```
!pip install numpy
!pip install matplotlib
```

```
Requirement already satisfied: numpy in
/usr/local/lib/python3.10/dist-packages (1.23.5)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.10/dist-packages (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.1.1)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (4.43.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.5)
Requirement already satisfied: numpy>=1.20 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.23.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (23.2)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7-
>matplotlib) (1.16.0)
```

```
import pandas as pd
import numpy as np
import os

# Get the current directory
current_directory = os.getcwd()

# Define the CSV file's name
csv_file_name = "Regression.csv"

# Construct the full path to the CSV file
csv_file_path = os.path.join(current_directory, csv_file_name)

# Load the dataset from CSV file
data = pd.read_csv(csv_file_name)

data.columns
data
```

```
      station        Date  Present_Tmax  Present_Tmin  LDAPS_RHmin  \
0         1.0  2013-06-30          28.7          21.4    58.255688
```

```
1         2.0  2013-06-30          31.9          21.6    52.263397
2         3.0  2013-06-30          31.6          23.3    48.690479
3         4.0  2013-06-30          32.0          23.4    58.239788
4         5.0  2013-06-30          31.4          21.9    56.174095
...       ...         ...           ...           ...          ...
7747     23.0  2017-08-30          23.3          17.1    26.741310
7748     24.0  2017-08-30          23.3          17.7    24.040634
7749     25.0  2017-08-30          23.2          17.4    22.933014
7750      NaN         NaN          20.0          11.3    19.794666
7751      NaN         NaN          37.6          29.9    98.524734

      LDAPS_RHmax  LDAPS_Tmax_lapse  LDAPS_Tmin_lapse   LDAPS_WS
LDAPS_LH  \
0       91.116364         28.074101         23.006936   6.818887
69.451805
1       90.604721         29.850689         24.035009   5.691890
51.937448
2       83.973587         30.091292         24.565633   6.138224
20.573050
3       96.483688         29.704629         23.326177   5.650050
65.727144
4       90.155128         29.113934         23.486480   5.735004
107.965535
...           ...               ...               ...        ...
...
7747    78.869858         26.352081         18.775678   6.148918
72.058294
7748    77.294975         27.010193         18.733519   6.542819
47.241457
7749    77.243744         27.939516         18.522965   7.289264
9.090034
7750    58.936283         17.624954         14.272646   2.882580  -
13.603212
7751   100.000153         38.542255         29.619342  21.857621
213.414006

      ...  LDAPS_PPT2  LDAPS_PPT3  LDAPS_PPT4      lat      lon
DEM  \
0     ...    0.000000    0.000000    0.000000  37.6046  126.991
212.3350
1     ...    0.000000    0.000000    0.000000  37.6046  127.032
44.7624
2     ...    0.000000    0.000000    0.000000  37.5776  127.058
33.3068
3     ...    0.000000    0.000000    0.000000  37.6450  127.022
45.7160
4     ...    0.000000    0.000000    0.000000  37.5507  127.135
35.0380
...   ...         ...         ...         ...      ...      ...
```

```
...
7747  ...    0.000000    0.000000    0.000000  37.5372  126.891
15.5876
7748  ...    0.000000    0.000000    0.000000  37.5237  126.909
17.2956
7749  ...    0.000000    0.000000    0.000000  37.5237  126.970
19.5844
7750  ...    0.000000    0.000000    0.000000  37.4562  126.826
12.3700
7751  ...   21.621661   15.841235   16.655469  37.6450  127.135
212.3350

         Slope  Solar radiation  Next_Tmax  Next_Tmin
0     2.785000      5992.895996       29.1       21.2
1     0.514100      5869.312500       30.5       22.5
2     0.266100      5863.555664       31.1       23.9
3     2.534800      5856.964844       31.7       24.3
4     0.505500      5859.552246       31.2       22.5
...        ...              ...        ...        ...
7747  0.155400      4443.313965       28.3       18.1
7748  0.222300      4438.373535       28.6       18.8
7749  0.271300      4451.345215       27.8       17.4
7750  0.098475      4329.520508       17.4       11.3
7751  5.178230      5992.895996       38.9       29.8

[7752 rows x 25 columns]

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7752 entries, 0 to 7751
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   station           7750 non-null   float64
 1   Date              7750 non-null   object
 2   Present_Tmax      7682 non-null   float64
 3   Present_Tmin      7682 non-null   float64
 4   LDAPS_RHmin       7677 non-null   float64
 5   LDAPS_RHmax       7677 non-null   float64
 6   LDAPS_Tmax_lapse  7677 non-null   float64
 7   LDAPS_Tmin_lapse  7677 non-null   float64
 8   LDAPS_WS          7677 non-null   float64
 9   LDAPS_LH          7677 non-null   float64
 10  LDAPS_CC1         7677 non-null   float64
 11  LDAPS_CC2         7677 non-null   float64
 12  LDAPS_CC3         7677 non-null   float64
 13  LDAPS_CC4         7677 non-null   float64
 14  LDAPS_PPT1        7677 non-null   float64
 15  LDAPS_PPT2        7677 non-null   float64
```

```
 16  LDAPS_PPT3         7677 non-null   float64
 17  LDAPS_PPT4         7677 non-null   float64
 18  lat                7752 non-null   float64
 19  lon                7752 non-null   float64
 20  DEM                7752 non-null   float64
 21  Slope              7752 non-null   float64
 22  Solar radiation    7752 non-null   float64
 23  Next_Tmax          7725 non-null   float64
 24  Next_Tmin          7725 non-null   float64
dtypes: float64(24), object(1)
memory usage: 1.5+ MB
```

```
# Remove the first two columns (station and date) and select columns
3-23 as features
data = data.iloc[:, 2:23]
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7752 entries, 0 to 7751
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Present_Tmax       7682 non-null   float64
 1   Present_Tmin       7682 non-null   float64
 2   LDAPS_RHmin        7677 non-null   float64
 3   LDAPS_RHmax        7677 non-null   float64
 4   LDAPS_Tmax_lapse   7677 non-null   float64
 5   LDAPS_Tmin_lapse   7677 non-null   float64
 6   LDAPS_WS           7677 non-null   float64
 7   LDAPS_LH           7677 non-null   float64
 8   LDAPS_CC1          7677 non-null   float64
 9   LDAPS_CC2          7677 non-null   float64
 10  LDAPS_CC3          7677 non-null   float64
 11  LDAPS_CC4          7677 non-null   float64
 12  LDAPS_PPT1         7677 non-null   float64
 13  LDAPS_PPT2         7677 non-null   float64
 14  LDAPS_PPT3         7677 non-null   float64
 15  LDAPS_PPT4         7677 non-null   float64
 16  lat                7752 non-null   float64
 17  lon                7752 non-null   float64
 18  DEM                7752 non-null   float64
 19  Slope              7752 non-null   float64
 20  Solar radiation    7752 non-null   float64
dtypes: float64(21)
memory usage: 1.2 MB
```

```
# Drop missing values (NaNs)
data.dropna(inplace=True)

def min_max_scaling(data):
```

```
    min_val = data.min()
    max_val = data.max()
    scaled_data = (data - min_val) / (max_val - min_val)
    return scaled_data

# Min-Max scaling
for col in data.columns:
    data[col] = min_max_scaling(data[col])

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7607 entries, 0 to 7751
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Present_Tmax      7607 non-null   float64
 1   Present_Tmin      7607 non-null   float64
 2   LDAPS_RHmin       7607 non-null   float64
 3   LDAPS_RHmax       7607 non-null   float64
 4   LDAPS_Tmax_lapse  7607 non-null   float64
 5   LDAPS_Tmin_lapse  7607 non-null   float64
 6   LDAPS_WS          7607 non-null   float64
 7   LDAPS_LH          7607 non-null   float64
 8   LDAPS_CC1         7607 non-null   float64
 9   LDAPS_CC2         7607 non-null   float64
 10  LDAPS_CC3         7607 non-null   float64
 11  LDAPS_CC4         7607 non-null   float64
 12  LDAPS_PPT1        7607 non-null   float64
 13  LDAPS_PPT2        7607 non-null   float64
 14  LDAPS_PPT3        7607 non-null   float64
 15  LDAPS_PPT4        7607 non-null   float64
 16  lat               7607 non-null   float64
 17  lon               7607 non-null   float64
 18  DEM               7607 non-null   float64
 19  Slope             7607 non-null   float64
 20  Solar radiation   7607 non-null   float64
dtypes: float64(21)
memory usage: 1.3 MB
```

