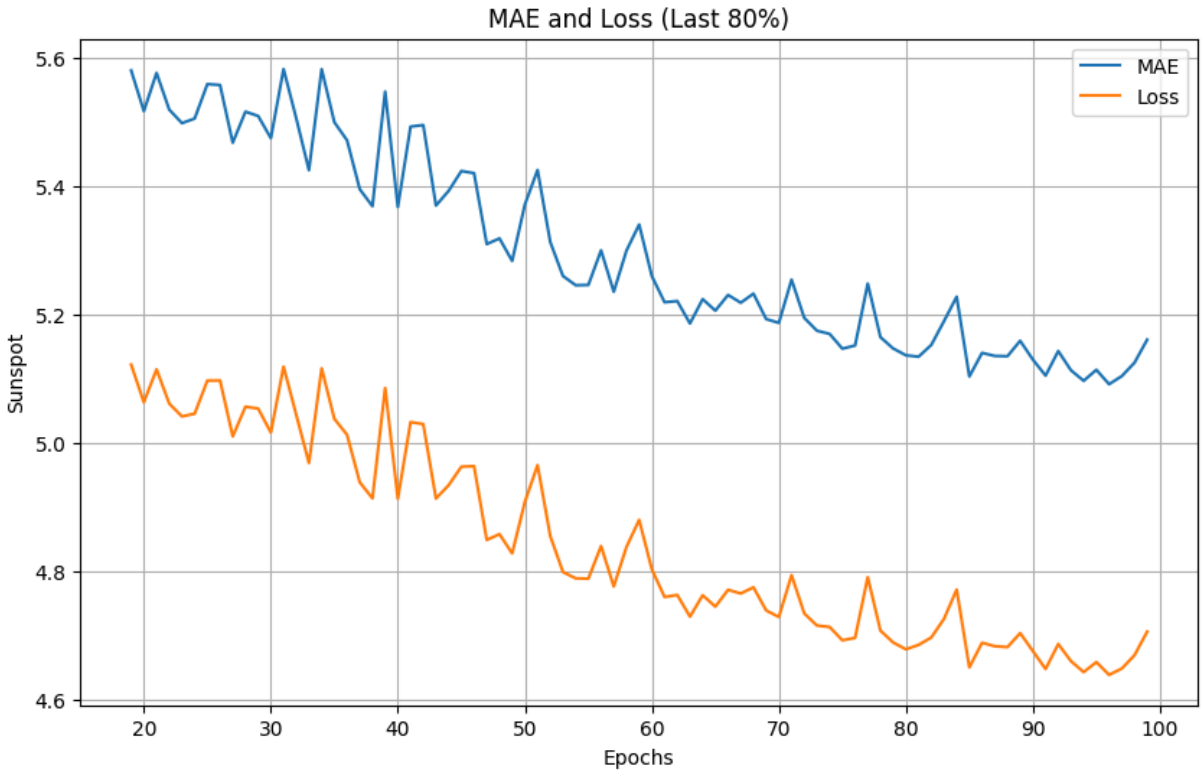
In [32]:
```
visualize_evaluation(history_LSTM_RNN)
```



LSTM-GRU Evaluation

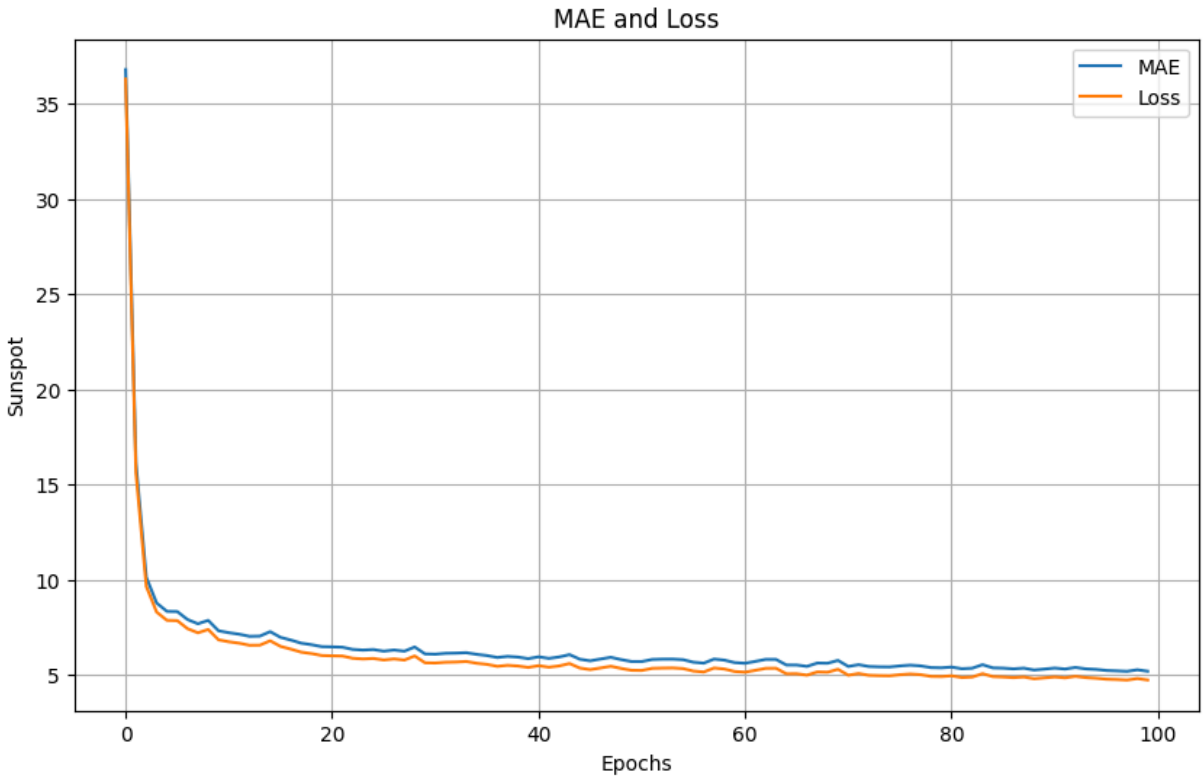
In [33]:
```
visualize_evaluation(history_LSTM_GRU)
```

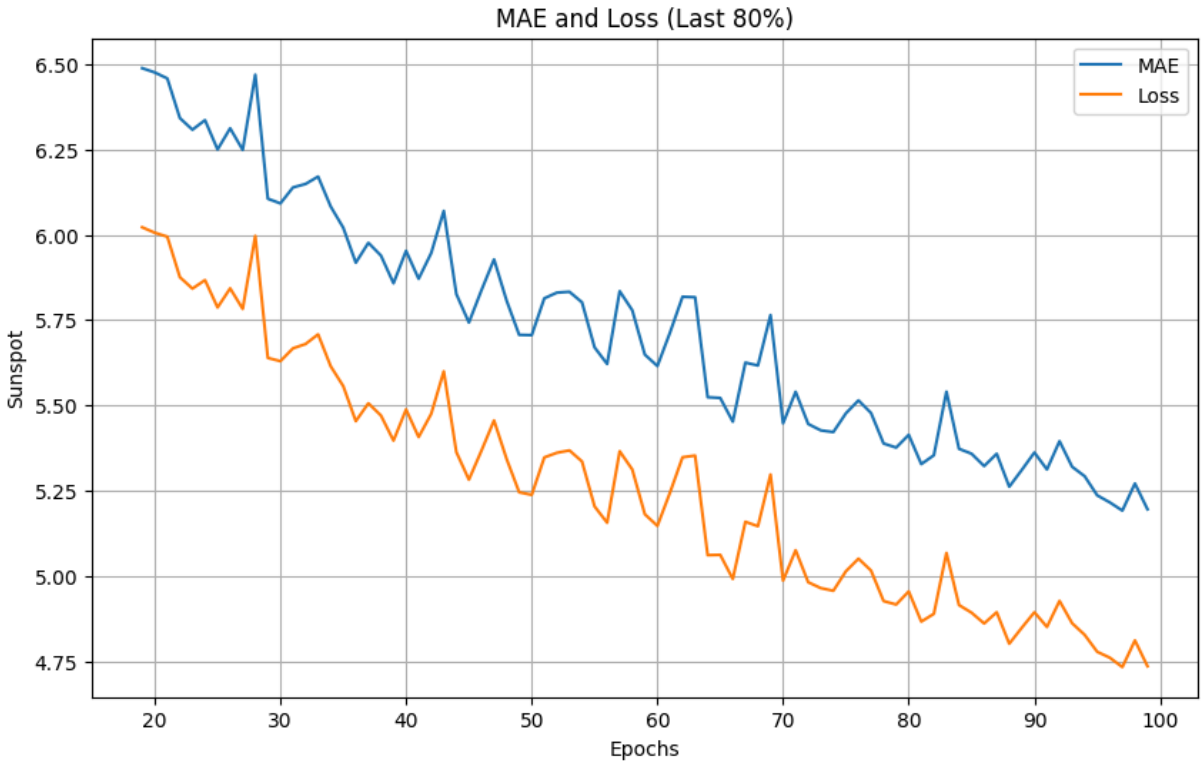




GRU-RNN Evaluation

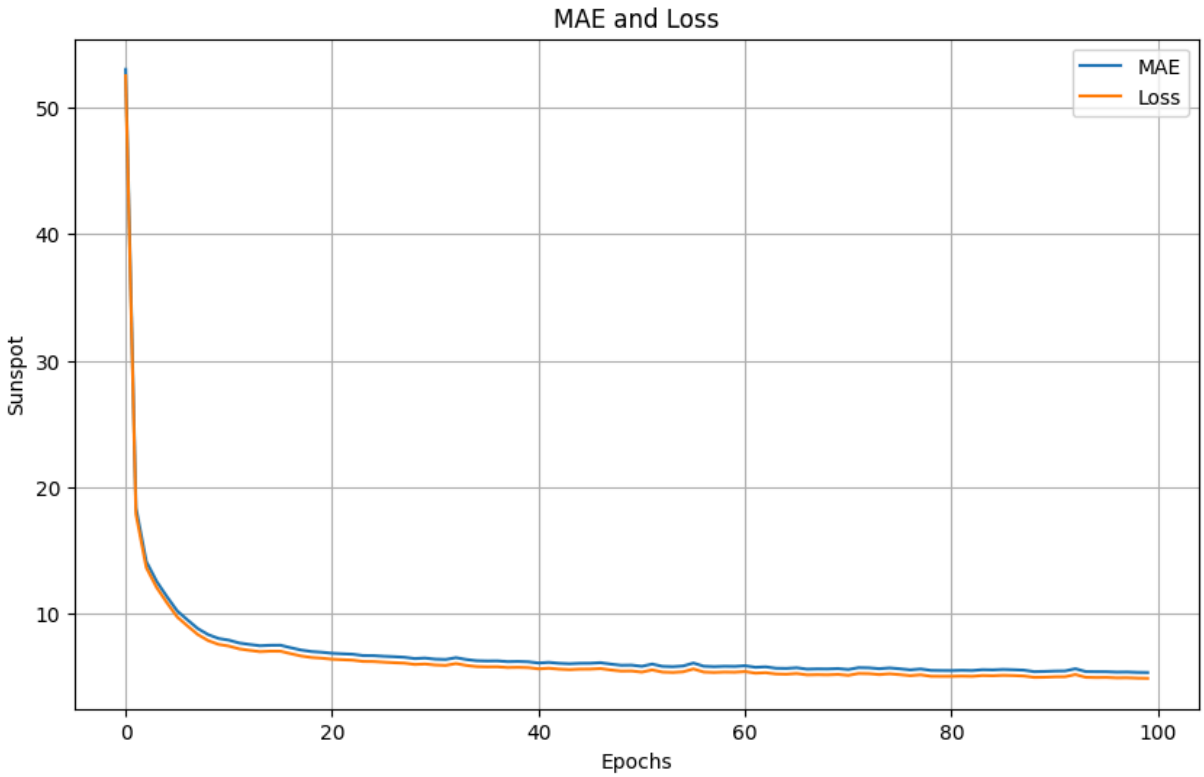
In [34]:
```
visualize_evaluation(history_GRU_RNN)
```

