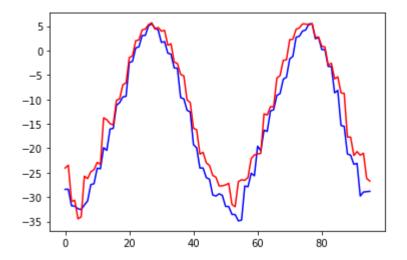
```
In [1]:
         import xarray as xr
         import pandas as pd
         import numpy as np
         from tensorflow import keras
         import matplotlib.pyplot as plt
         from sklearn.model selection import train test split
         from tensorflow.keras.layers import *
         from tensorflow.keras.optimizers import SGD, Adam
         from tensorflow.keras.models import Sequential
         from tensorflow.keras.utils import to categorical
         import tensorflow as tf
         from tensorflow.keras import backend as K
In [2]:
         temp_dir = r"C:\Users\Muji\Documents\Columbia\Courses\Earth and Environmental Engineeri
         evap dir = r"C:\Users\Muji\Documents\Columbia\Courses\Earth and Environmental Engineeri
         ssr dir = r"C:\Users\Muji\Documents\Columbia\Courses\Earth and Environmental Engineerin
         albedo dir = r"C:\Users\Muji\Documents\Columbia\Courses\Earth and Environmental Enginee
         co2 dir = r"C:\Users\Muji\Documents\Columbia\Courses\Earth and Environmental Engineerin
         DS temp = xr.open dataset(temp dir)
         DS_evap = xr.open_dataset(evap_dir)
         DS_ssr = xr.open_dataset(ssr_dir)
         DS albedo = xr.open dataset(albedo dir)
         co2 array = np.array(pd.read csv(co2 dir))
In [3]:
         time range = []
         for year in range(1973,2021):
             for month in range(1,13):
                 for day in [1,15]:
                     for hour in ['00:00:00','12:00:00']:
                         time_range.append('{}-{}-{} {}'.format(year,month,day,hour))
         time len = len(time range)
In [4]:
         #Computing the arctic average for each variable for every hour
         temp avg = []
         albedo_avg = []
         evap avg = []
         ssr avg = []
         co2_avg = []
         for time in time_range:
             da temp = DS temp.sel(time = "{}".format(time))
             T time = da temp.mean().to array()
             temp_avg.append(float(T_time)-273.15)
             da albedo = DS albedo.sel(time = "{}".format(time))
             albedo time = da albedo.mean().to array()
             albedo_avg.append(float(albedo_time))
             da_evap = DS_evap.sel(time = "{}".format(time))
             evap time = da evap.mean().to array()
             evap avg.append(float(evap time))
```

```
da ssr = DS ssr.sel(time = "{}".format(time))
              ssr time = da ssr.mean().to array()
              ssr_avg.append(float(ssr_time))
          for i in range(time len):
              co2 avg.append(float(co2 array[i]))
 In [5]:
          temp_avg = temp_avg/(np.std(temp_avg))
          albedo_avg = albedo_avg/(np.std(albedo_avg))
          evap avg = evap avg/(np.std(evap avg))
          ssr_avg = ssr_avg/(np.std(ssr_avg))
          co2_std = np.std(co2_avg)
          co2_avg = co2_avg/co2_std
 In [6]:
          # Display training progress by printing a single dot for each completed epoch
          class PrintDot(keras.callbacks.Callback):
              def on_epoch_end(self, epoch, logs):
                  if epoch % 100 == 0: print('')
                  print('.', end='')
          # Function to plot how the model is doing during training
          # Visualize the model's training progress using the stats stored in the history object.
          # We want to use this data to determine how long to train before the model stops making
          def plot history accuracy(history):
              plt.figure()
              plt.xlabel('Epoch')
              plt.ylabel('Accuracy')
              plt.plot(history.epoch, np.array(history.history['accuracy']),
                     label='Train accuracy')
              plt.plot(history.epoch, np.array(history.history['val_accuracy']),
                     label = 'Val accuracy')
              plt.legend()
          def plot history mae(history):
              plt.figure()
              plt.xlabel('Epoch')
              plt.ylabel('Mean Abs Error')
              plt.plot(history.epoch, np.array(history.history['mae']),
                     label='Train Loss')
              plt.plot(history.epoch, np.array(history.history['val_mae']),
                     label = 'Val loss')
              plt.legend()
In [13]:
          plt.plot(temp_avg[:96],"b")
          plt.plot(temp avg[-96:],"r")
         [<matplotlib.lines.Line2D at 0x209527a7088>]
Out[13]:
```