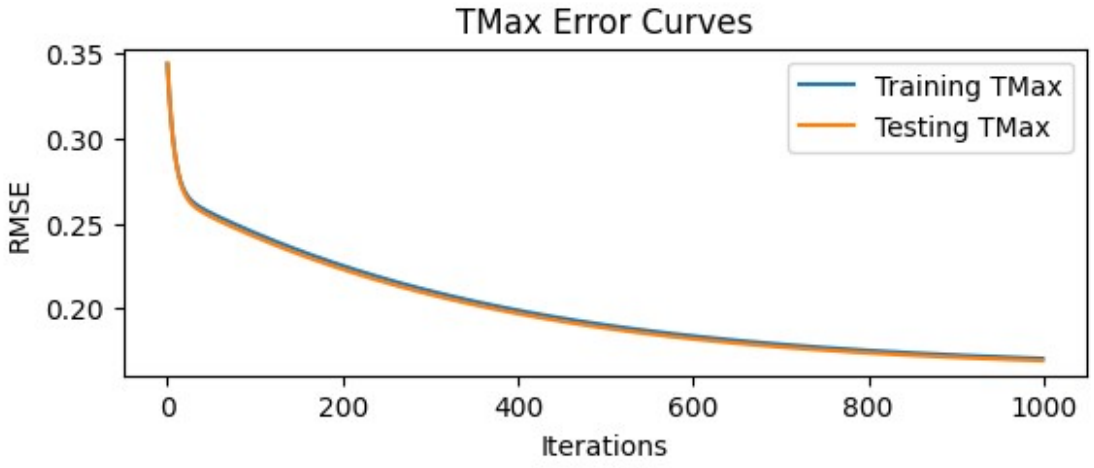
```
def gradient_descent(X, y, theta, alpha, num_iterations):
    m = len(y)
    for iteration in range(num_iterations):
        gradients = -2/m * X.T @ (y - X @ theta)
        theta -= alpha * gradients
    return theta

# Number of trials
num_trials = 10
```

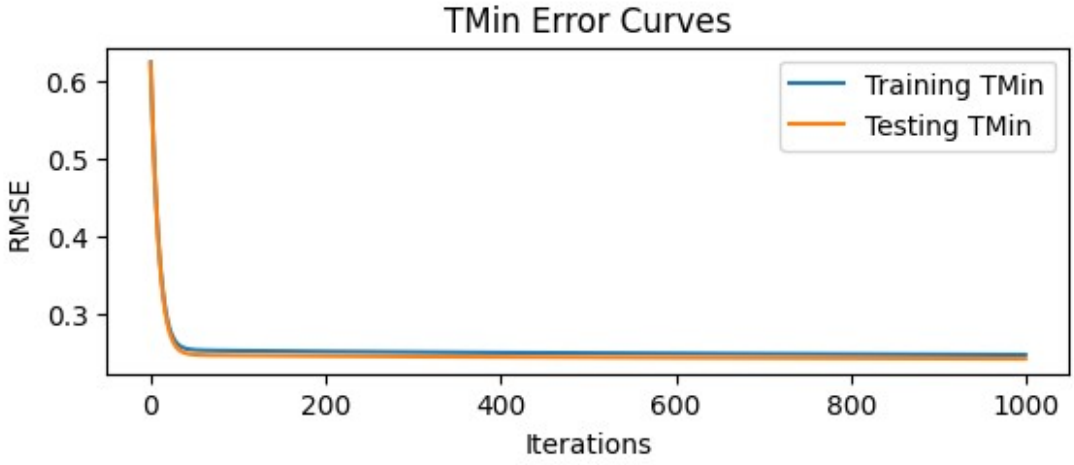
```
# Initialize arrays to store RMSE values
mean_training_rmse_tmax = []
mean_testing_rmse_tmax = []
mean_training_rmse_tmin = []
mean_testing_rmse_tmin = []


import matplotlib.pyplot as plt

# Repeat the process for 10 trials
for trial in range(num_trials):
    print(f"Trial {trial + 1}:")

    # Shuffle the data to ensure randomness
    data = data.sample(frac=1).reset_index(drop=True)

    # Split the data into training and testing sets (80% training, 20%
testing)
    train_size = int(0.8 * len(data))
    training_data = data[:train_size]
    testing_data = data[train_size:]

    # Extract features and target variables
    X_train = training_data.iloc[:, :-2].values
    y_train = training_data.iloc[:, -2:].values
    X_test = testing_data.iloc[:, :-2].values
    y_test = testing_data.iloc[:, -2:].values

    # Initialize theta with zeros
    theta = np.zeros((X_train.shape[1], 2))

    # Define hyperparameters
    alpha = 0.01  # Learning rate
    num_iterations = 1000  # Number of iterations

    # Initialize arrays to store error values during training
    training_errors_tmax = []
    testing_errors_tmax = []
    training_errors_tmin = []
    testing_errors_tmin = []

    for i in range(num_iterations):
        # Perform gradient descent to train the linear regression
model
        theta = gradient_descent(X_train, y_train, theta, alpha, 1)

        # Make predictions using the trained model
        predicted_train = X_train @ theta
        predicted_test = X_test @ theta

        # Calculate RMSE for TMax and TMin separately
```

```
        training_rmse_tmax = np.sqrt(np.mean((y_train[:, 0] -
predicted_train[:, 0]) ** 2))
        testing_rmse_tmax = np.sqrt(np.mean((y_test[:, 0] -
predicted_test[:, 0]) ** 2))

        training_rmse_tmin = np.sqrt(np.mean((y_train[:, 1] -
predicted_train[:, 1]) ** 2))
        testing_rmse_tmin = np.sqrt(np.mean((y_test[:, 1] -
predicted_test[:, 1]) ** 2))

        # Append RMSE values to the arrays
        training_errors_tmax.append(training_rmse_tmax)
        testing_errors_tmax.append(testing_rmse_tmax)
        training_errors_tmin.append(training_rmse_tmin)
        testing_errors_tmin.append(testing_rmse_tmin)

    print(f"Training RMSE for TMax: {training_rmse_tmax}, Testing RMSE
for TMax: {testing_rmse_tmax}")
    print(f"Training RMSE for TMin: {training_rmse_tmin}, Testing RMSE
for TMin: {testing_rmse_tmin}")

    # Append RMSE values to the lists for each trial
    mean_training_rmse_tmax.append(training_rmse_tmax)
    mean_testing_rmse_tmax.append(testing_rmse_tmax)
    mean_training_rmse_tmin.append(training_rmse_tmin)
    mean_testing_rmse_tmin.append(testing_rmse_tmin)

    # Plot error curves for this trial
    plt.figure()
    plt.subplot(2, 1, 1)
    plt.plot(range(num_iterations), training_errors_tmax,
label="Training TMax")
    plt.plot(range(num_iterations), testing_errors_tmax,
label="Testing TMax")
    plt.xlabel("Iterations")
    plt.ylabel("RMSE")
    plt.legend()
    plt.title("TMax Error Curves")
    # Show all the error curve plots
    plt.show()

    plt.subplot(2, 1, 2)
    plt.plot(range(num_iterations), training_errors_tmin,
label="Training TMin")
    plt.plot(range(num_iterations), testing_errors_tmin,
label="Testing TMin")
    plt.xlabel("Iterations")
    plt.ylabel("RMSE")
    plt.legend()
    plt.title("TMin Error Curves")
```

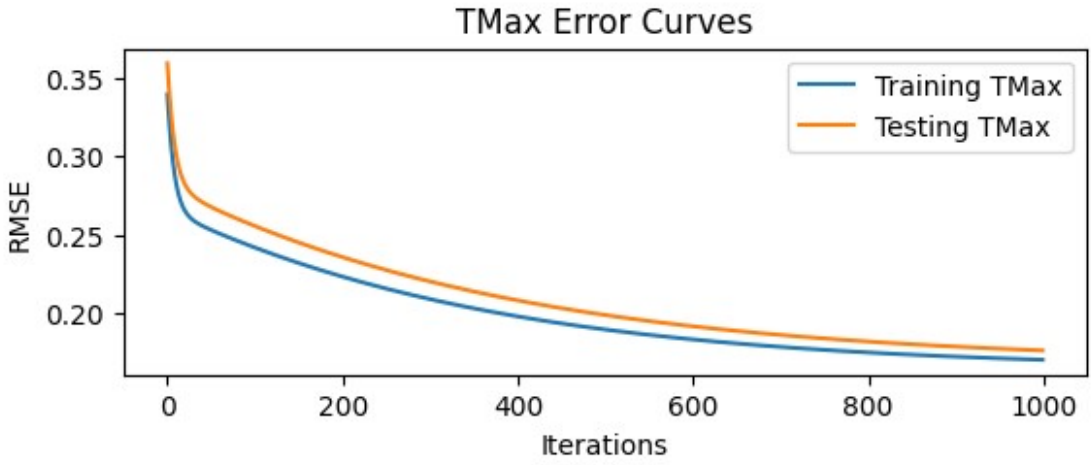
```
    # Show all the error curve plots
    plt.show()

# Calculate and print the mean RMSE over all trials
mean_training_rmse_tmax = np.mean(mean_training_rmse_tmax)
mean_testing_rmse_tmax = np.mean(mean_testing_rmse_tmax)
mean_training_rmse_tmin = np.mean(mean_training_rmse_tmin)
mean_testing_rmse_tmin = np.mean(mean_testing_rmse_tmin)
print(f"Mean Training RMSE for TMax: {mean_training_rmse_tmax}, Mean
Testing RMSE for TMax: {mean_testing_rmse_tmax}")
print(f"Mean Training RMSE for TMin: {mean_training_rmse_tmin}, Mean
Testing RMSE for TMin: {mean_testing_rmse_tmin}")
```