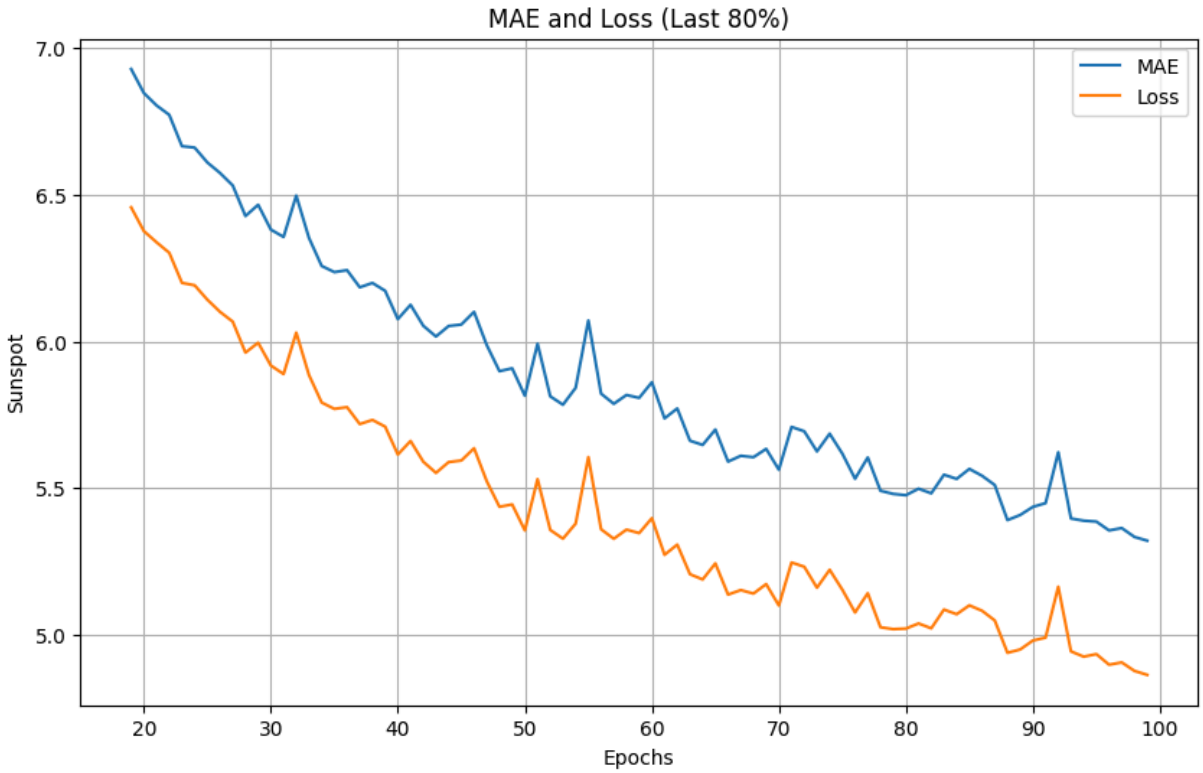




GRU-LSTM Evaluation

In [35]:
```
visualize_evaluation(history_GRU_LSTM)
```





7. Model Prediction

Analysis outcome of clustering for whale transaction characteristic

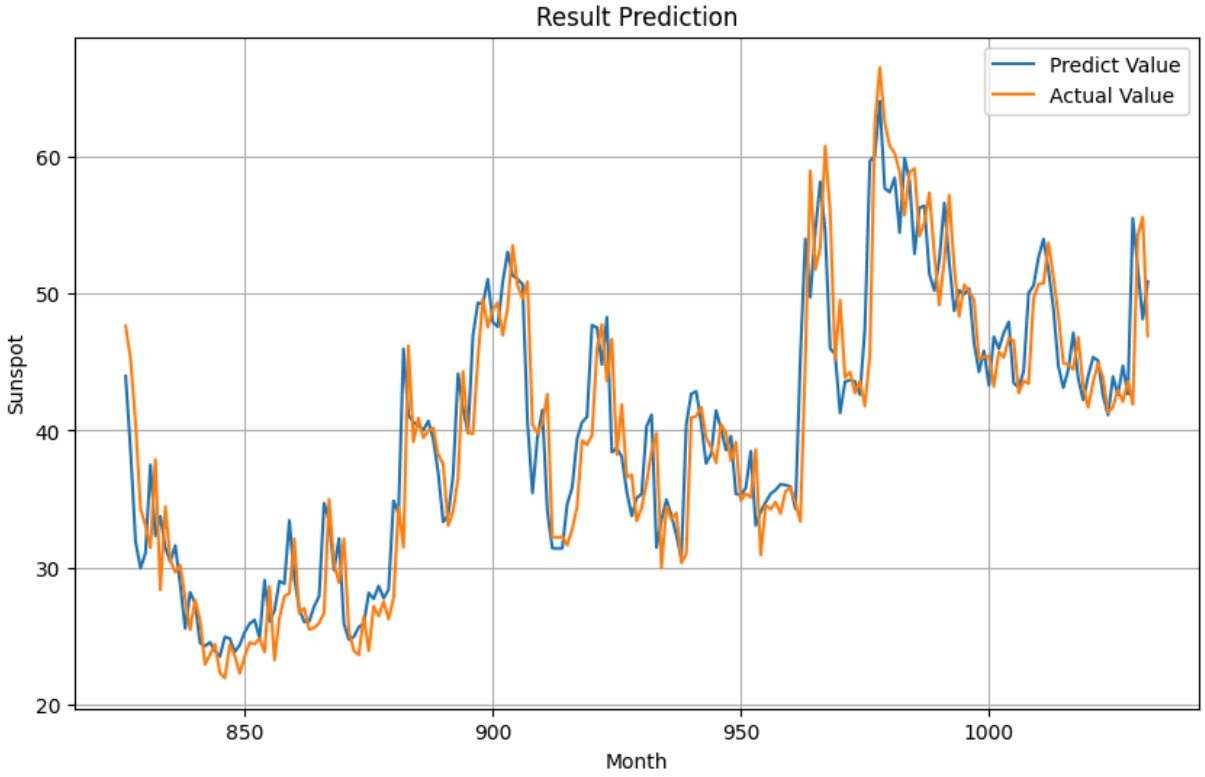
In [36]:
```
def model_forecast(model, series, window_size, batch_size):
    dataset = tf.data.Dataset.from_tensor_slices(series)
    dataset = dataset.window(window_size, shift=1, drop_remainder=True)
    dataset = dataset.flat_map(lambda w: w.batch(window_size))
    dataset = dataset.batch(batch_size).prefetch(1)
    forecast = model.predict(dataset)
    return forecast
```

In [37]:
```
def predict(model):
  forecast_series = series[split_time-window_size:-1]
  forecast = model_forecast(model, forecast_series, window_size, batch_size)
  results = forecast.squeeze()
  plot_series(time_valid, (x_valid, results, ), title='Result Prediction',
  xlabel='Month',
  ylabel='Sunspot',
  legend=['Predict Value', 'Actual Value'])
```

RNN Prediction

In [38]:
```
predict(model_RNN)
```

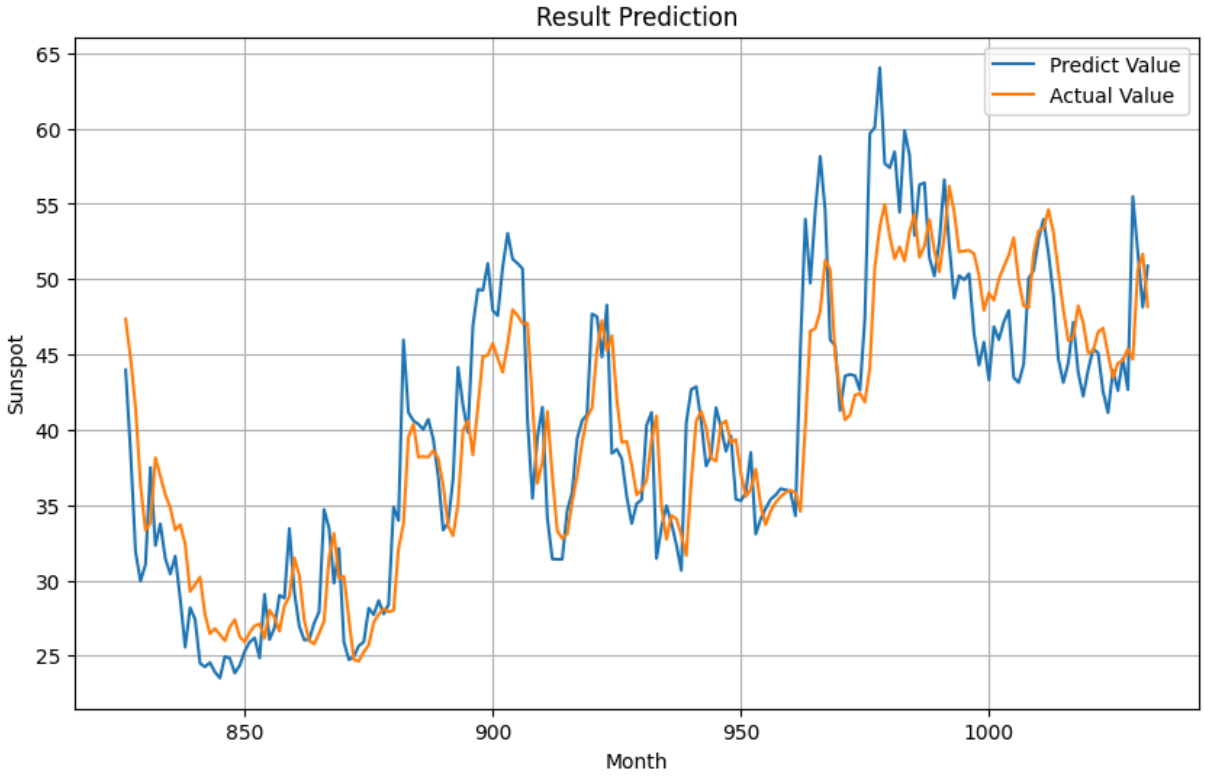
```
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 48ms/step
```



LSTM Prediction

In [39]:
```
predict(model_LSTM)
```

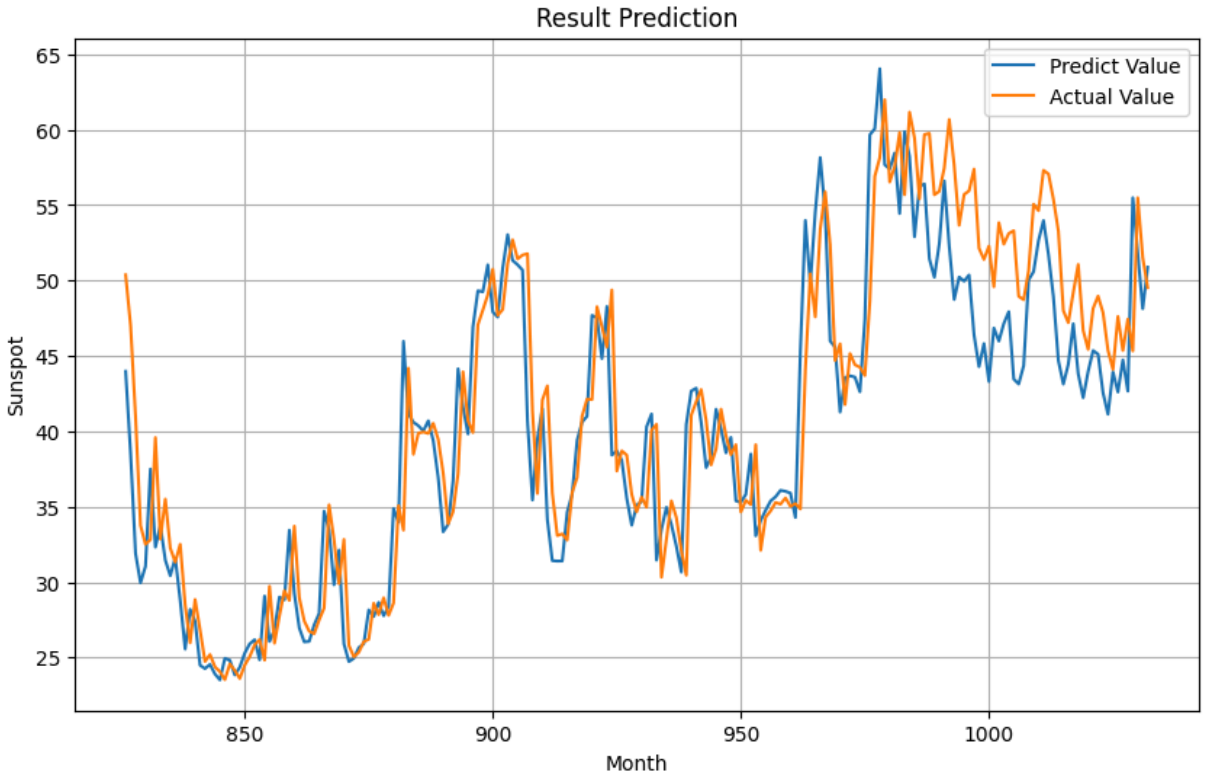
```
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 60ms/step
```



GRU Prediction

In [40]:
```
predict(model_GRU)
```

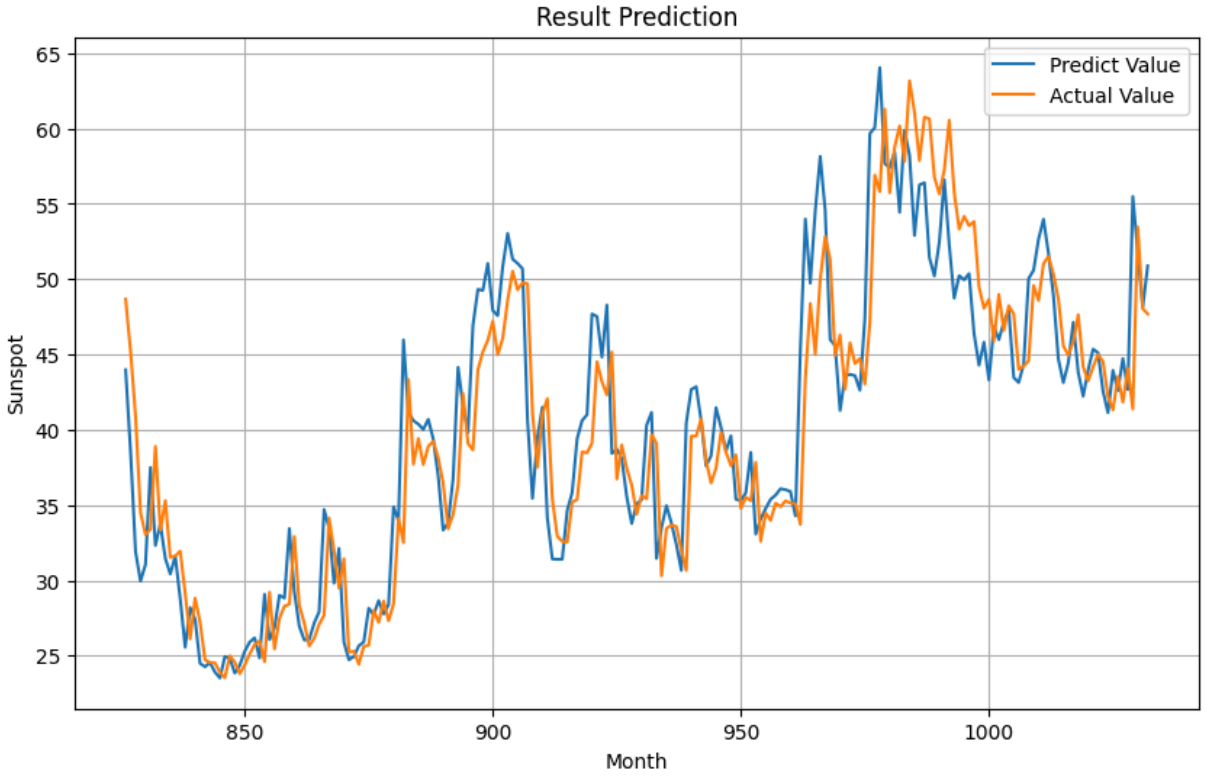
```
WARNING:tensorflow:5 out of the last 15 calls to <function TensorFlowTrainer.make_predict_funct
ion.<locals>.one_step_on_data_distributed at 0x7ef1d08dc700> triggered tf.function retracing. T
racing is expensive and the excessive number of tracings could be due to (1) creating @tf.funct
ion repeatedly 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.tensor
flow.org/api_docs/python/tf/function for  more details.
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 106ms/step
```