## Date to date regression

```
In [105...
          X = []
          Y = []
          for i in range(time_len):
              X.append(np.array([temp_avg[i],albedo_avg[i],evap_avg[i],ssr_avg[i],co2_avg[i]]))
              Y.append(np.array([temp_avg[i],albedo_avg[i],evap_avg[i],ssr_avg[i]]))
          x = np.array(X[:-1])
          y = np.array(Y[1:])
          X_train,X_test,Y_train,Y_test = train_test_split(x,y,test_size = 0.2)
```

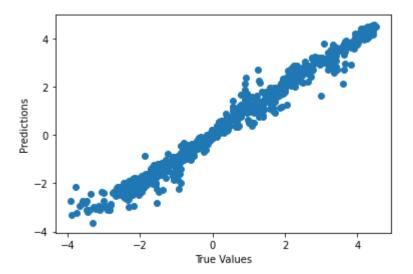
```
In [106...
          model_nn_single = keras.Sequential([
              keras.layers.Dense(25, input_shape=((5,)), activation=tf.nn.relu),
              keras.layers.Dense(25, activation=tf.nn.relu),
              keras.layers.Dropout(0.1),
              keras.layers.Dense(4)])
          model_nn_single.compile(loss='mse',optimizer='adam',metrics=['mae'])
          model_nn_single.summary()
```

Model: "sequential\_24"

Output Shape	Param #
(None, 25)	150
(None, 25)	650
(None, 25)	0
(None, 4)	104
	(None, 25) (None, 25)

Total params: 904 Trainable params: 904 Non-trainable params: 0

```
# If you train too long, you are prone to over-fitting
In [107...
          # this prevents the model from generalizing to data it has never seen before
          # early stopping is one way to go about this
          # The patience parameter is the amount of epochs to check for improvement
          early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=50)
          K.set_value(model_nn_single.optimizer.learning_rate, 0.001)
          # Store training stats
          history = model_nn_single.fit(X_train, Y_train, epochs=500,
                                validation_split=0.2, verbose=0,
                                callbacks=[early_stop, PrintDot()])
          plot_history_mae(history)
           [loss, mae] = model_nn_single.evaluate(X_test, Y_test, verbose=0)
           print("Testing set Mean Abs Error: {}".format(mae ))
          Testing set Mean Abs Error: 0.13784269988536835
            1.4
                                                        Train Loss
                                                        Val loss
            1.2
            1.0
         Mean Abs Error
            0.8
            0.6
            0.4
            0.2
                                  200
                                                    400
                         100
                                           300
                                                             500
                                      Epoch
In [108...
          test_predictions = model_nn_single.predict(X_test).flatten()
          test_labels = Y_test.flatten()
           plt.scatter(Y_test, test_predictions)
          plt.xlabel('True Values')
           plt.ylabel('Predictions')
           plt.plot()
```



## Multiple dates regression

dense\_7 (Dense)

```
In [24]:
          length = 8
         X = []
         Y = []
         for i in range(time_len-length):
             features = []
             for j in range(length):
                 features.append(temp avg[i+j])
                 features.append(albedo_avg[i+j])
                 features.append(evap_avg[i+j])
                 features.append(ssr_avg[i+j])
                 features.append(co2_avg[i+j])
             X.append(np.array(features))
             Y.append(np.array([temp_avg[i+length],albedo_avg[i+length],evap_avg[i+length],ssr_a
         x = np.array(X)
         y = np.array(Y)
         X_train,X_test,Y_train,Y_test = train_test_split(x,y,test_size = 0.2)
In [25]:
         model_nn_multiple = keras.Sequential([
             keras.layers.Dense(75, input_shape=((5*length,)), activation=tf.nn.relu),
             keras.layers.Dense(75, activation=tf.nn.relu),
             #keras.Layers.Dropout(0.1),
             keras.layers.Dense(4)])
         model_nn_multiple.compile(loss='mse',optimizer='adam',metrics=['mae'])
         model_nn_multiple.summary()
         Model: "sequential_2"
         Layer (type)
                                    Output Shape
                                                             Param #
         ______
         dense 6 (Dense)
                                    (None, 75)
                                                             3075
```

(None, 75)

5700

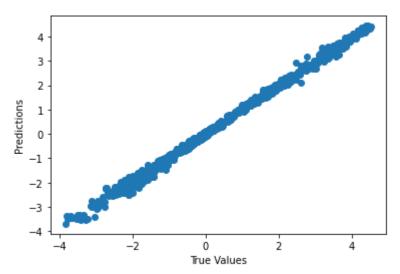
```
dense 8 (Dense)
                             (None, 4)
                                                      304
______
Total params: 9,079
Trainable params: 9,079
Non-trainable params: 0
# If you train too long, you are prone to over-fitting
# this prevents the model from generalizing to data it has never seen before
# early stopping is one way to go about this
# The patience parameter is the amount of epochs to check for improvement
early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=75)
K.set_value(model_nn_multiple.optimizer.learning_rate, 0.001)
# Store training stats
history = model_nn_multiple.fit(X_train, Y_train, epochs=1000,
                    validation_split=0.2, verbose=0,
                    callbacks=[early_stop, PrintDot()])
plot_history_mae(history)
 [loss, mae] = model nn multiple.evaluate(X test, Y test, verbose=0)
 print("Testing set Mean Abs Error: {}".format(mae ))
                                   .....Testing set Mean Abs Error: 0.0633960366249084
5
                                            Train Loss
  0.6
                                           Val loss
  0.5
Mean Abs Error
  0.4
  0.3
  0.2
  0.1
               100
                         200
                                   300
                                            400
       0
                          Epoch
test_predictions = model_nn_multiple.predict(X_test).flatten()
test_labels = Y_test.flatten()
 plt.scatter(Y_test, test_predictions)
```

In [26]:

In [27]:

```
plt.xlabel('True Values')
plt.ylabel('Predictions')
plt.plot()
```

Out[27]: []



## **LSTM**

```
In [24]:

X = []
Y = []
length = 48
for i in range(0,time_len,length):
    batch = []
    for j in range(length-1):
        batch.append(np.array([temp_avg[i+j],albedo_avg[i+j],evap_avg[i+j],ssr_avg[
        X.append(batch)
        Y.append(np.array([temp_avg[i+length-1],albedo_avg[i+length-1],evap_avg[i+length-1]]
    #Y.append(np.array([temp_avg[i+length-1]]))

x = np.array(X)
y = np.array(Y)
X_train,X_test,Y_train,Y_test = train_test_split(x,y,test_size = 0.2)
```

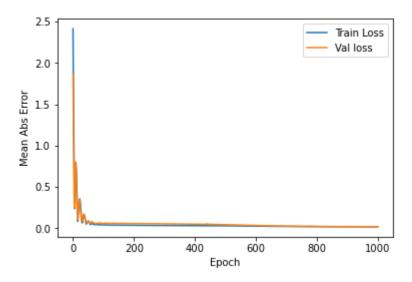
```
In [25]:
    model_LSTM = keras.Sequential()
    model_LSTM.add(LSTM(150,input_shape=(length-1,5),activation = tf.nn.tanh))
    model_LSTM.add(Dense(120))
    #model_LSTM.add(Dropout(0.1))
    model_LSTM.add(Dense(4))

    model_LSTM.compile(loss='mse',optimizer='adam',metrics=['mae'])
    model_LSTM.summary()
```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 150)	93600

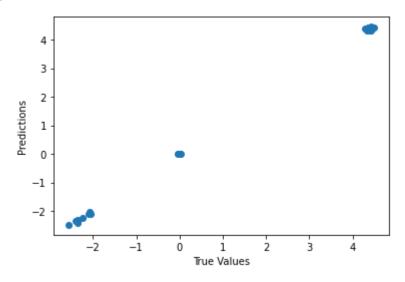
```
In [26]:
          # If you train too long, you are prone to over-fitting
          # this prevents the model from generalizing to data it has never seen before
          # early stopping is one way to go about this
          # The patience parameter is the amount of epochs to check for improvement
          early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=30)
          K.set_value(model_LSTM.optimizer.learning_rate, 0.001)
          # Store training stats
          history = model_LSTM.fit(X_train, Y_train, epochs=1000,
                              validation_split=0.2, verbose=0,
                              callbacks=[early_stop, PrintDot()])
          plot_history_mae(history)
          [loss, mae] = model_LSTM.evaluate(X_test, Y_test, verbose=0)
          print("Testing set Mean Abs Error: {}".format(mae ))
         Testing set Mean Abs Error: 0.024045681580901146
```



```
test_predictions = model_LSTM.predict(X_test).flatten()
test_labels = Y_test.flatten()

plt.scatter(test_labels, test_predictions)
plt.xlabel('True Values')
plt.ylabel('Predictions')
plt.plot()
```

Out[27]: []

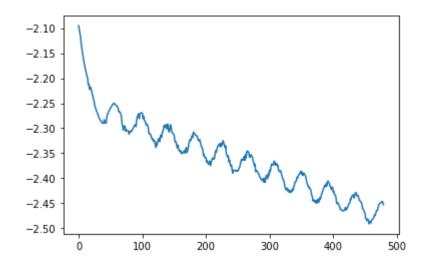


## **Predictions**

```
In [28]:
    normal_array = np.array(pd.read_csv(r"C:\Users\Muji\Documents\Columbia\Courses\Earth an
    exp_decreasing_array = np.array(pd.read_csv(r"C:\Users\Muji\Documents\Columbia\Courses\
    exp_increasing_array = np.array(pd.read_csv(r"C:\Users\Muji\Documents\Columbia\Courses\
    normal = []
    exp_decreasing = []
    exp_increasing = []
    for i in range(len(normal_array)):
        normal.append(float(normal_array[i]))
        exp_decreasing.append(float(exp_decreasing_array[i]))
```

```
exp_increasing.append(float(exp_increasing_array[i]))
          normal = (normal/co2_std)[:]
          exp_decreasing = (exp_decreasing/co2_std)[:]
          exp_increasing = (exp_increasing/co2_std)[:]
In [29]:
          plt.plot(normal)
          plt.plot(exp_decreasing, "r")
          plt.plot(exp_increasing)
          [<matplotlib.lines.Line2D at 0x17b0c2d4a48>]
Out[29]:
          20
          18
          16
          14
          12
              Ò
                       100
                                200
                                         300
                                                  400
                                                           500
In [30]:
          co2_scenario = exp_decreasing
          current_values = []
          for i in range(length-1,0,-1):
              current_values.append(np.array([temp_avg[-i],albedo_avg[-i],evap_avg[-i],ssr_avg[-i
          prediction = []
          for i in range(len(co2_scenario)):
              cv = np.array([current_values[:]])
              pred = list(model_LSTM.predict(cv)[0])
              prediction.append(pred)
              pred.append(co2_scenario[i])
              current_values.append(pred)
              current values.pop(0)
In [31]:
          prediction = np.array(prediction)
          temp_pred = (prediction[:,0])
          albedo_pred = (prediction[:,1])
          evap_pred = (prediction[:,2])
          ssr_pred = (prediction[:,3])
          plt.plot(temp_pred)
          #plt.plot(albedo_pred)
          #plt.plot(evap_pred)
          #plt.plot(ssr_pred)
          #plt.plot(co2_scenario)
```

Out[31]: [<matplotlib.lines.Line2D at 0x17b0b1df288>]



In [ ]: