In this project, we predict the Indoor Room Temperature by correlation and machine learning from the data of sun irradiation and outdoor temperature.

Units of data used:

1. Date: in UTC.
2. Time: in UTC.
3. Indoor temperature (room), in ºC.
4. Lighting (room), in Lux.
5. Sun irradiance, in W/m2.
6. Outdoor temperature, in ºC.
7. Outdoor relative humidity, in %.

First of all, Let us import required modules!

```
In [1]: import os,numpy as np,pandas as pd,matplotlib.pyplot as plt,seaborn as sns
```

Now changing the working directory

```
In [2]: os.chdir("C:\Users\Eternal\Dropbox\Building Project\PythonProject\CSV_Files")
```

We also supress the copy warning

```
In [3]: pd.set_option('mode.chained_assignment', None)
```

Lets read the Initial data from the .csv file and convert it into a dataframe.We also change the format of index to Date Time format.

From the data, we selected 3 days data from 13/03/2012 to 31/03/2012.

In [4]:
```
DF_initialDataset=pd.read_csv("BuildingDataSet.csv",sep=",",index_col=0)
NewparsedIndex = pd.to_datetime(DF_initialDataset.index)  #Parsed into Date Time index format and setting as index
DF_initialDataset.index=NewparsedIndex
DF_targetDataset=DF_initialDataset["13-03-2012":"31-03-2012"]
DF_targetDataset.describe()  #Describing targeted dataset
```

Out[4]:

	Temperature_Comedor_Sensor	Temperature_Habitacion_Sensor	Weather_Ten
count	1777.000000	1777.000000	1777.000000
mean	18.726861	18.359944	13.358433
std	3.100814	3.056219	4.381213
min	11.352000	11.076000	0.000000
25%	16.694000	16.280000	9.000000
50%	18.853300	18.544700	15.000000
75%	21.042700	20.624000	16.000000
max	25.540000	24.944000	26.000000

8 rows × 22 columns

We select specific columns from data so to corelate target and features. Here, we will use Indoor temperature, Sun Irradiance,Outdoor Temperature,Lighting of room, Outdoor Humidity.

In [5]:
```
DF_selected=DF_targetDataset[['Temperature_Habitacion_Sensor','Meteo_Exterior_Piranometro','Temperature_Exterior_Sensor','Lighting_Habitacion_Sensor','Humedad_Exterior_Sensor']]  #Selecting few columns
DF_selected.rename(columns={"Temperature_Habitacion_Sensor":"Indoor Room Temperature","Meteo_Exterior_Piranometro":"Sun Irradiance", "Temperature_Exterior_Sensor":"Outdoor Temperature","Lighting_Habitacion_Sensor":"Lighting Room","Humedad_Exterior_Sensor":"Outdoor Humidity"},inplace=True)  #Renaming columns
DF_selected["Sun Irradiance"][DF_selected["Sun Irradiance"]<0.0]=0  #Setting the negative value as zero
```

For giving lagged features, we first create the copy of our selected data frame. Then defining and using the function,we will create the lagged features for Sun Irradiation and Outdoor Temperature.

NOTE: The function used here only gives lagged values for Sun Irradiation(3rd,4th,5th and 6th hour) and for Outdoor temperature(1st,2nd,3rd and 4th hour)

In [6]:
```
DF_lagged=DF_selected.copy()

'''A function to create lag columns of selected columns passed as argument
s'''
def lag_column(df,column_names,lag_period):    #df> pandas dataframe,column
_names> names of column/columns as a list,lag_period>number of steps to lag
    for column_name in column_names:
        if(column_name=="Sun Irradiance"):
            for i in range(3,lag_period+1):
                new_column_name = column_name+" -"+str(i)+"hr"
                df[new_column_name]=(df[column_name]).shift(i*4)
        else:
            for i in range(1,lag_period-1):
                new_column_name = column_name+" -"+str(i)+"hr"
                df[new_column_name]=(df[column_name]).shift(i*4)
    return df

DF_lagged=lag_column(DF_lagged,["Sun Irradiance","Outdoor Temperature"],6)
 #Passing values in function
DF_lagged.dropna(inplace=True)
```

Now to corelate the data, we create a heat map which provide visiual insight to correlation.