RNN-LSTM Prediction

In [41]:
```
predict(model_RNN_LSTM)
```

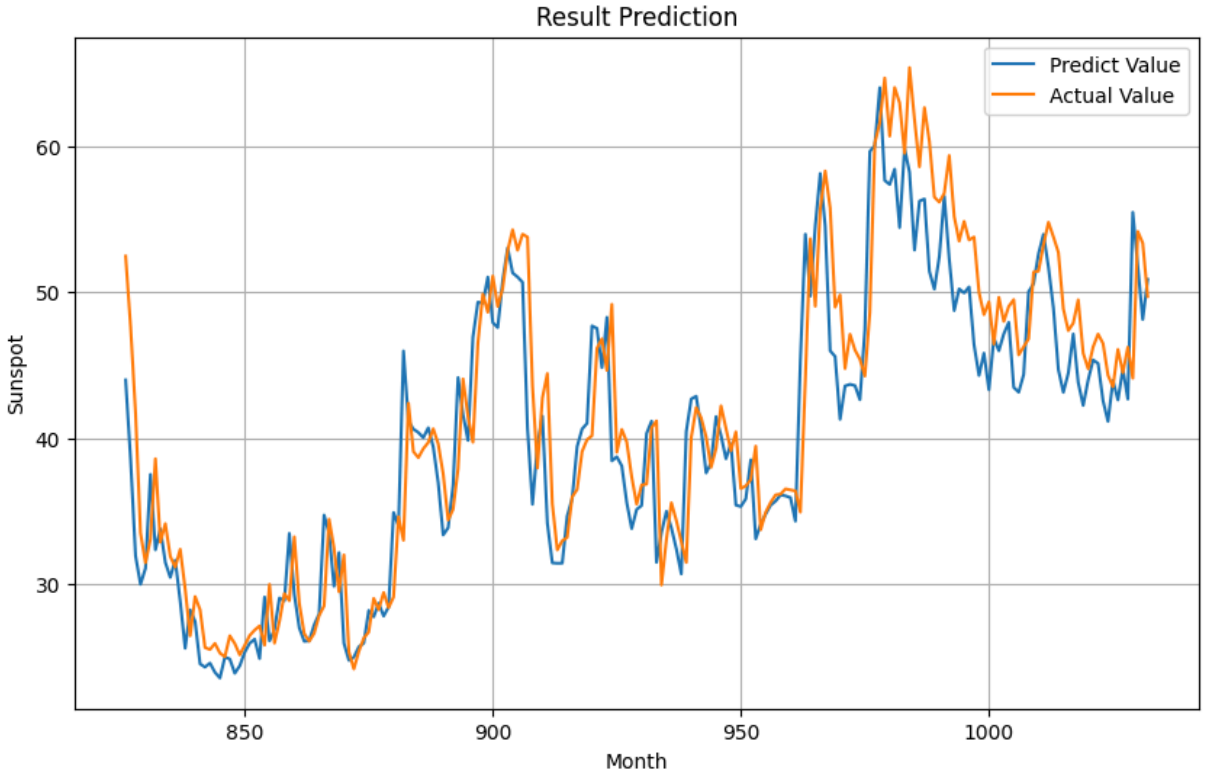
```
WARNING:tensorflow:5 out of the last 15 calls to <function TensorFlowTrainer.make_predict_funct
ion.<locals>.one_step_on_data_distributed at 0x7ef1cf659b40> triggered tf.function retracing. T
racing is expensive and the excessive number of tracings could be due to (1) creating @tf.funct
ion repeatedly 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.tensor
flow.org/api_docs/python/tf/function for  more details.
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 87ms/step
```



RNN-GRU Prediction

In [42]:
```
predict(model_RNN_GRU)
```

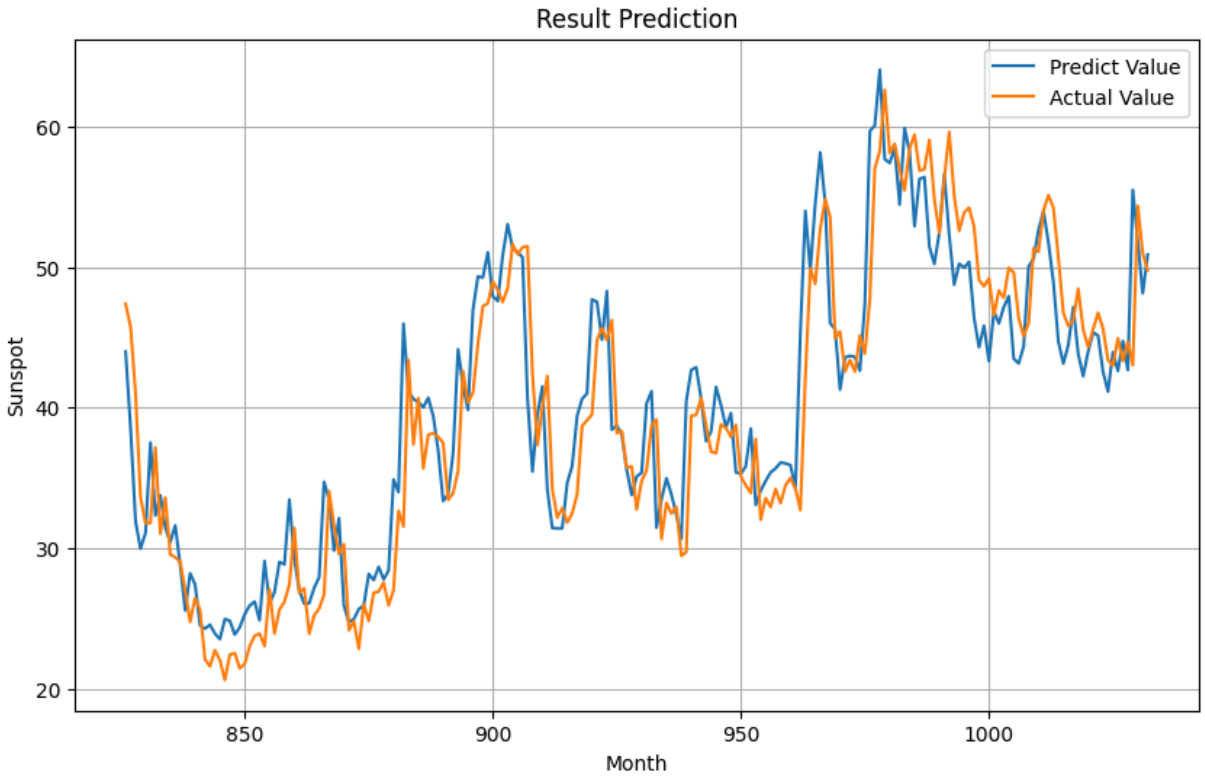
```
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 60ms/step
```



LSTM-RNN Prediction

In [43]:
```
predict(model_LSTM_RNN)
```

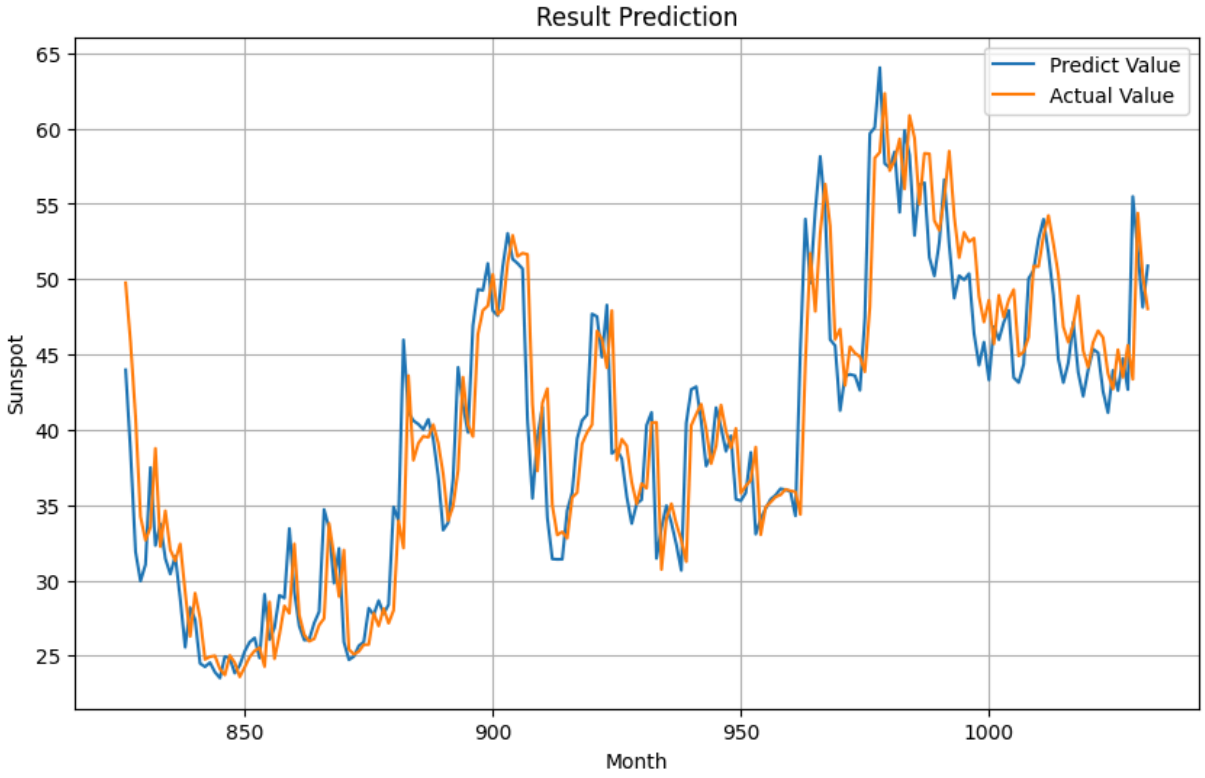
```
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 57ms/step
```



LSTM-GRU Prediction

In [44]:
```
predict(model_LSTM_GRU)
```

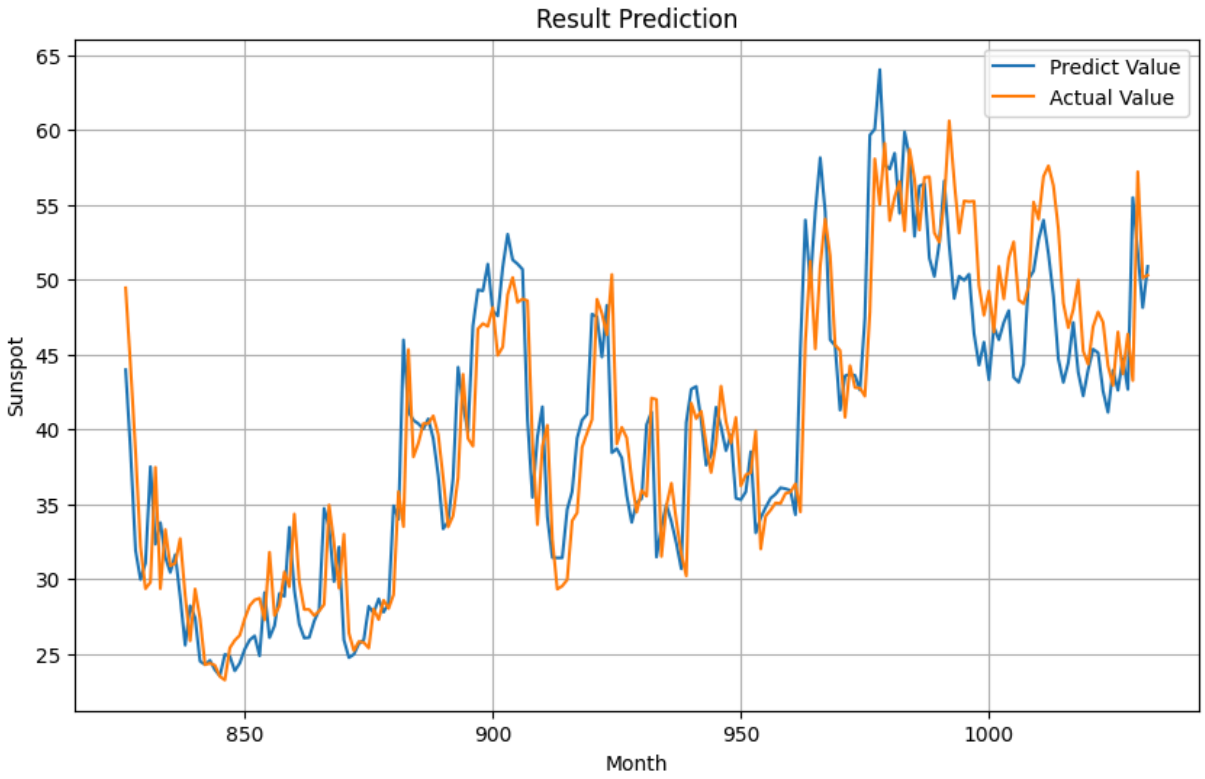
```
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 66ms/step
```