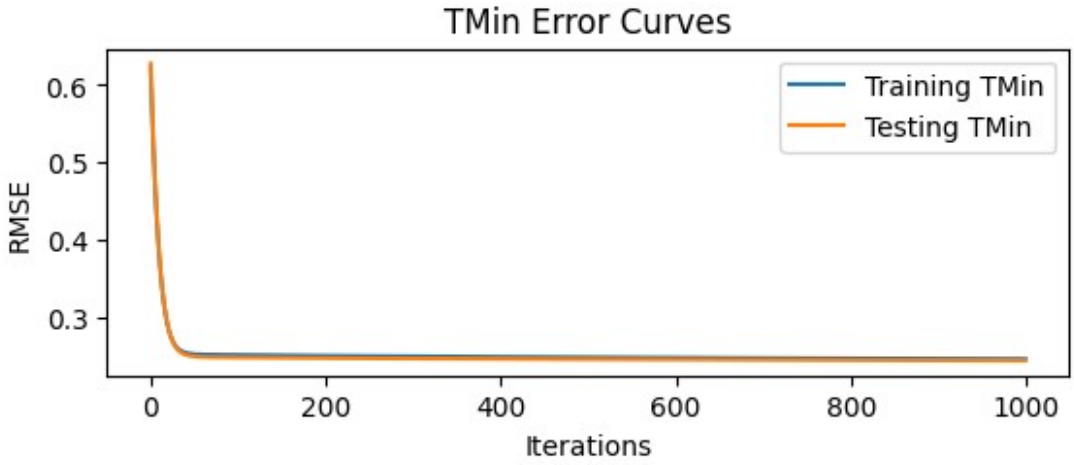
```
Trial 1:
Training RMSE for TMax: 0.17063527646260018, Testing RMSE for TMax:
0.1694633642162574
Training RMSE for TMin: 0.24723635215505882, Testing RMSE for TMin:
0.24196286868984512
```



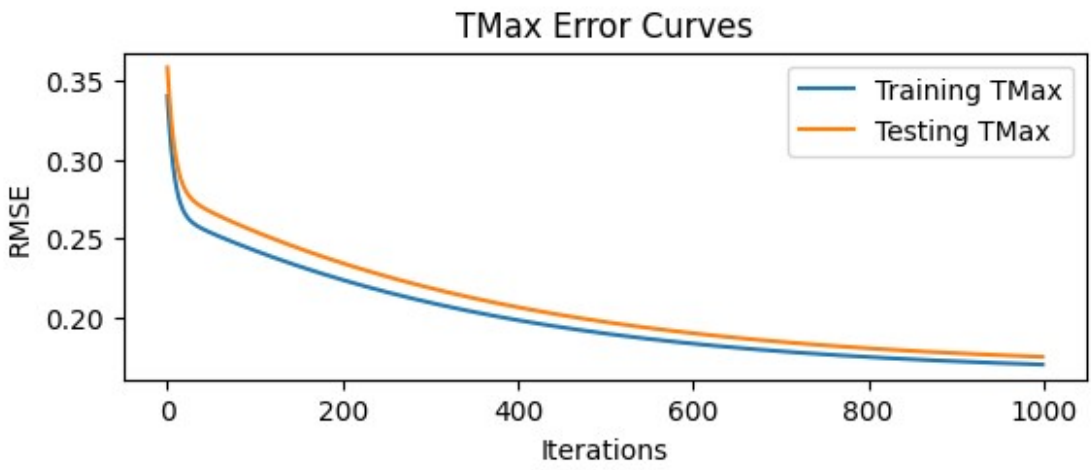


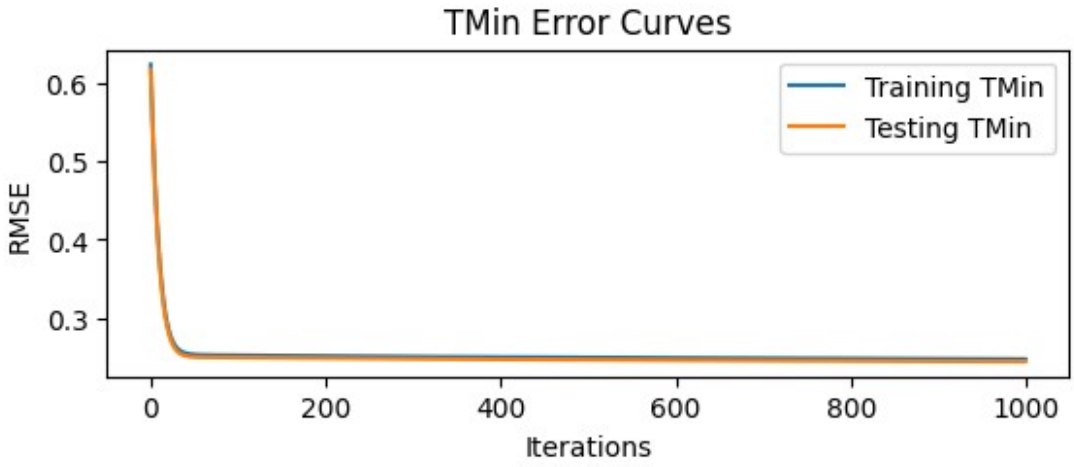
```
Trial 2:
Training RMSE for TMax: 0.17004381724547424, Testing RMSE for TMax:
0.17598605109466572
Training RMSE for TMin: 0.24658145878505758, Testing RMSE for TMin:
0.24458585770102015
```