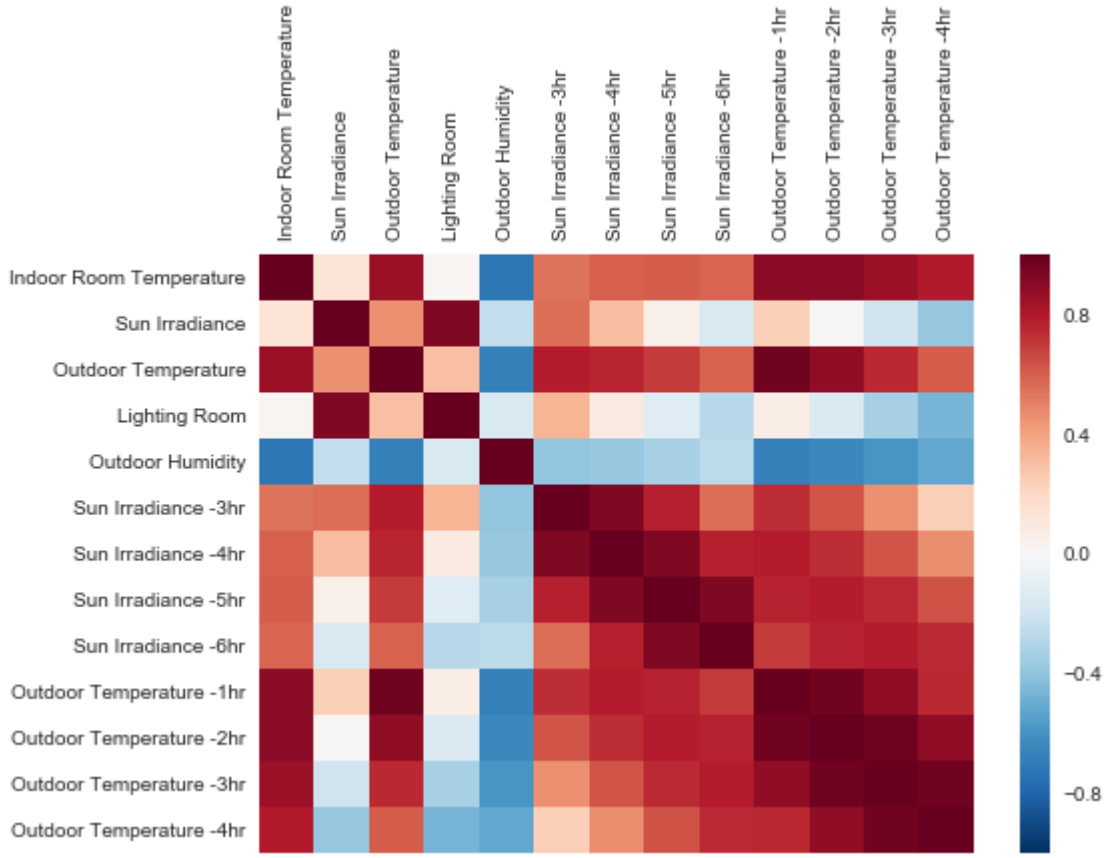
From the image below,

1)We can see that Indoor temperature of the room depends on outdoor temperature at that same hour but the sun irradiance takes time to heat up the room.

2)Lighting of the room and Outdoor Humidity doesn't contribute to Inddor temperature at all

NOTE:DARKER color means the correlation is strong and the darker blue color indicates poor coorelation.

In [7]:
```
#Creating a plot using heatmap functionality to provide correlations betwee
n columns of dataset
fig = plt.figure("Figure for proving insight about Corelations")
plot = fig.add_axes()
plot = sns.heatmap(DF_lagged.corr(), annot=False)
plot.xaxis.tick_top()
plt.yticks(rotation=0)
plt.xticks(rotation=90)
plt.show()
```



Plotting Indoor temperature,Sun Irradiation and Outdoor Temperature will give us greater understanding on how one depends on another.

To do so we introduce a function to normalize the data and eliminate the problem of different unit.

In the normalized graph below,

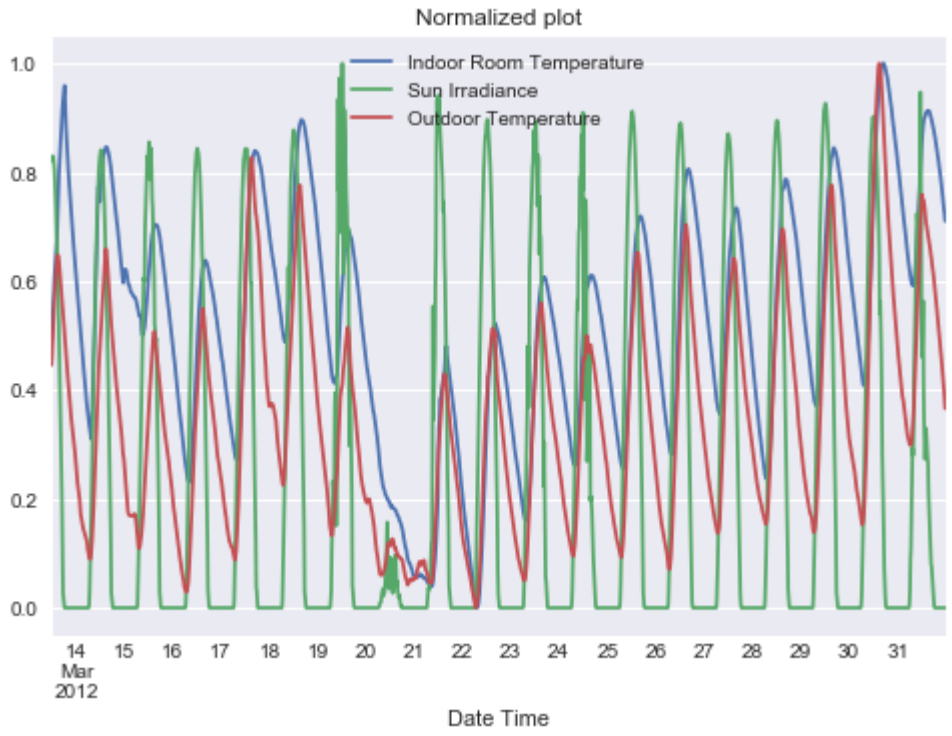
1)We can see that the Indoor temperature is increasing w.r.t. outdoor temperature in real time but it takes time for sun irradiation to heat up the room walls/roof,so the Sun Irradiation will spike up before room indoor temperature.

2)At some instances,Sun Irradiance is irregular.We can assume that sun Irradiance is irregular due to rainy/cloudy environment.

3)During night time, Sun Irradiation is zero.

In [8]:
```
'''A function to normalize dataset's columns values to provide a ranged ins
ight'''
def normalize(df):
    return (df-df.min())/(df.max()-df.min())

#Plotting the normalized dataframe with selected columns
normalizedDF=normalize(DF_selected)
PlotDF=normalizedDF[["Indoor Room Temperature","Sun Irradiance","Outdoor Te
mperature"]]
PlotDF.plot()
plt.title("Normalized plot")
plt.show()
```



Let's add some time related features now like hour,Day of Week,Month, Day or night,Weekend or not etc.

We use a function to detect weekend and drop all the NaN values.

In [9]:
```
#Adding time-related features
DF_lagged['hour'] = DF_lagged.index.hour
DF_lagged['day_of_week'] = DF_lagged.index.dayofweek
DF_lagged['month'] = DF_lagged.index.month
DF_lagged['day_night'] = np.where((DF_lagged['hour']>=6)&(DF_lagged['hour']
<=17), 1, 0)

'''A function to label a day of week as weekend or not'''
def weekend_detector(day):
    if (day==5 or day==6):
        weekend = 1
    else:
        weekend = 0
    return weekend
DF_lagged['weekend'] = [weekend_detector(s) for s in DF_lagged['day_of_wee
k']]
DF_lagged.dropna(inplace=True) #Dropping nan values

DF_lagged.head()
```

Out[9]:

	Indoor Room Temperature	Sun Irradiance	Outdoor Temperature	Lighting Room	Outdoor Humidity	Sun Irradiance -3hr	Sun Irradiar -4hr
Date Time							
2012-03-13 17:45:00	24.1413	15.57000	19.7560	23.2427	47.0693	582.869	699.392
2012-03-13 18:00:00	24.2680	5.00933	19.5273	21.4213	49.5467	544.533	677.675
2012-03-13 18:15:00	24.3800	0.00000	19.3013	13.3620	52.2027	503.744	648.427
2012-03-13 18:30:00	24.0707	0.00000	19.0413	13.1027	53.8053	460.523	615.680
2012-03-13 18:45:00	23.5880	0.00000	18.7680	13.6067	54.9280	415.744	582.869

Now we have our dataframe with target and features(Time and Lagged):

In [10]:
```
target = DF_lagged[['Indoor Room Temperature']]
features = DF_lagged[[c for c in DF_lagged.columns if c not in ["Indoor Roo
m Temperature"]]]
```

Creating a training dataset for machine learning and providing an independent testset which follows same probabilistic distribution of training!

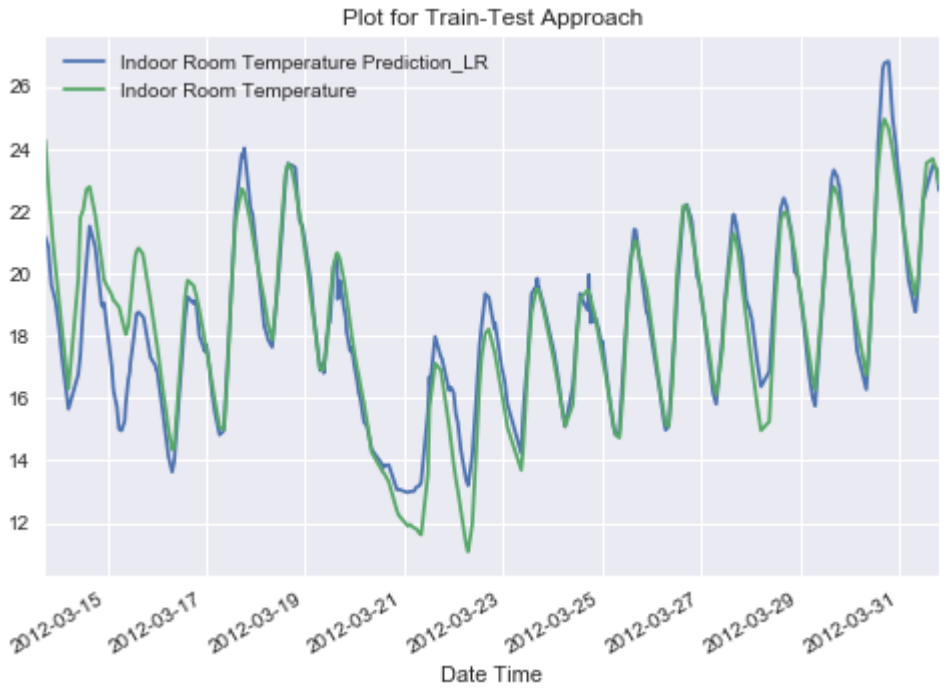
In [11]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, target, test_
size=0.2, random_state=123524)
```

Implementing Linear regression technique of scikit-learn machine learning module to make

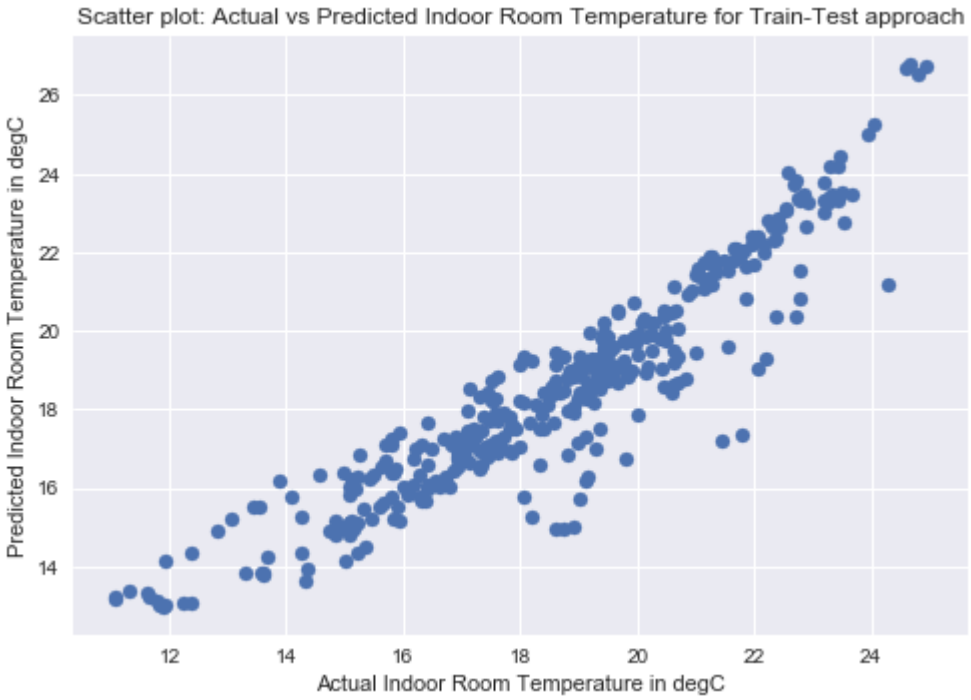
In [12]:
```
from sklearn import linear_model
linear_reg = linear_model.LinearRegression()
linear_reg.fit(X_train,y_train)
prediction = linear_reg.predict(X_test)
predict_series = pd.Series(prediction.ravel(),index=y_test.index).rename('I
ndoor Room Temperature Prediction_LR')
LearnedDataset = pd.DataFrame(predict_series).join(y_test).dropna()
```

Plotting the learned dataset and verifying the predicted values with actual ones

In [13]:
```
LearnedDataset.plot()
plt.title("Plot for Train-Test Approach")
plt.show()
```



In [14]:
```
plt.figure()
plt.scatter(LearnedDataset['Indoor Room Temperature'],LearnedDataset['Indoo
r Room Temperature Prediction_LR'])
plt.xlabel("Actual Indoor Room Temperature in degC")
plt.ylabel("Predicted Indoor Room Temperature in degC")
plt.title("Scatter plot: Actual vs Predicted Indoor Room Temperature for Tr
ain-Test approach")
plt.show()
```



Calculating the accuracy metrics of implemented machine learning model

In [15]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
metric_R2_score = r2_score(y_test,prediction) #Perfectly accurate model giv
es metric_R2_score as 1 and co-efficient of variation as 0, this values var
ies from 0 to 1(inclusive)
metric_mean_absolute_error = mean_absolute_error(y_test,prediction)
metric_mean_squared_error = mean_squared_error(y_test,prediction)
coeff_variation = np.sqrt(metric_mean_squared_error)/float(y_test.mean())

print "The R2_score is "+str(metric_R2_score)
print "The mean absoulute error is "+str(metric_mean_absolute_error)
print "The mean squared error is "+str(metric_mean_squared_error)
print "Coefficient variation : "+str(coeff_variation)
```

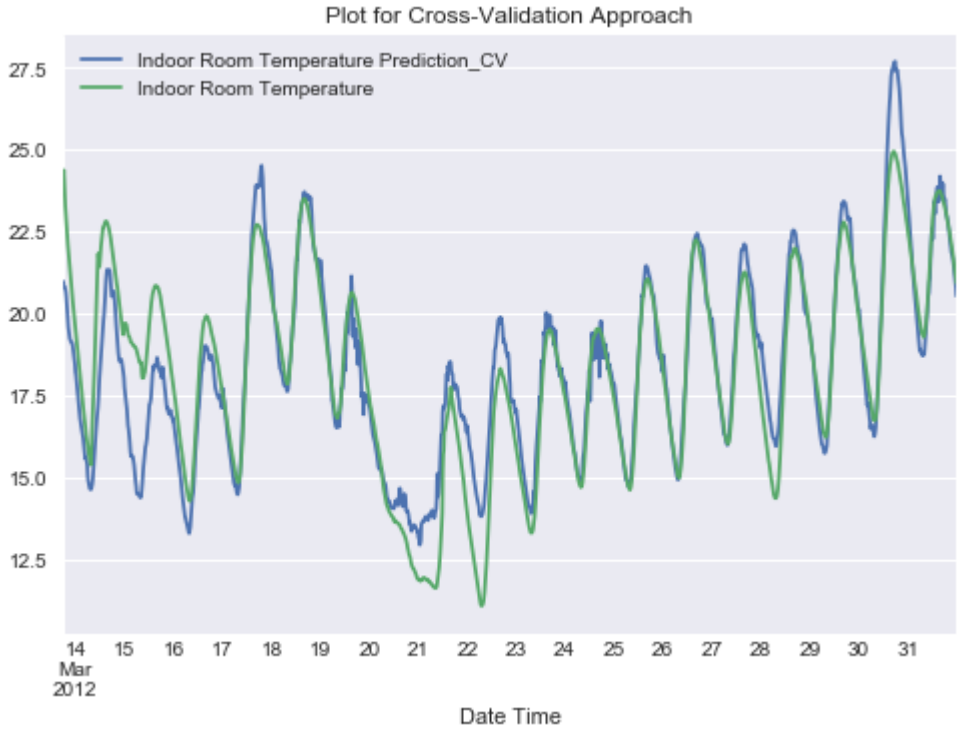
```
The R2_score is 0.85960194484
The mean absoulute error is 0.754894065927
The mean squared error is 1.17948808638
Coefficient variation : 0.0585514891301
```