GRU-RNN Prediction

In [45]:
```
predict(model_GRU_RNN)
```

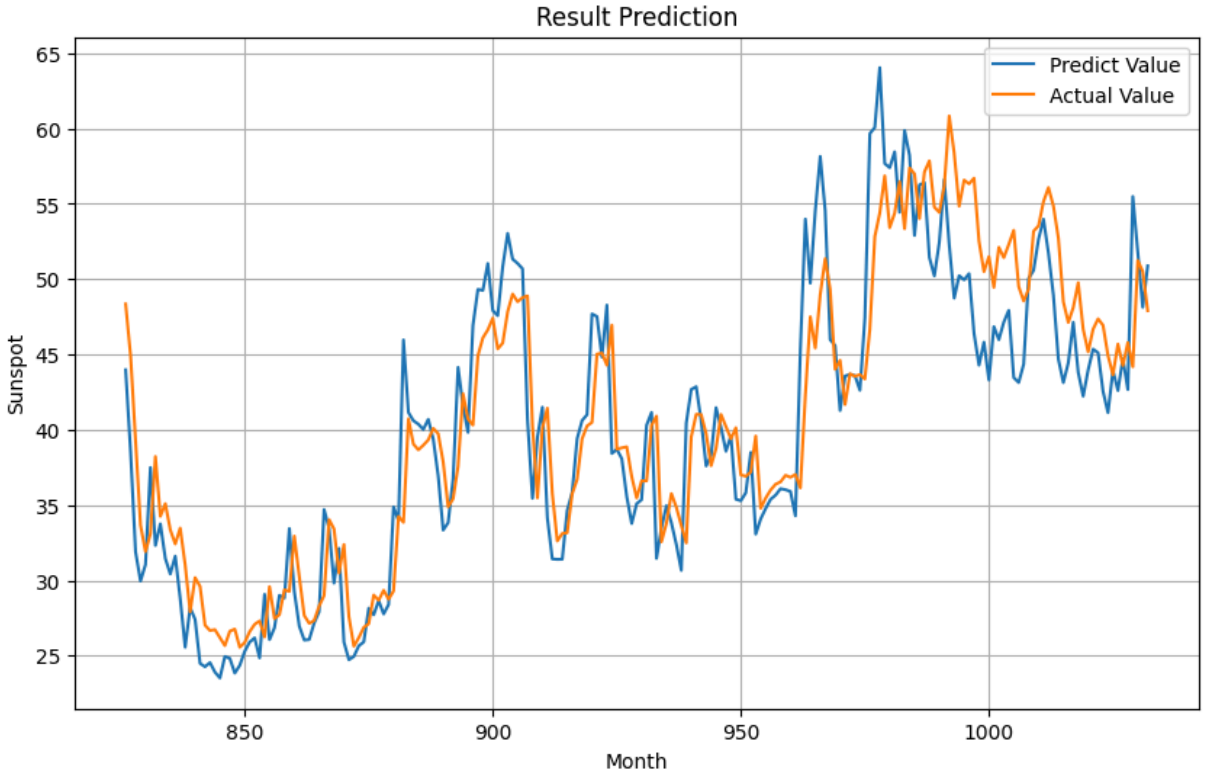
```
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 61ms/step
```



GRU-LSTM Prediction

In [46]:
```
predict(model_GRU_LSTM)
```

```
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step
```



Confident Interval

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import files
import time
```

Donwload Data

RNN

In [ ]:
```
!gdown 1dy_cvZMu9GEih7XJ5_qNzw8LPyqqXg-Q
!gdown 1AkKbVgI-HwdyFZWb7uyfseR5J-F9Hnw5
!gdown 1-qA9uOMkKEumT1MhrtMKOqVEjrjn7EAV
!gdown 1RP404GspPAsdEb_xBKAf8pFnR1SRecgE
!gdown 1JOwC0UN2z6JPK20OX1VgvOdBtFjrJAVy
```

LSTM

In [ ]:
```
!gdown 1ek2LrQEmi9kH98jtLZuD1rzKYdLswrcK
!gdown 1Y8eAijF4Zehrng5tpKyMFJ1ZEu9sxtA3
!gdown 1-AVY6E8UV4KuReuexQjwckSe-gDAYeJ4
!gdown 1DOkptkv8uiE3BwguxmFjsF8YRl4U-6ht
!gdown 1IJjiJMO48CiT32bJmreBe-7PxmzCqIdh
```

GRU

In [ ]:
```
!gdown 1D6ptowJZ3Dt04QAhfkB0AEi3doutcDoh
!gdown 1CnWWdLQEICuMAzAgoMa3ZMuHYteUVNTD
!gdown 1XKIbo7yb_9a-RFqqJ4GrVGNUw-tlmGYq
!gdown 1ncY7FLHJsSNjKxipWQLg9yAZnpVEQEbh
!gdown 1mJEKKy20pmczLrcchqcZTzwZCz7r4jY0
```

RNN-LSTM

In [ ]:
```
!gdown 1Y8-y9ZQ7AbEQNnh5ABiSRXLVWt8_cZLd
!gdown 1U_DR-mizdvJ4z-pDFf8vyxCbi31CCtj0
!gdown 1WNK8MG7qILDs7vR_-h2b15vt9N8eTkZP
!gdown 1yZrI6VmJsKp22byajzVjYhCzN2QgfDwF
!gdown 1p9CEqsWM4pq2f7lTjpdhZkTx71SpyRTp
```

RNN-GRU

In [ ]:
```
!gdown 1vfag8vScvoEa_3_mxyzk4OFozMlmC4up
!gdown 19C0BgDp8LrvERVdsGSqulEkz_l9XInQH
!gdown 1WovGGEGYNoa-Pe-XQHbvoEy6dV-jKQb-
!gdown 1UopC67xwvVPX-Mc12kN-XSIPtqPSYvkH
!gdown 1cgWGQ4OPt1l4zPBEf8jBSKokqdo_Efvi
```

LSTM-RNN

In [ ]:
```
!gdown 1VomAv7QXYkBleRM3bbZkUlPHtwQ-BDJ0
!gdown 1seeOoYqCH7TJKS8sE7oirWbg1ruK4bFQ
!gdown 14ClrSSNu2e--YqvOtwsnxHZsGd-isA4j
!gdown 1wmaoWfxjLkTW4b89kovrmOWtb9GbY1OX
!gdown 1Gz7G03X8y8WD7mG3KN7_mTJVPkuMexi4
```

LSTM-GRU

In [ ]:
```
!gdown 1CwuhIWWBqYXmWWsZHs2wzbp6KW_dsnYN
!gdown 1qAjGQNxr1T66E55YmvkT4mTkEfIPKYb2
!gdown 1jszRT5McI9ukT9GBZn0vEVq_oMKO1S40
!gdown 1iYUflkad60Vmq2XU37VGHTidOnks5pNs
!gdown 1EZ7tRYNi8vG9GZo44RuZKHOGq1j2p8MH
```

Viz

In [ ]:
```
from re import X
def shade_plot(temp, x_valid='0', line='MAE', predict=''):
  import matplotlib.pyplot as plt

  if predict == '':
    redline = f'Mean {line}'
    axis = 'Epochs'
  else:
    redline = 'Actual Value'
    axis = 'Days'

  #SORT
  temp = temp.apply(lambda x: x.sort_values().reset_index(drop=True))

  #CUT 2.5%
  n = int(len(temp) * 0.025)
  temp = temp.iloc[n:-n]

  batas_atas = temp.max().tolist()
  batas_bawah = temp.min().tolist()
  rata = temp.mean().tolist()

  # Replace these lists with your actual data
  # Dataset 1
  x1 = [i for i in range(0,len(batas_atas))]
  y1 = batas_atas

  # Dataset 2
  x2 = [i for i in range(0,len(batas_bawah))]
  y2 = batas_bawah

  if(x_valid=='0'):
    # Dataset 3
    x3 = [i for i in range(0,len(rata))]
    y3 = rata
  else:
    x3 = [i for i in range(0,len(x_valid))]
    y3 = x_valid

  # Create the plot
  plt.figure(figsize=(8, 6))

  # Plot the first linear dataset
  plt.plot(x1, y1, label=f'Predicted Value (Max)', color='blue')

  # Plot the second linear dataset
  plt.plot(x2, y2, label=f'Predicted Value (Min)', color='green')

  plt.plot(x3, y3, label=f'{redline}', color='red')

  # Create a mask for the shaded area where y1 >= y2
  mask = [y1_val >= y2_val for y1_val, y2_val in zip(y1, y2)]

  # Shade the area between the two datasets
  plt.fill_between(x1, y1, y2, where=mask, interpolate=True, color='gray', alpha=0.5)

  # Add labels and legend
  plt.xlabel(f'{axis}')
```

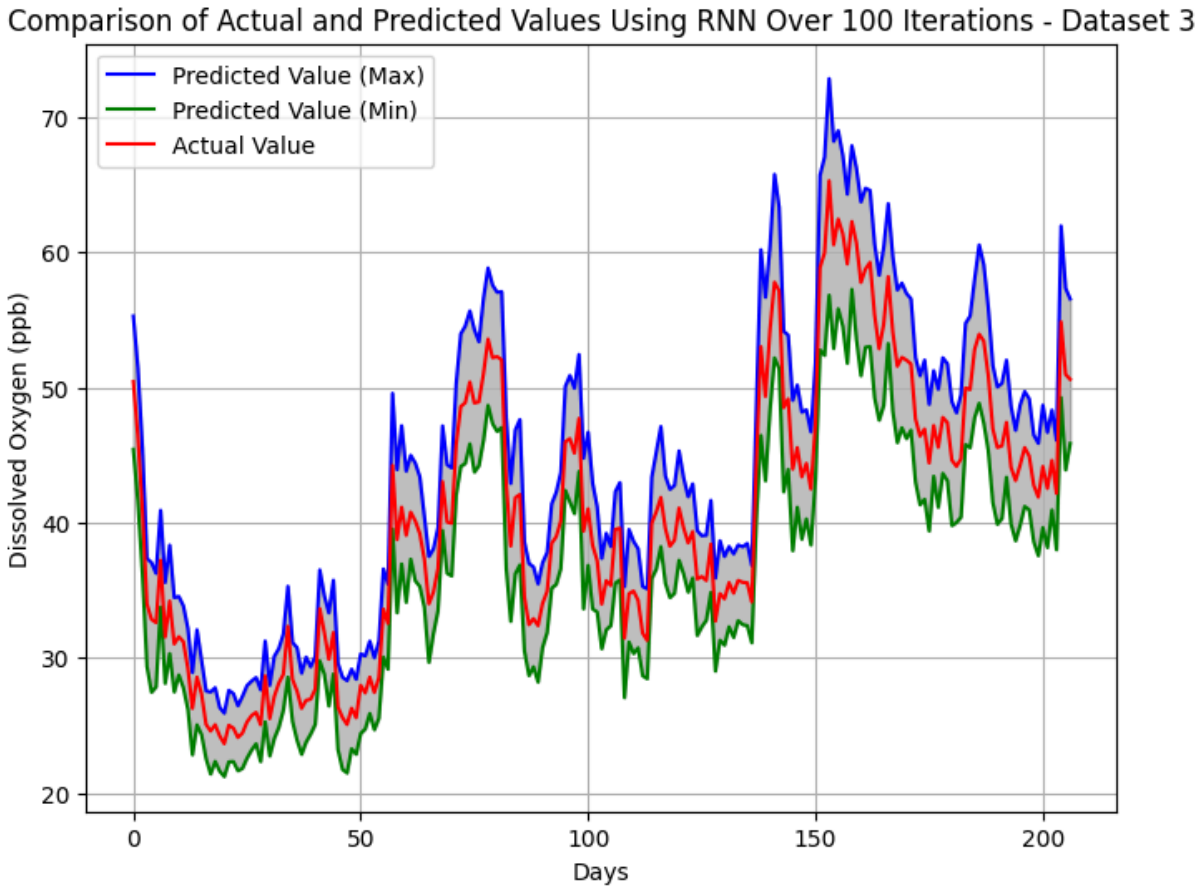
```
  plt.ylabel('Dissolved Oxygen (ppb)')
  plt.title(f'Comparison of Actual and Predicted Values Using {line} Over 100 Iterations - Data
  plt.legend()
  plt.savefig(f"Predicted_Actual_Value_Dataset3_{line}.pdf", dpi=300)
  files.download(f"Predicted_Actual_Value_Dataset3_{line}.pdf")
  # Show the plot
  plt.grid(True)
  plt.show()
```

In [ ]:
```
file2 = pd.read_excel('DissolvedOxygen.xlsx')
def take(file):
  time_step = []
  sunspots = []

  for i in range(len(file)):
    time_step.append(i)
    sunspots.append(file.iloc[i][1])
  time = np.array(time_step)
  series = np.array(sunspots)
  return time, series
time, series = take(file2)
split_time = int(len(time)*0.8)
def divide(time, series):
  split_time = int(len(time)*0.8)
  time_train = time[:split_time]
  x_train = series[:split_time]
  time_valid = time[split_time:]
  x_valid = series[split_time:]
  return x_train, time_train, time_valid, x_valid

def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
    dataset = tf.data.Dataset.from_tensor_slices(series)
    dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)
    dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))
    dataset = dataset.map(lambda window: (window[:-1], window[-1]))
    dataset = dataset.shuffle(shuffle_buffer)
    dataset = dataset.batch(batch_size).prefetch(1)
    return dataset

window_size = 30
batch_size = 32
shuffle_buffer_size = 1000


window_size = 30
batch_size = 32
shuffle_buffer_size = 1000

time, series = take(file2)
x_train, time_train, time_valid, x_valid = divide(time, series)
```

```
<ipython-input-12-23662f301f4f>:8: FutureWarning: Series.__getitem__ treating keys as positions
is deprecated. In a future version, integer keys will always be treated as labels (consistent w
ith DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  sunspots.append(file.iloc[i][1])
```

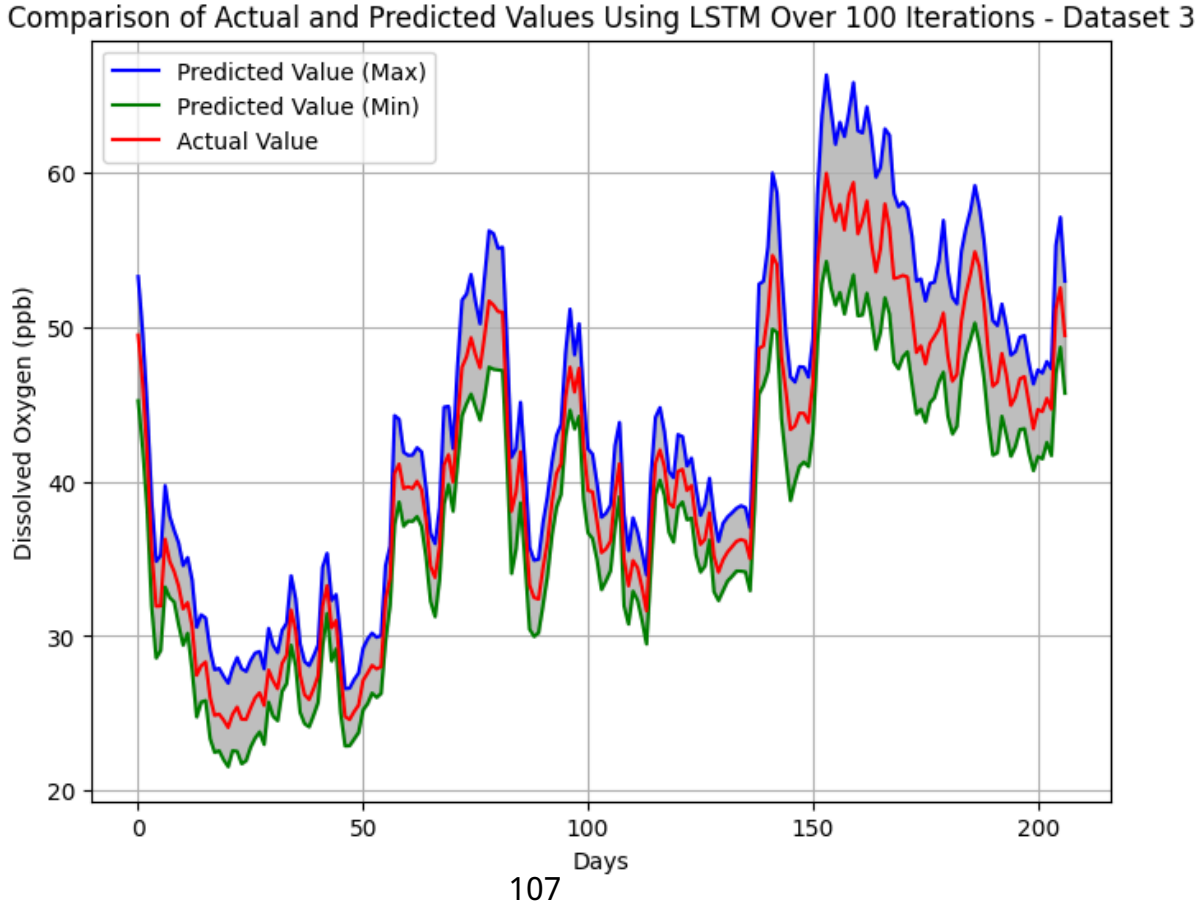
RNN

In [ ]:
```
temp = pd.read_excel('RNN_PREDICT.xlsx')
shade_plot(temp, line='RNN', predict='YES')
```



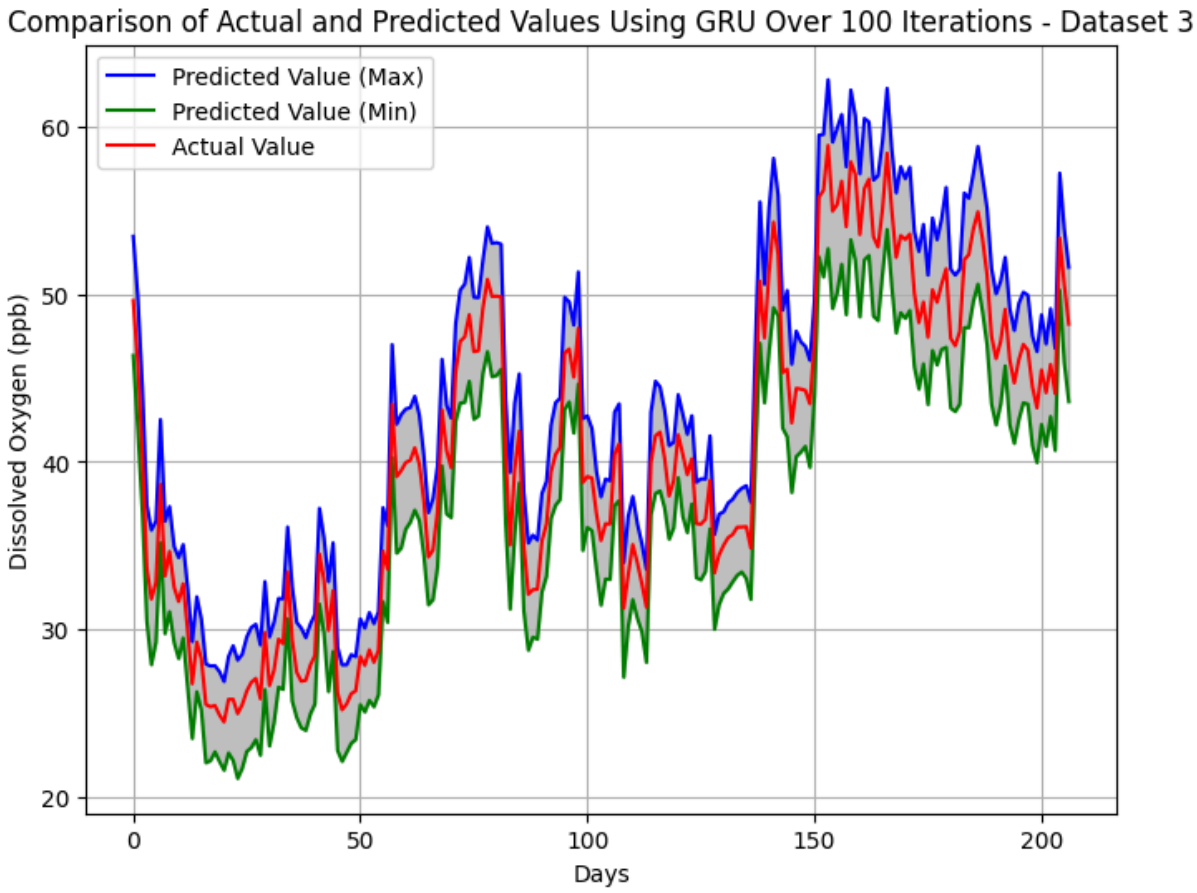
LSTM

In [ ]:
```
temp = pd.read_excel('LSTM_PREDICT.xlsx')
shade_plot(temp, line='LSTM', predict='YES')
```



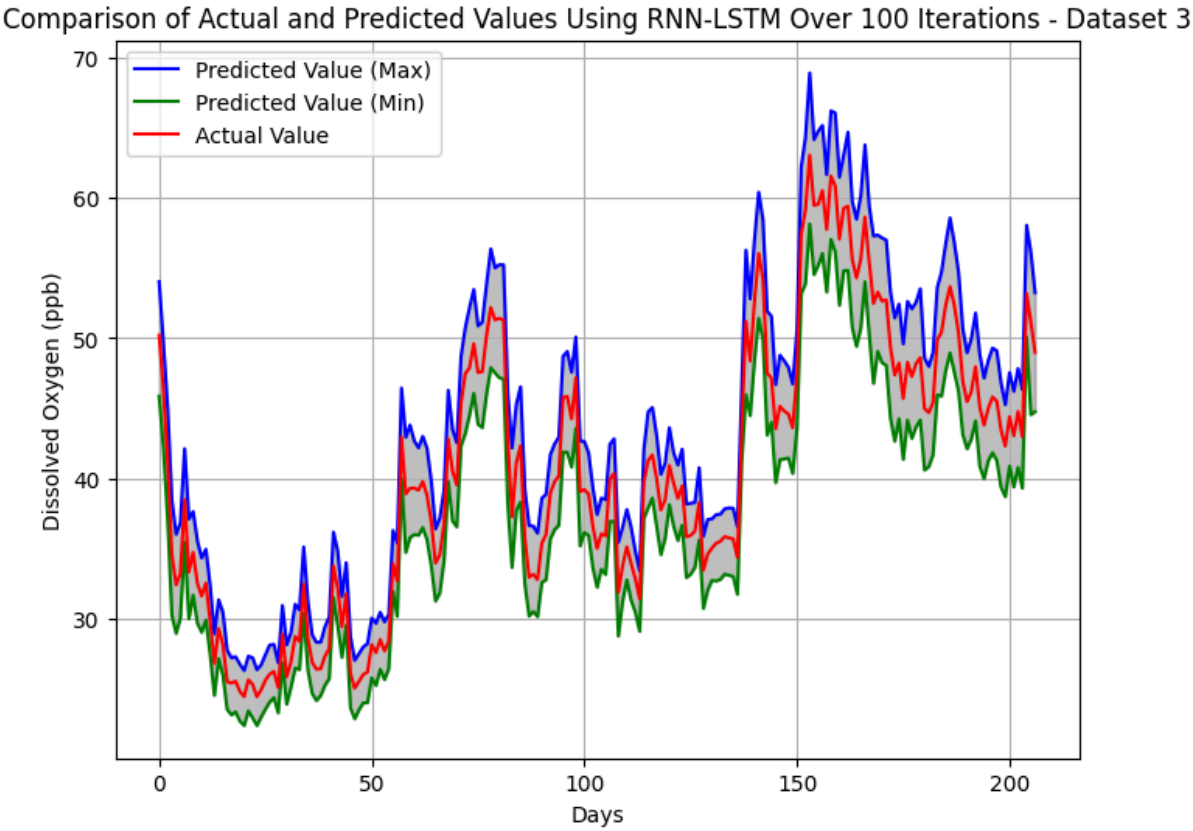
GRU

In [ ]:
```
temp = pd.read_excel('GRU_PREDICT.xlsx')
shade_plot(temp, line='GRU', predict='YES')
```



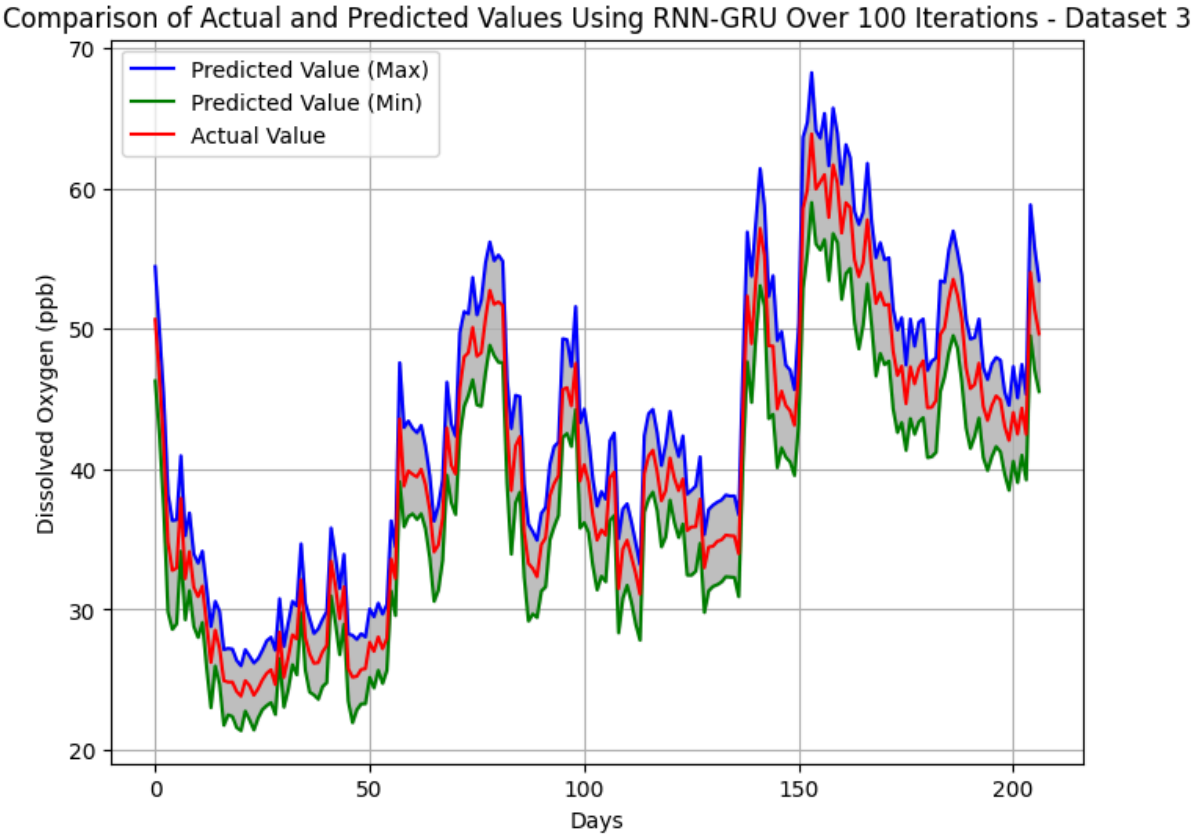
RNN-LSTM

In [ ]:
```
temp = pd.read_excel('RNN-LSTM_PREDICT.xlsx')
shade_plot(temp, line='RNN-LSTM', predict='YES')
```



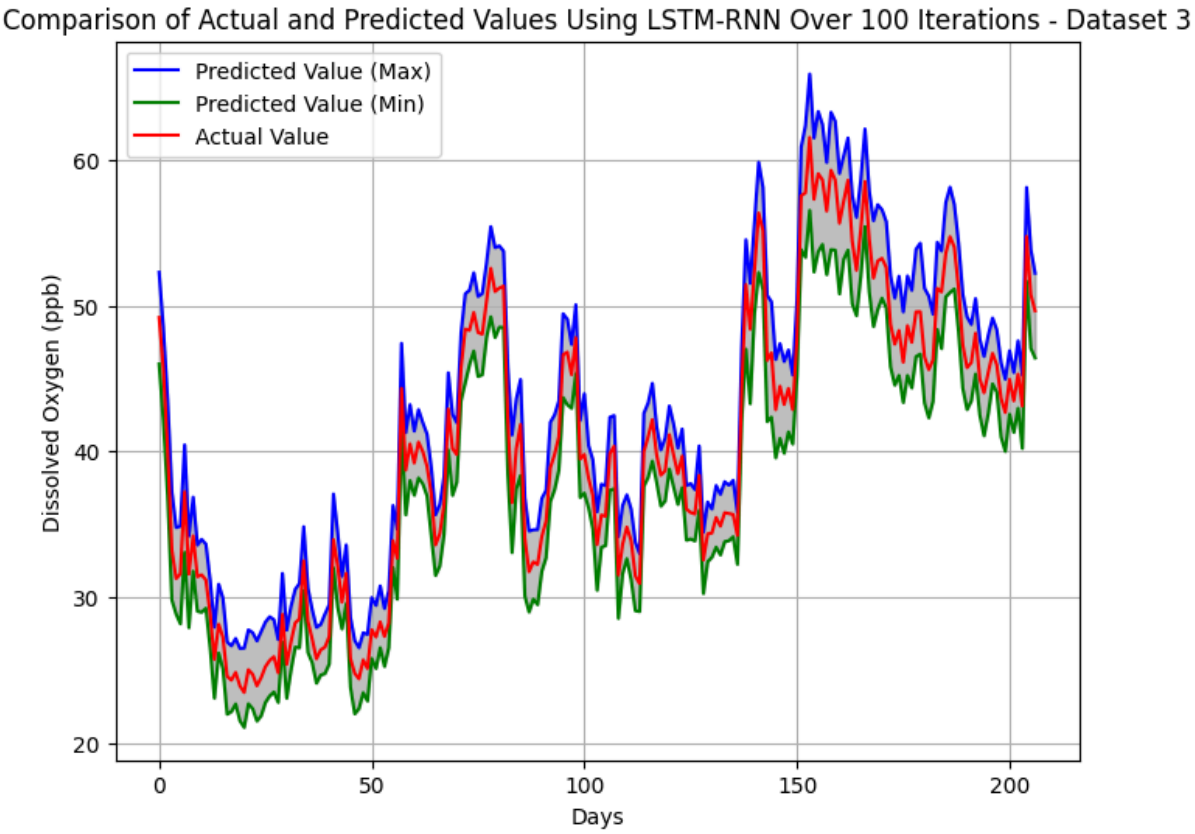
RNN-GRU

In [ ]:
```
temp = pd.read_excel('RNN-GRU_PREDICT.xlsx')
shade_plot(temp, line='RNN-GRU', predict='YES')
```



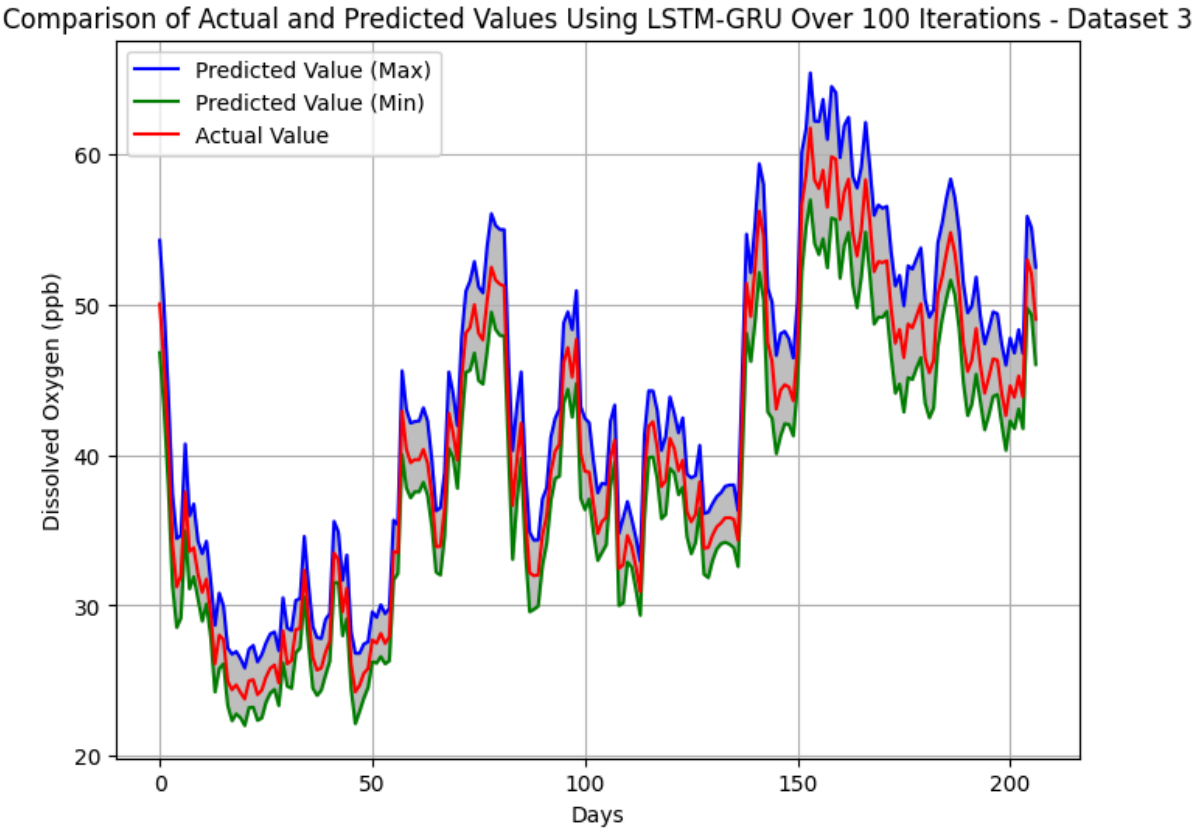
LSTM-RNN

In [ ]:
```
temp = pd.read_excel('LSTM-RNN_PREDICT.xlsx')
shade_plot(temp, line='LSTM-RNN', predict='YES')
```



LSTM-GRU

In [ ]:
```
temp = pd.read_excel('LSTM-GRU_PREDICT.xlsx')
shade_plot(temp, line='LSTM-GRU', predict='YES')
```


Comparison of Actual and Predicted Values Using LSTM-GRU Over 100 Iterations - Dataset 3
Predicted Value (Max)
Predicted Value (Min)
Actual Value
Dissolved Oxygen (ppb)
Days
20
30
40
50
60
0
50
100
150
200

Donwload Data

GRU-RNN

In [ ]:
```
!gdown 1t7-iBKRzQIu9xyVEvAGwMwtJ4_-PdtH0
!gdown 1lkWnA9uiWtsXQgCPy1vmEyODXcTUma1E
!gdown 1yr9Iaj7aC3rhcs4ZOXpGChB8DZDJh9G9
!gdown 1LlKEROW_YGadtr1r3L9Lo8OSkoLWxHpv
!gdown 1hJ3d58Un9Ym3AeCGQURp_pq5sczWU-8H
```

GRU-LSTM

In [ ]:
```
!gdown 1QdQWUlWbVoi0mT7LwJD-DYu1Db-py2Bv
!gdown 1__szgBSVNnyRh5Zw-83Aotu_YEzZxIWf
!gdown 1vdGkz58BeqRNNr6BxfMCHcNOvcvGirVD
!gdown 1_rPgnFGmk_e1NlZ4LHS9Hde_63TUucMw
!gdown 1eL4hMtU3L6wG3yf3Mf6UoCP1ZTW6Di6r
```

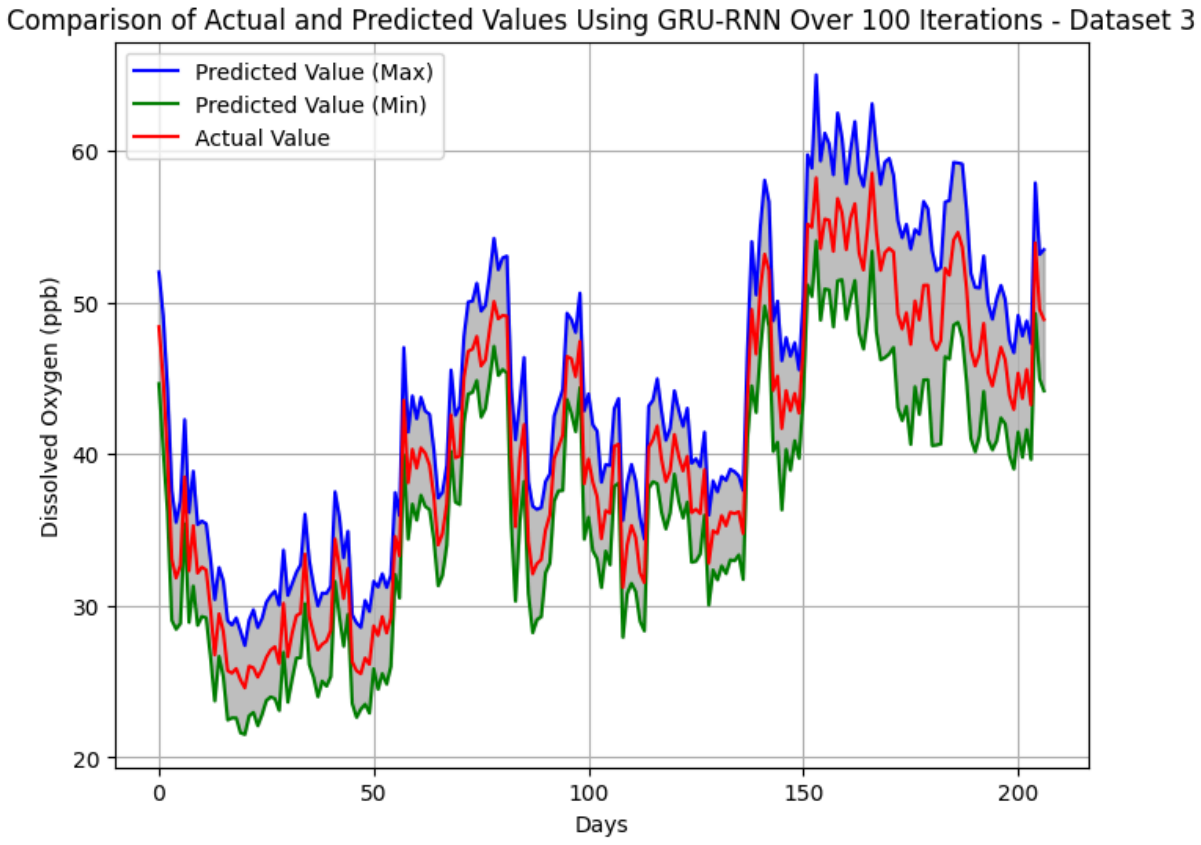
Viz

In [ ]:
```
from re import X
def shade_plot(temp, x_valid='0', line='MAE', predict=''):
  import matplotlib.pyplot as plt

  if predict == '':
    redline = f'Mean {line}'
    axis = 'Epochs'
  else:
    redline = 'Actual Value'
    axis = 'Days'

  #SORT
  temp = temp.apply(lambda x: x.sort_values().reset_index(drop=True))

  #CUT 2.5%
  n = int(len(temp) * 0.025)
  temp = temp.iloc[n:-n]

  batas_atas = temp.max().tolist()
  batas_bawah = temp.min().tolist()
  rata = temp.mean().tolist()

  # Replace these lists with your actual data
  # Dataset 1
  x1 = [i for i in range(0,len(batas_atas))]
  y1 = batas_atas

  # Dataset 2
  x2 = [i for i in range(0,len(batas_bawah))]
  y2 = batas_bawah

  if(x_valid=='0'):
    # Dataset 3
    x3 = [i for i in range(0,len(rata))]
    y3 = rata
  else:
    x3 = [i for i in range(0,len(x_valid))]
    y3 = x_valid

  # Create the plot
  plt.figure(figsize=(8, 6))

  # Plot the first linear dataset
  plt.plot(x1, y1, label=f'Predicted Value (Max)', color='blue')
```

```
# Plot the second linear dataset
plt.plot(x2, y2, label=f'Predicted Value (Min)', color='green')

plt.plot(x3, y3, label=f'{redline}', color='red')

# Create a mask for the shaded area where y1 >= y2
mask = [y1_val >= y2_val for y1_val, y2_val in zip(y1, y2)]

# Shade the area between the two datasets
plt.fill_between(x1, y1, y2, where=mask, interpolate=True, color='gray', alpha=0.5)

# Add labels and legend
plt.xlabel(f'{axis}')
plt.ylabel('Dissolved Oxygen (ppb)')
plt.title(f'Comparison of Actual and Predicted Values Using {line} Over 100 Iterations - Data
plt.legend()
plt.savefig(f"Predicted_Actual_Value_Dataset3_{line}.pdf", dpi=300)
files.download(f"Predicted_Actual_Value_Dataset3_{line}.pdf")
# Show the plot
plt.grid(True)
plt.show()
```

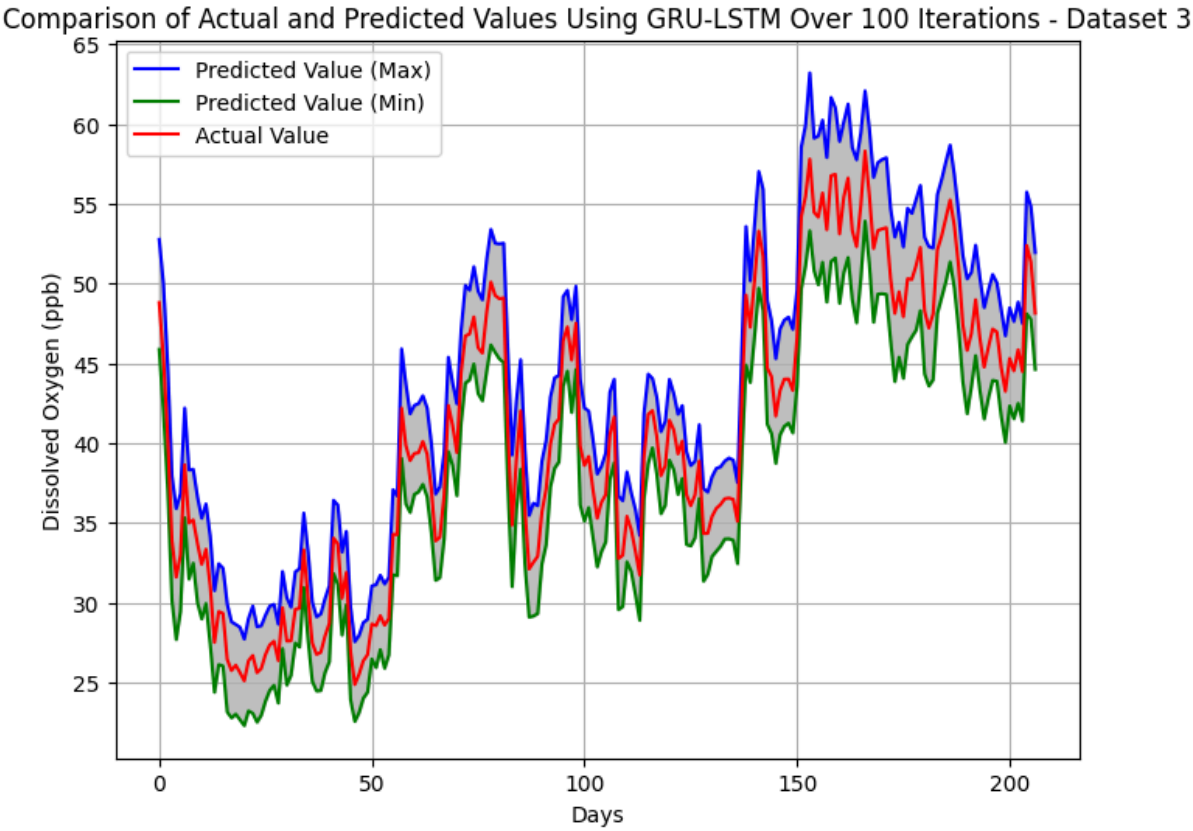
GRU-RNN

In [ ]:
```
temp = pd.read_excel('GRU-RNN_PREDICT.xlsx')
shade_plot(temp, line='GRU-RNN', predict='YES')
```



GRU-LSTM

In [ ]:
```
temp = pd.read_excel('GRU-LSTM_PREDICT.xlsx')
shade_plot(temp, line='GRU-LSTM', predict='YES')
```


Comparison of Actual and Predicted Values Using GRU-LSTM Over 100 Iterations - Dataset 3
Predicted Value (Max)
Predicted Value (Min)
Actual Value
Dissolved Oxygen (ppb)
Days
65
60
55
50
45
40
35
30
25
0
50
100
150
200

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import files
```

DONWLOAD DATA

In [ ]:
```
!gdown 1_bfo8AtzgY1aTlBMkCQTeXZJgvpya_jy
!gdown 1Yfwmvc33LCqBRolk0cht_U0z8Dm2e94r
!gdown 1SlDSpcjwyok5cvllKSBIkhmgcEMsniXw
!gdown 1keYxJghjd3PS_RKCG8pAMZ_rKED9bR1I
!gdown 1C-8SpOb3URkXvOfv2MT_8F1BXhG_z6yC
!gdown 1lWRg123gdALQdFHd8Y7YKBBuFWV9AJz3
!gdown 1ABT_xEk_8wSQ7GAUdb4_zl_P5aqao3AC
!gdown 1KhQuc5NO8DM2lSsQHFMc_Asj8AC_gCix
!gdown 1j0grY7SJMdeOUE8xJ_C8pAfzSLxWn32p
```

In [ ]:
```
!gdown 1u3QM7s9U4X1zwhXoIyMUlUHL9MP2m7lA
!gdown 1n-qg3c_F7CdKRu4J-pvosOPifeOFpyXT
!gdown 1eHWoOj9Hjnqq953qF7GnuOqBHAZO6btU
!gdown 14CvG2kBlZc0iGIN2yiE3IHbYTJp1lcbX
!gdown 11wAUYeSh6ABH5CdguGh9Db8m206b1BHy
!gdown 1Hs82CjFvveFxVVhq7khEN80zw5JgX2YW
!gdown 1Yu32XV9IWjqMmIlD58hccDKvXhfYBRz-
!gdown 18fIbFzz1IDCieyI3AzCOw51TLMD4jNE_
!gdown 1rvpQ9cuZ2oz_vJfR71wbAAiT2WAvkOaN
```

In [ ]:
```
!gdown 1pFi3Ak4tDjpP_bqFlq-TpIsY3BdN9iKB
!gdown 1ZMIRCHq8ixaqIbMNBKezMbJF_1HxufSm
!gdown 1ZWkYruyNyXxzfen4nX35EGqMhU8RqfCm
!gdown 1-R3HgWubX2WPGExnivgaDkngXCC4gwwI
!gdown 1jZRd9ZPvhqdMoqkrOSWAZF-VTnOpGVBT
!gdown 1u9v7m9DhtGDBxMRC5nIpeP2WdxDQzYCv
!gdown 1heElB_3Y-EfZ3NvRQyJfEaVtjKYbT7IJ
!gdown 1tzPKVzJQWdvOb3VlcaFb2Cl-OlbUzaoj
!gdown 1yfnad4_9xfyV07ChCwNY2QVO6CMwwY8C
```

In [ ]:
```
!gdown 1LgzOypyseSxSi6npx4uqU06qQlYiLaBW
!gdown 1UPlXMWGCECg95bikCPMQL4S74ulyDiJf
!gdown 1WC68Tph806l4Lh9M8OoC-k0mbYTCdmvg
!gdown 1FtcLm4T-Kf7NFUtaJFRt4G0XB1iHMLt3
!gdown 1_wKEcb1Y-4Ixm7kCeTwvSDPKmXDGBLMv
!gdown 19xKB1I7u4y-OeE89eKRBX6w7aVpT_ZTA
!gdown 1Wq8TYAz_HUf7ixW8k3wvALsxjnGwbMy2
!gdown 1QyL2vIpZEbo84zcZxdB0W4B3_J-CzLvG
!gdown 1hraImwtrxdcxxwPsLAiwtqXNxCc-z4Kz
```

Metrik Evaluation

MAE

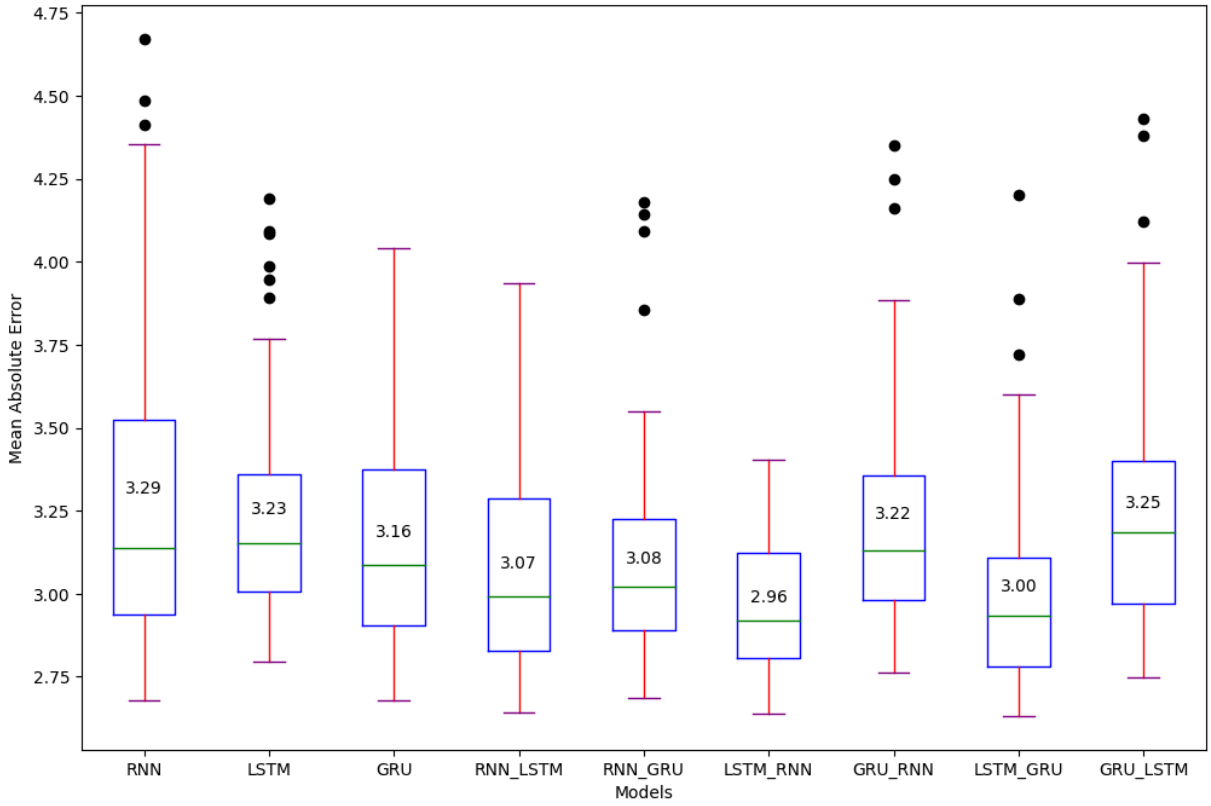
In [ ]:
```
df1 =  pd.read_excel('/content/RNN_FORECASTMae.xlsx')
df2 =  pd.read_excel('/content/LSTM_FORECASTMae.xlsx')
df3 =  pd.read_excel('/content/GRU_FORECASTMae.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_FORECASTMae.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_FORECASTMae.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_FORECASTMae.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_FORECASTMae.xlsx')
df8 =  pd.read_excel('/content/LSTM-GRU_FORECASTMae.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_FORECASTMae.xlsx')
```

In [ ]:
```
df = pd.DataFrame()
df['RNN'] =  df1[0]
```

```
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]

# n = int(len(df) * (20 / 100))
n = int(len(df) * (2.5 / 100))
df = df.iloc[n:-n]
```

In [ ]:

```
df = pd.DataFrame()
df['RNN'] =  sorted(df1[0])
df['LSTM'] =  sorted(df2[0])
df['GRU'] =  sorted(df3[0])
df['RNN_LSTM'] =  sorted(df4[0])
df['RNN_GRU'] =  sorted(df5[0])
df['LSTM_RNN'] = sorted(df6[0])
df['GRU_RNN'] =  sorted(df7[0])
df['LSTM_GRU'] = sorted(df8[0])
df['GRU_LSTM'] = sorted(df9[0])


# n = int(len(df)*0.15)
n = int(len(df) * 0.025)
df = df[:].iloc[n:-n]
data = df[:]

box_color = 'blue'
whisker_color = 'red'
median_color = 'green'
flier_color = 'black'
cap_color = 'purple'

fig, ax = plt.subplots(figsize=(12, 8))

plt.boxplot(data.values, labels=data.columns,
            boxprops=dict(color=box_color),
            whiskerprops=dict(color=whisker_color),
            capprops=dict(color=cap_color),
            flierprops=dict(markerfacecolor=flier_color, marker='o', markersize=6),
            medianprops=dict(color=median_color))

for i, column in enumerate(data.columns):
    mean = np.mean(data[column])
    plt.text(i + 1, mean, f'{mean:.2f}', ha='center', va='bottom', color='black')

# plt.title('Predict with Boxplot')
plt.xlabel('Models')
plt.ylabel('Mean Absolute Error')
plt.savefig("Comparison_MAE_Dataset1.pdf", dpi=300)
files.download("Comparison_MAE_Dataset1.pdf")

plt.show()
```

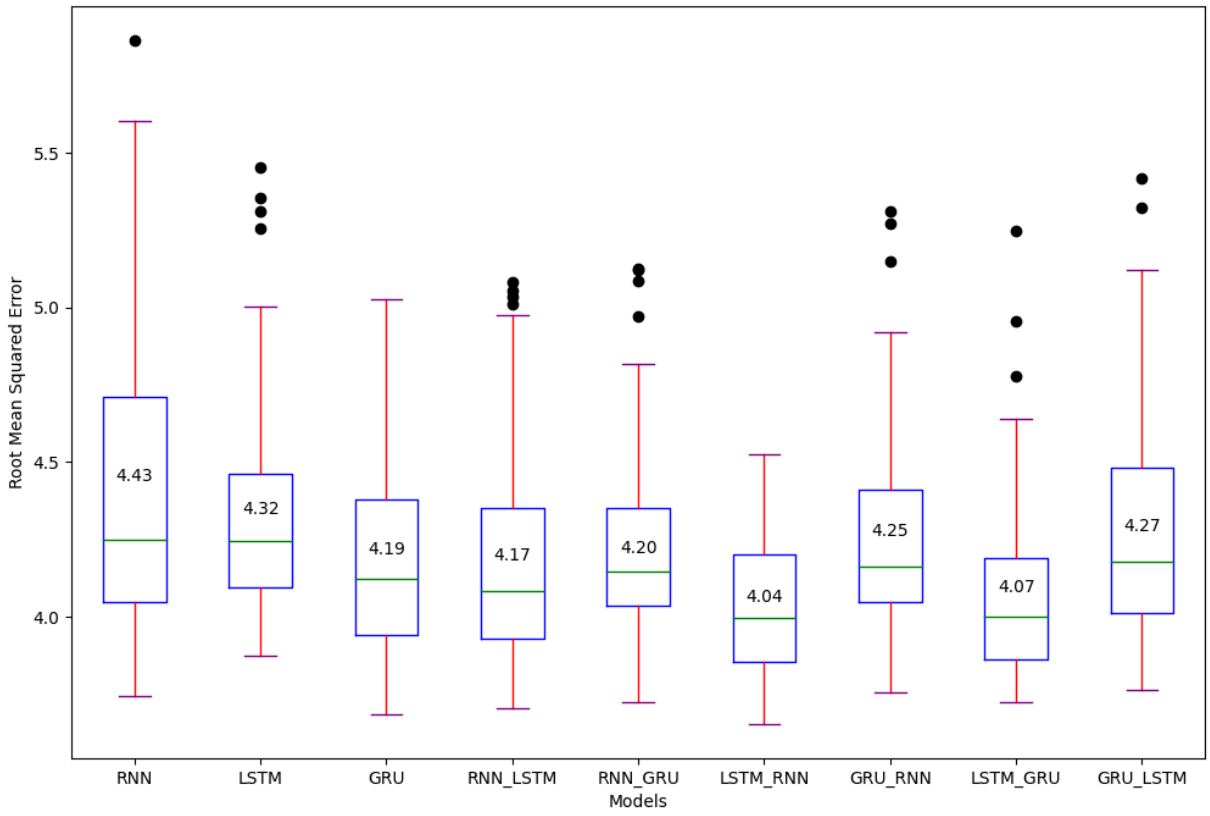


RMSE

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_FORECASTRMse.xlsx')
df2 =  pd.read_excel('/content/LSTM_FORECASTRMse.xlsx')
df3 =  pd.read_excel('/content/GRU_FORECASTRMse.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_FORECASTRMse.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_FORECASTRMse.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_FORECASTRMse.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_FORECASTRMse.xlsx')
df8 =  pd.read_excel('/content/LSTM-GRU_FORECASTRMse.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_FORECASTRMse.xlsx')
df = pd.DataFrame()
df['RNN'] =  df1[0]
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]

# n = int(len(df) * (20 / 100))
n = int(len(df) * (2.5 / 100))
df = df.iloc[n:-n]
```

In [ ]:
```
df = pd.DataFrame()
df['RNN'] =  sorted(df1[0])
df['LSTM'] =  sorted(df2[0])
df['GRU'] =  sorted(df3[0])
df['RNN_LSTM'] =  sorted(df4[0])
df['RNN_GRU'] =  sorted(df5[0])
df['LSTM_RNN'] = sorted(df6[0])
df['GRU_RNN'] =  sorted(df7[0])
df['LSTM_GRU'] = sorted(df8[0])
df['GRU_LSTM'] = sorted(df9[0])


# n = int(len(df)*0.15)
n = int(len(df) * 0.025)
```

```
df = df[:].iloc[n:-n]
data = df[:]

box_color = 'blue'
whisker_color = 'red'
median_color = 'green'
flier_color = 'black'
cap_color = 'purple'

fig, ax = plt.subplots(figsize=(12, 8))

plt.boxplot(data.values, labels=data.columns,
            boxprops=dict(color=box_color),
            whiskerprops=dict(color=whisker_color),
            capprops=dict(color=cap_color),
            flierprops=dict(markerfacecolor=flier_color, marker='o', markersize=6),
            medianprops=dict(color=median_color))

for i, column in enumerate(data.columns):
    mean = np.mean(data[column])
    plt.text(i + 1, mean, f'{mean:.2f}', ha='center', va='bottom', color='black')

# plt.title('Predict with Boxplot')
plt.xlabel('Models')
plt.ylabel('Root Mean Squared Error')
plt.savefig("Comparison_RMSE_Dataset1.pdf", dpi=300)
files.download("Comparison_RMSE_Dataset1.pdf")

plt.show()
```



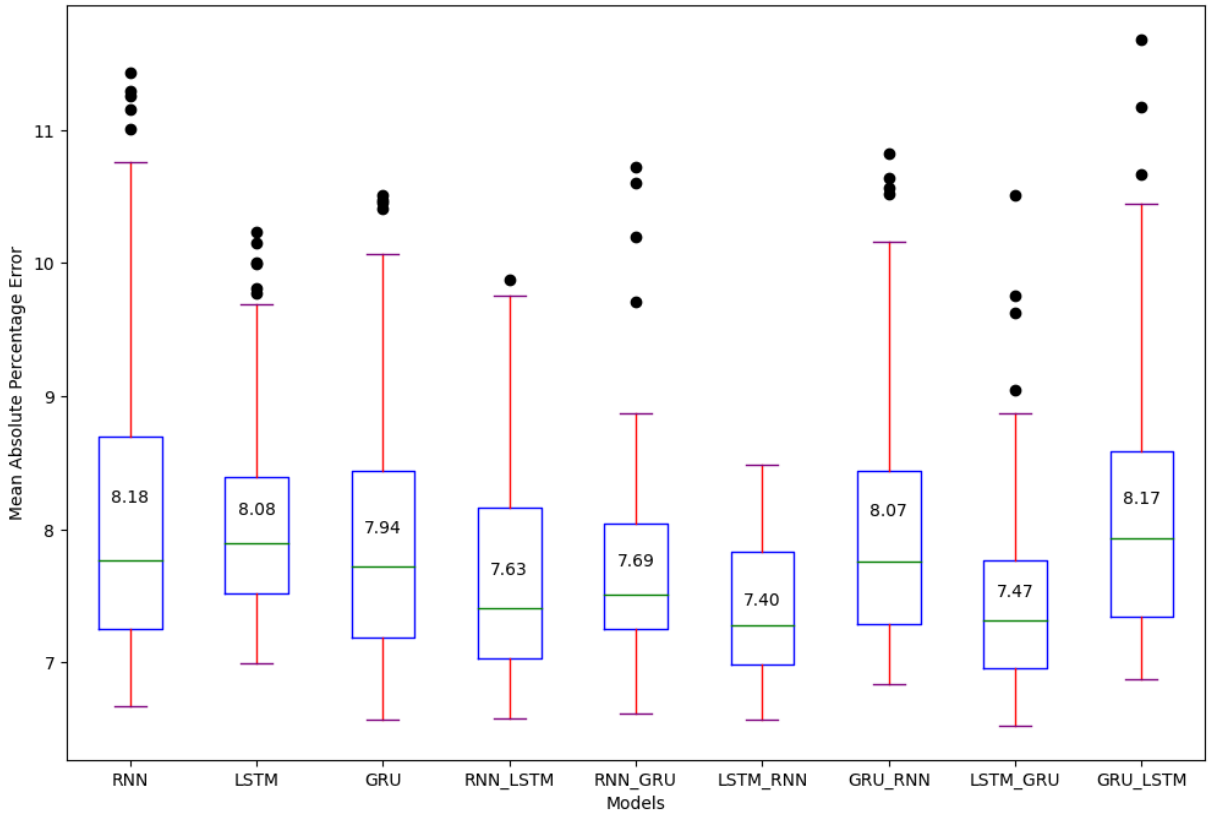
MAPE

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_FORECASTMpe.xlsx')
df2 =  pd.read_excel('/content/LSTM_FORECASTMpe.xlsx')
df3 =  pd.read_excel('/content/GRU_FORECASTMpe.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_FORECASTMpe.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_FORECASTMpe.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_FORECASTMpe.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_FORECASTMpe.xlsx')
```

```
df8 =  pd.read_excel('/content/LSTM-GRU_FORECASTMpe.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_FORECASTMpe.xlsx')
df = pd.DataFrame()
df['RNN'] =  df1[0]
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]

# n = int(len(df) * (20 / 100))
n = int(len(df) * (2.5 / 100))
df = df.iloc[n:-n]
```

In [ ]:

```
df = pd.DataFrame()
df['RNN'] =  sorted(df1[0])
df['LSTM'] =  sorted(df2[0])
df['GRU'] =  sorted(df3[0])
df['RNN_LSTM'] =  sorted(df4[0])
df['RNN_GRU'] =  sorted(df5[0])
df['LSTM_RNN'] = sorted(df6[0])
df['GRU_RNN'] =  sorted(df7[0])
df['LSTM_GRU'] = sorted(df8[0])
df['GRU_LSTM'] = sorted(df9[0])


# n = int(len(df)*0.15)
n = int(len(df) * 0.025)
df = df[:].iloc[n:-n]
data = df[:]

box_color = 'blue'
whisker_color = 'red'
median_color = 'green'
flier_color = 'black'
cap_color = 'purple'

fig, ax = plt.subplots(figsize=(12, 8))

plt.boxplot(data.values, labels=data.columns,
            boxprops=dict(color=box_color),
            whiskerprops=dict(color=whisker_color),
            capprops=dict(color=cap_color),
            flierprops=dict(markerfacecolor=flier_color, marker='o', markersize=6),
            medianprops=dict(color=median_color))

for i, column in enumerate(data.columns):
    mean = np.mean(data[column])
    plt.text(i + 1, mean, f'{mean:.2f}', ha='center', va='bottom', color='black')

# plt.title('Predict with Boxplot')
plt.xlabel('Models')
plt.ylabel('Mean Absolute Percentage Error')
plt.savefig("Comparison_MAPE_Dataset1.pdf", dpi=300)
files.download("Comparison_MAPE_Dataset1.pdf")

plt.show()
```



Time Comparison

In [ ]:
```
df1 =  pd.read_excel('/content/RNN_TIME.xlsx')
df2 =  pd.read_excel('/content/LSTM_TIME.xlsx')
df3 =  pd.read_excel('/content/GRU_TIME.xlsx')
df4 =  pd.read_excel('/content/RNN-LSTM_TIME.xlsx')
df5 =  pd.read_excel('/content/RNN-GRU_TIME.xlsx')
df6 =  pd.read_excel('/content/LSTM-RNN_TIME.xlsx')
df7 =  pd.read_excel('/content/GRU-RNN_TIME.xlsx')
df8 =  pd.read_excel('/content/LSTM-GRU_TIME.xlsx')
df9 =  pd.read_excel('/content/GRU-LSTM_TIME.xlsx')
df = pd.DataFrame()
df['RNN'] =  df1[0]
df['LSTM'] =  df2[0]
df['GRU'] =  df3[0]
df['RNN_LSTM'] =  df4[0]
df['RNN_GRU'] =  df5[0]
df['LSTM_RNN'] =  df6[0]
df['GRU_RNN'] =  df7[0]
df['LSTM_GRU'] =  df8[0]
df['GRU_LSTM'] =  df9[0]
```

In [ ]:
```
# Calculate the average time for each model
average_times = df.mean()

# Create a bar chart
plt.figure(figsize=(10, 6))
average_times.plot(kind='bar', color='skyblue')
plt.title('Comparison of Computational Time Across Different Models')
plt.xlabel('Models')
plt.ylabel('Avarage Time (Seconds)')
plt.xticks(rotation=45)
plt.tight_layout()

# Display the average times on top of the bars
for i, v in enumerate(average_times):
    plt.text(i, v, f"{v:.2f}", ha='center', va='bottom')

plt.savefig("Comparison_Time_Dataset1.pdf", dpi=300)
```

```
files.download("Comparison_Time_Dataset1.pdf")
plt.show()
```