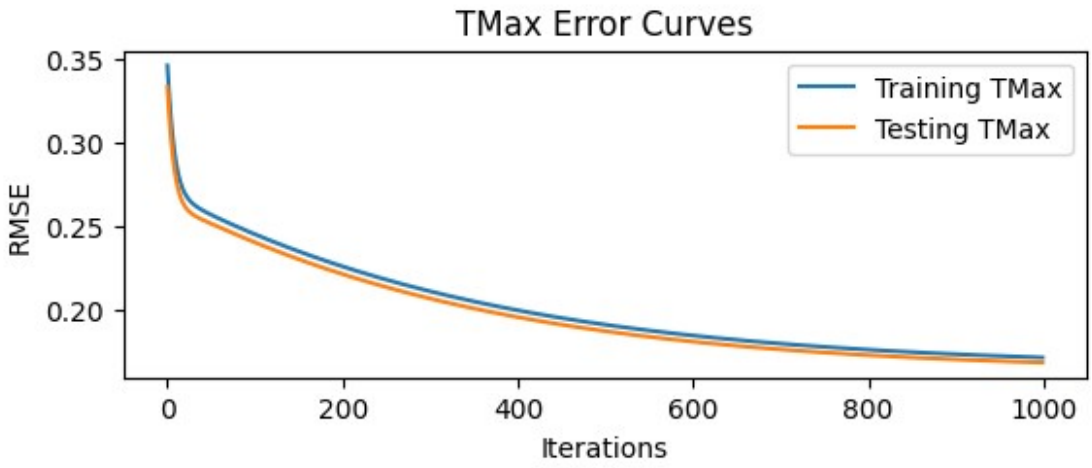


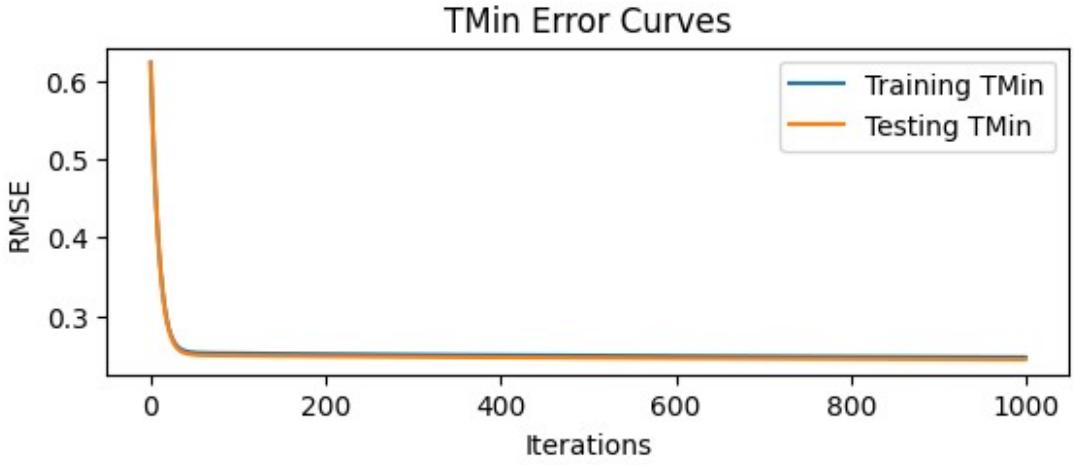

```
Trial 3:
Training RMSE for TMax: 0.17000677126661776, Testing RMSE for TMax:
0.1748772491004664
Training RMSE for TMin: 0.24686987562473395, Testing RMSE for TMin:
0.24373692871286998
```



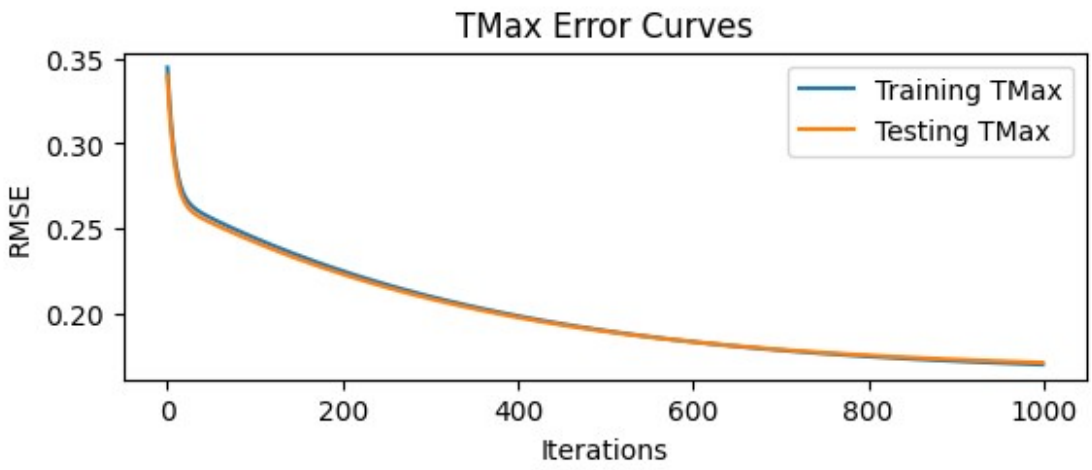


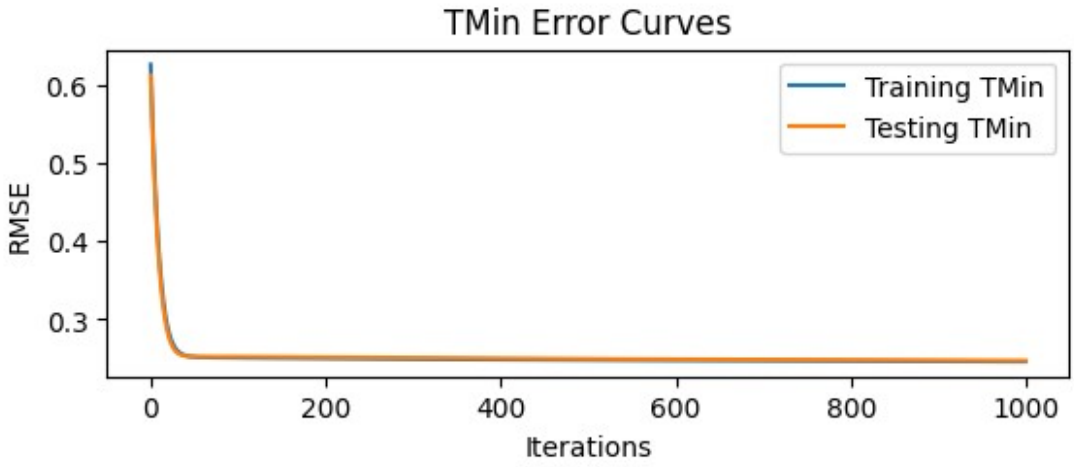

```
Trial 4:
Training RMSE for TMax: 0.17098692030689933, Testing RMSE for TMax:
0.1680057400455115
Training RMSE for TMin: 0.24678694130406179, Testing RMSE for TMin:
0.24381092371211863
```



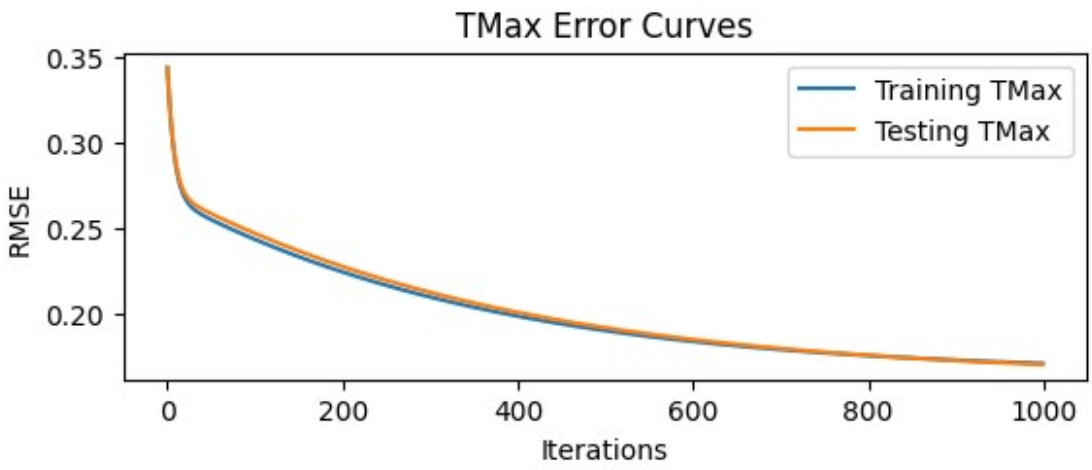


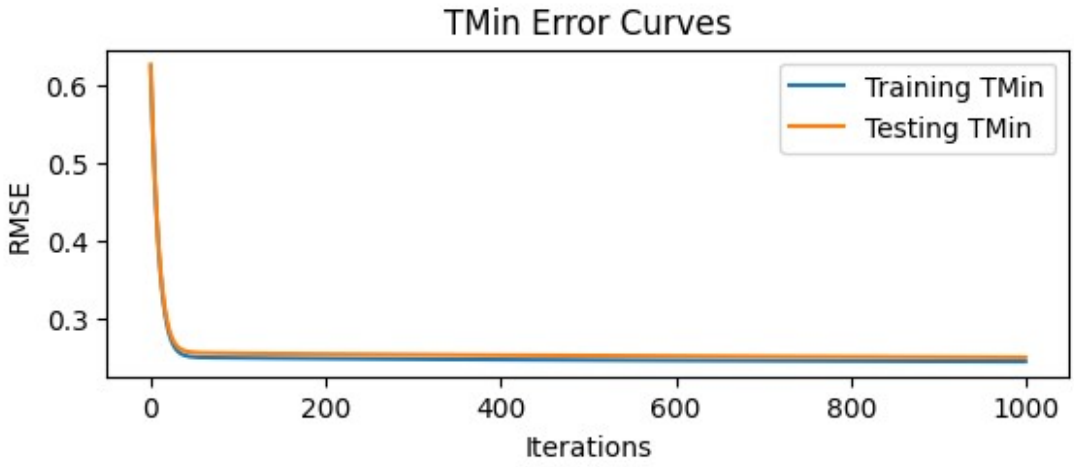

```
Trial 5:
Training RMSE for TMax: 0.17012847646832308, Testing RMSE for TMax:
0.17127991508309567
Training RMSE for TMin: 0.2460622820538406, Testing RMSE for TMin:
0.24730660096866067
```



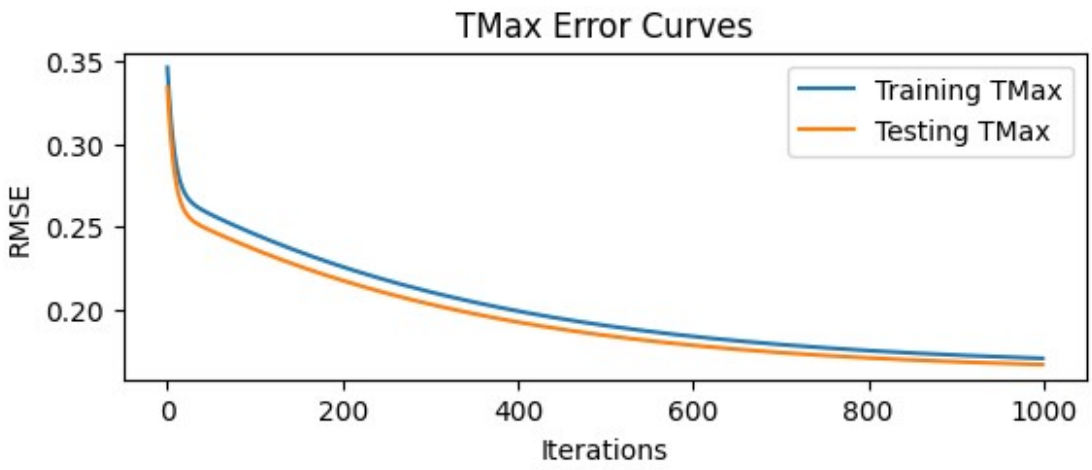


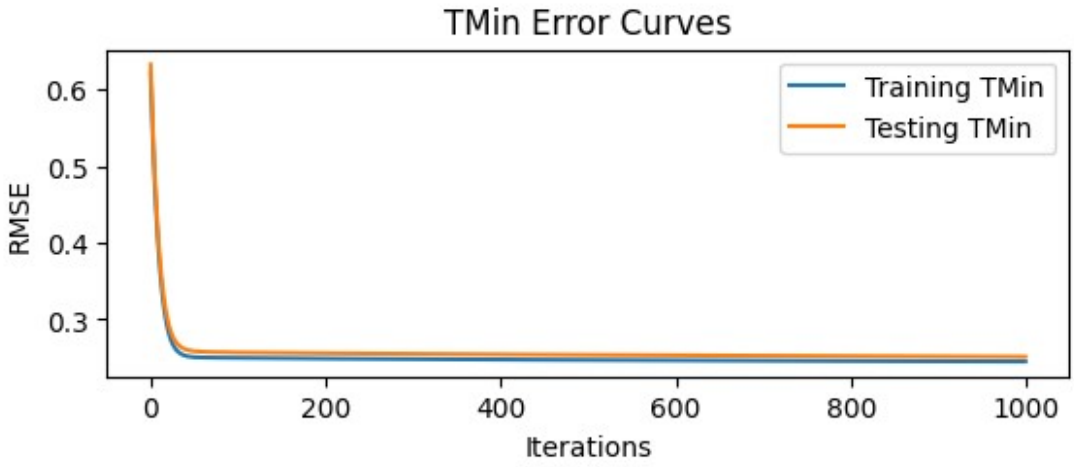

```
Trial 6:
Training RMSE for TMax: 0.17101418765328733, Testing RMSE for TMax:
0.17038899723213533
Training RMSE for TMin: 0.24527028047275387, Testing RMSE for TMin:
0.2506363394671873
```



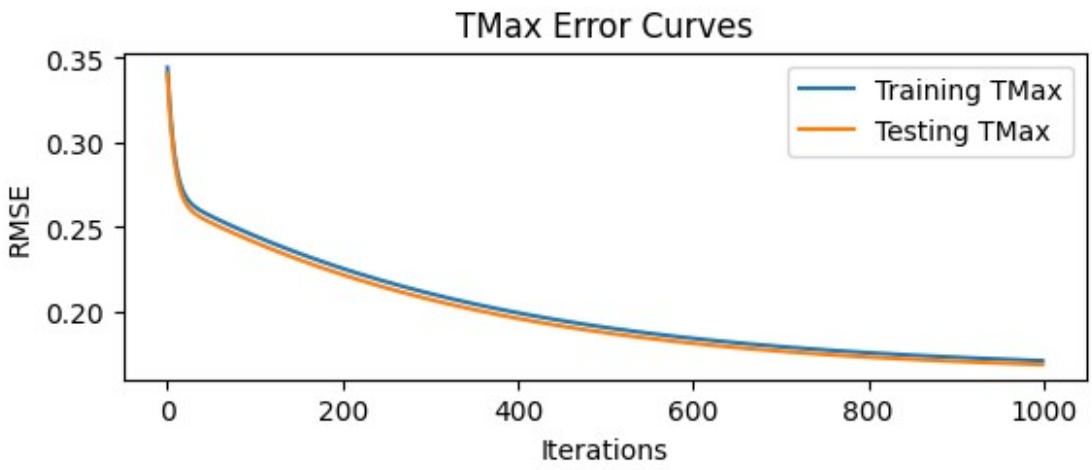


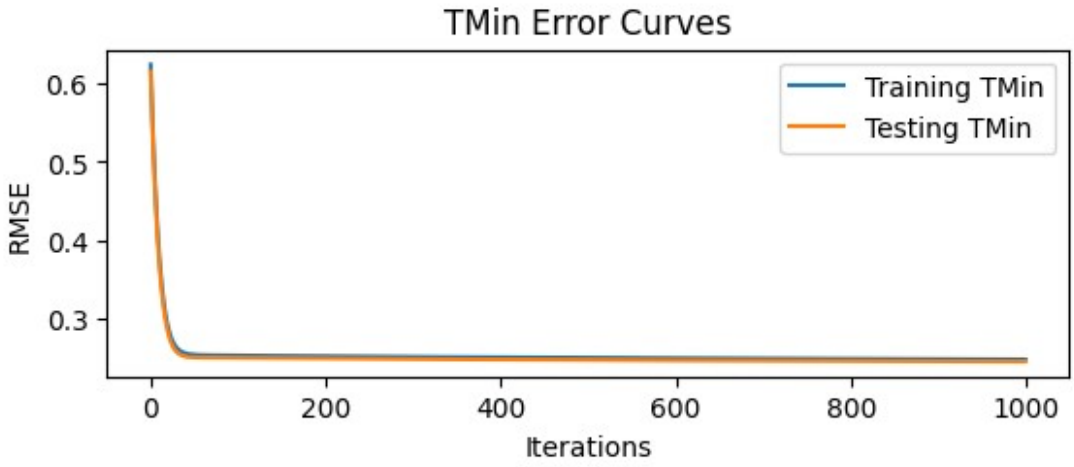

```
Trial 7:
Training RMSE for TMax: 0.17084766529112988, Testing RMSE for TMax:
0.1671296999832878
Training RMSE for TMin: 0.24503321419379276, Testing RMSE for TMin:
0.2513254925242216
```



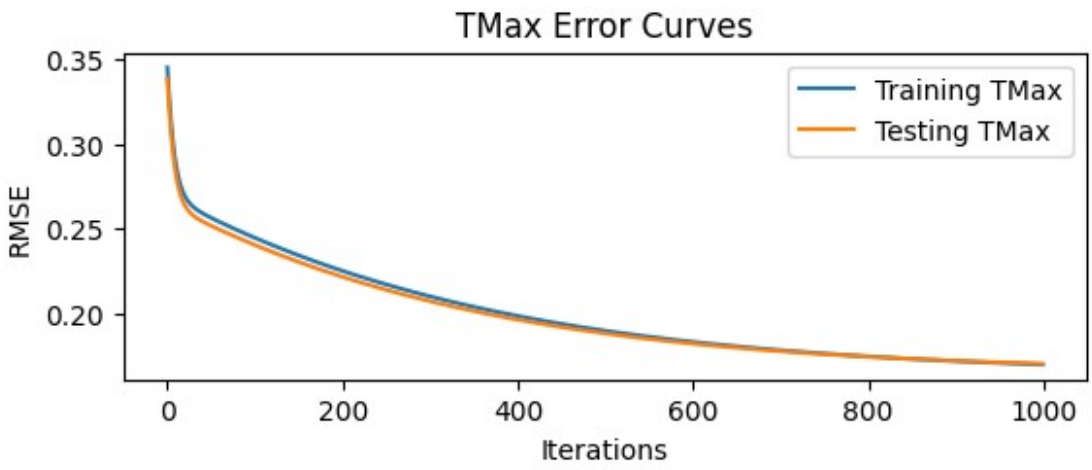


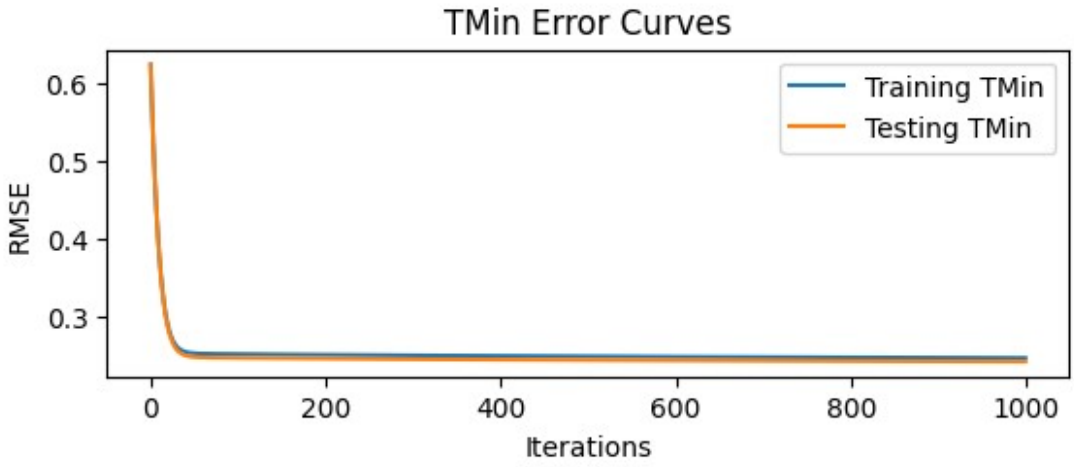

```
Trial 8:
Training RMSE for TMax: 0.17097758218902176, Testing RMSE for TMax:
0.16873270277782987
Training RMSE for TMin: 0.24670919813658798, Testing RMSE for TMin:
0.24399437401744853
```



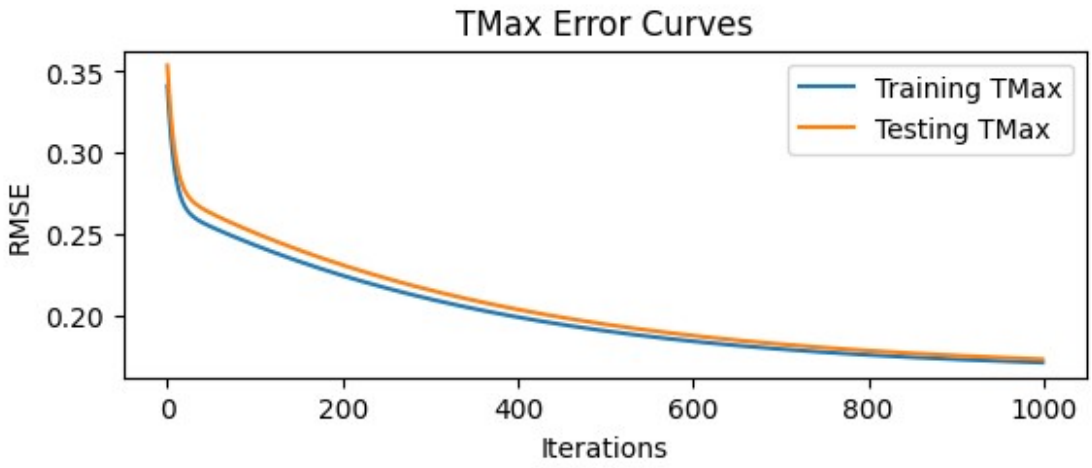


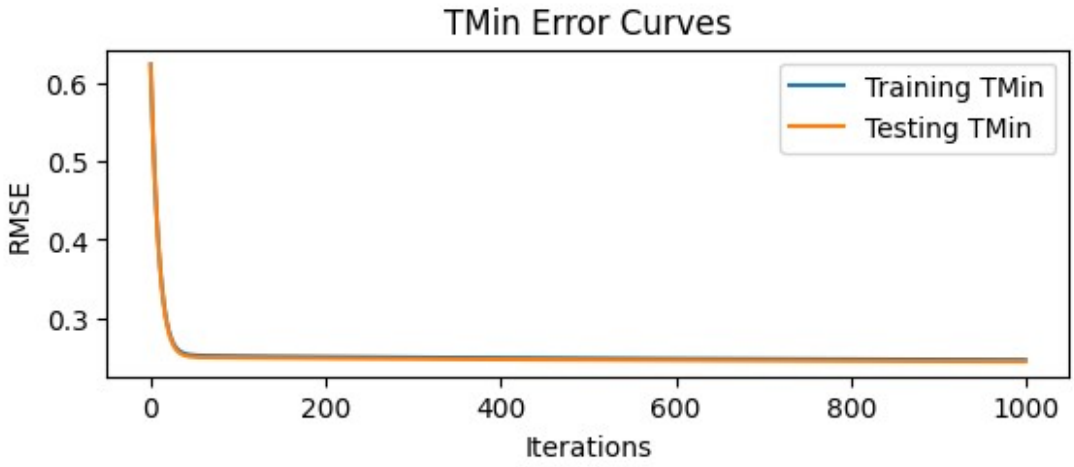

```
Trial 9:
Training RMSE for TMax: 0.170155933057318, Testing RMSE for TMax:
0.17063426118530853
Training RMSE for TMin: 0.24704636419614837, Testing RMSE for TMin:
0.24256783042204463
```






```
Trial 10:
Training RMSE for TMax: 0.17051287117039787, Testing RMSE for TMax:
0.17254713396319155
Training RMSE for TMin: 0.24668986863814624, Testing RMSE for TMin:
0.2445582843801485
```






```
Mean Training RMSE for TMax: 0.17053095011110694, Mean Testing RMSE
for TMax: 0.17090451146817495
Mean Training RMSE for TMin: 0.24642858355601818, Mean Testing RMSE
for TMin: 0.24544855005955651
```

- Impact of Learning Rate: The learning rate is a crucial hyperparameter in gradient descent. Setting it too high can result in overshooting the minimum of the cost function and lead to divergence. Setting it too low can result in slow convergence. It's important to experiment with different learning rates to find the one that results in the fastest convergence without divergence.
- Impact of Data Preprocessing: Data preprocessing, including handling missing values and normalization, can have a significant impact on prediction performance. For example, removing rows with missing values may lead to loss of valuable data, while various normalization techniques can affect the scale and distribution of features. It's essential to carefully choose preprocessing methods based on the characteristics of your data.

- Impact of Random Initialization: The initial random weights can significantly affect the training process. In the case of linear regression, the initial values of theta can affect convergence speed. Random initialization of theta can lead to different results in different runs. Experimenting with different random seeds can provide insights into the stability and reproducibility of the model.
- Impact of the Number of Iterations: The number of iterations in gradient descent is another hyperparameter. Too few iterations may result in an underfitted model, while too many iterations may lead to overfitting. Monitoring the cost function's convergence and early stopping when it stops improving can save computation time.