Implementing cross-validation approach to test the performance of the machine learning model

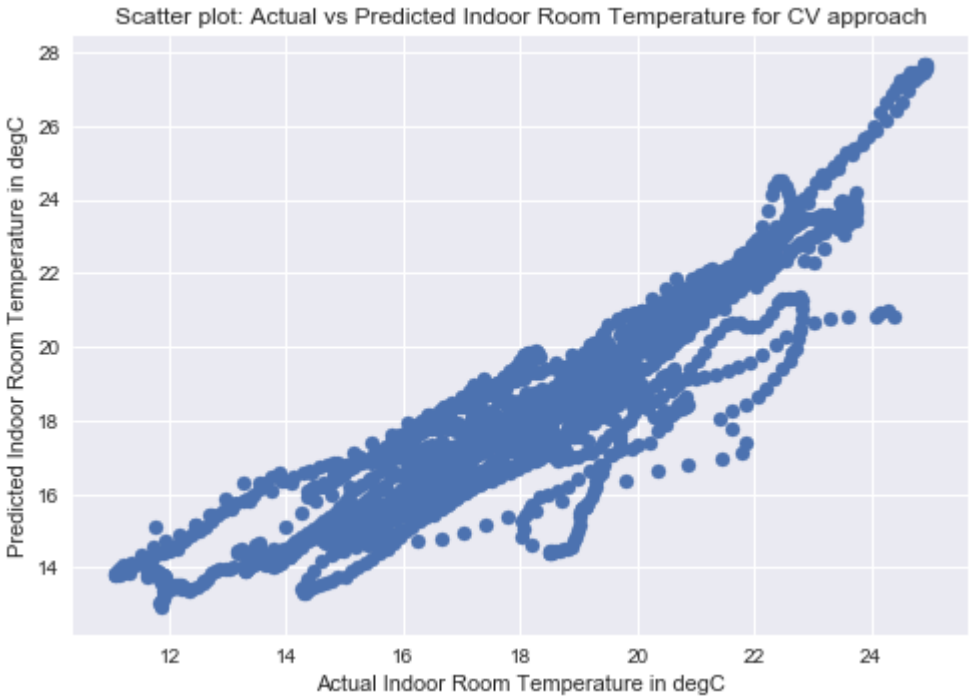
In [16]:
```
from sklearn.model_selection import cross_val_predict
predict_linearReg_CV = cross_val_predict(linear_reg,features,target,cv=10)
predict_DF_linearReg_CV=pd.DataFrame(predict_linearReg_CV, index = target.i
ndex,columns=["Indoor Room Temperature Prediction_CV"])
predict_DF_linearReg_CV = predict_DF_linearReg_CV.join(target)
```

Plotting the learned dataset and verifying the predicted values with actual ones

In [17]:
```
predict_DF_linearReg_CV.plot()
plt.title("Plot for Cross-Validation Approach")
plt.show()
```



In [18]:
```
plt.figure()
plt.scatter(predict_DF_linearReg_CV['Indoor Room Temperature'],predict_DF_l
inearReg_CV['Indoor Room Temperature Prediction_CV'])
plt.xlabel("Actual Indoor Room Temperature in degC")
plt.ylabel("Predicted Indoor Room Temperature in degC")
plt.title("Scatter plot: Actual vs Predicted Indoor Room Temperature for CV
 approach")
plt.show()
```



In [ ]: