A COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR PREDICTION OF SOLAR GENERATION

These datasets are meteorological data from the HI-SEAS weather station from four months (September through December 2016) between Mission IV and Mission V.

For each dataset, the fields are:

A row number (1-n) useful in sorting this export's results The UNIX time_t date (seconds since Jan 1, 1970). Useful in sorting this export's results with other export's results The date in yyyy-mm-dd format The local time of day in hh:mm:ss 24-hour format The numeric data, if any (may be an empty string) The text data, if any (may be an empty string)

The units of each dataset are:

Solar radiation: watts per meter^2

Temperature: degrees Fahrenheit

Humidity: percent

Barometric pressure: Hg

Wind direction: degrees

Wind speed: miles per hour

Sunrise/sunset: Hawaii time

Data can be downloaded from this link: https://www.kaggle.com/dronio/SolarEnergy

In [ ]:

```
# Import library
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder
import statsmodels.formula.api as smf
from sklearn import preprocessing
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import pandas
```

In [8]:

```
#import the data file
df=pd.read_csv("SolarPrediction.csv")
#print(df1)
```

In [3]:

```
df.info()
print("\n")
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32686 entries, 0 to 32685
Data columns (total 11 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   UNIXTime                32686 non-null  int64
 1   Data                    32686 non-null  object
 2   Time                    32686 non-null  object
 3   Radiation               32686 non-null  float64
```

```
 4   Temperature             32686 non-null  int64
 5   Pressure                32686 non-null  float64
 6   Humidity                32686 non-null  int64
 7   WindDirection(Degrees)  32686 non-null  float64
 8   Speed                   32686 non-null  float64
 9   TimeSunRise             32686 non-null  object
 10  TimeSunSet              32686 non-null  object
dtypes: float64(4), int64(3), object(4)
memory usage: 2.7+ MB
```

Out[3]:

	UNIXTime	Data	Time	Radiation	Temperature	Pressure	Humidity	WindDirection(Degrees)	Speed	TimeSunRise
0	1475229326	9/29/2016 12:00:00 AM	23:55:26	1.21	48	30.46	59	177.39	5.62	06:13:00
1	1475229023	9/29/2016 12:00:00 AM	23:50:23	1.21	48	30.46	58	176.78	3.37	06:13:00
2	1475228726	9/29/2016 12:00:00 AM	23:45:26	1.23	48	30.46	57	158.75	3.37	06:13:00
3	1475228421	9/29/2016 12:00:00 AM	23:40:21	1.21	48	30.46	60	137.71	3.37	06:13:00
4	1475228124	9/29/2016 12:00:00 AM	23:35:24	1.17	48	30.46	62	104.95	5.62	06:13:00

In [4]:

```
df.tail()
```

Out[4]:

	UNIXTime	Data	Time	Radiation	Temperature	Pressure	Humidity	WindDirection(Degrees)	Speed	TimeSur
32681	1480587604	12/1/2016 12:00:00 AM	00:20:04	1.22	44	30.43	102	145.42	6.75	06:
32682	1480587301	12/1/2016 12:00:00 AM	00:15:01	1.17	44	30.42	102	117.78	6.75	06:
32683	1480587001	12/1/2016 12:00:00 AM	00:10:01	1.20	44	30.42	102	145.19	9.00	06:
32684	1480586702	12/1/2016 12:00:00 AM	00:05:02	1.23	44	30.42	101	164.19	7.87	06:
32685	1480586402	12/1/2016 12:00:00 AM	00:00:02	1.20	44	30.43	101	83.59	3.37	06:

In [5]:

```
#step 3
print(df.describe())
```

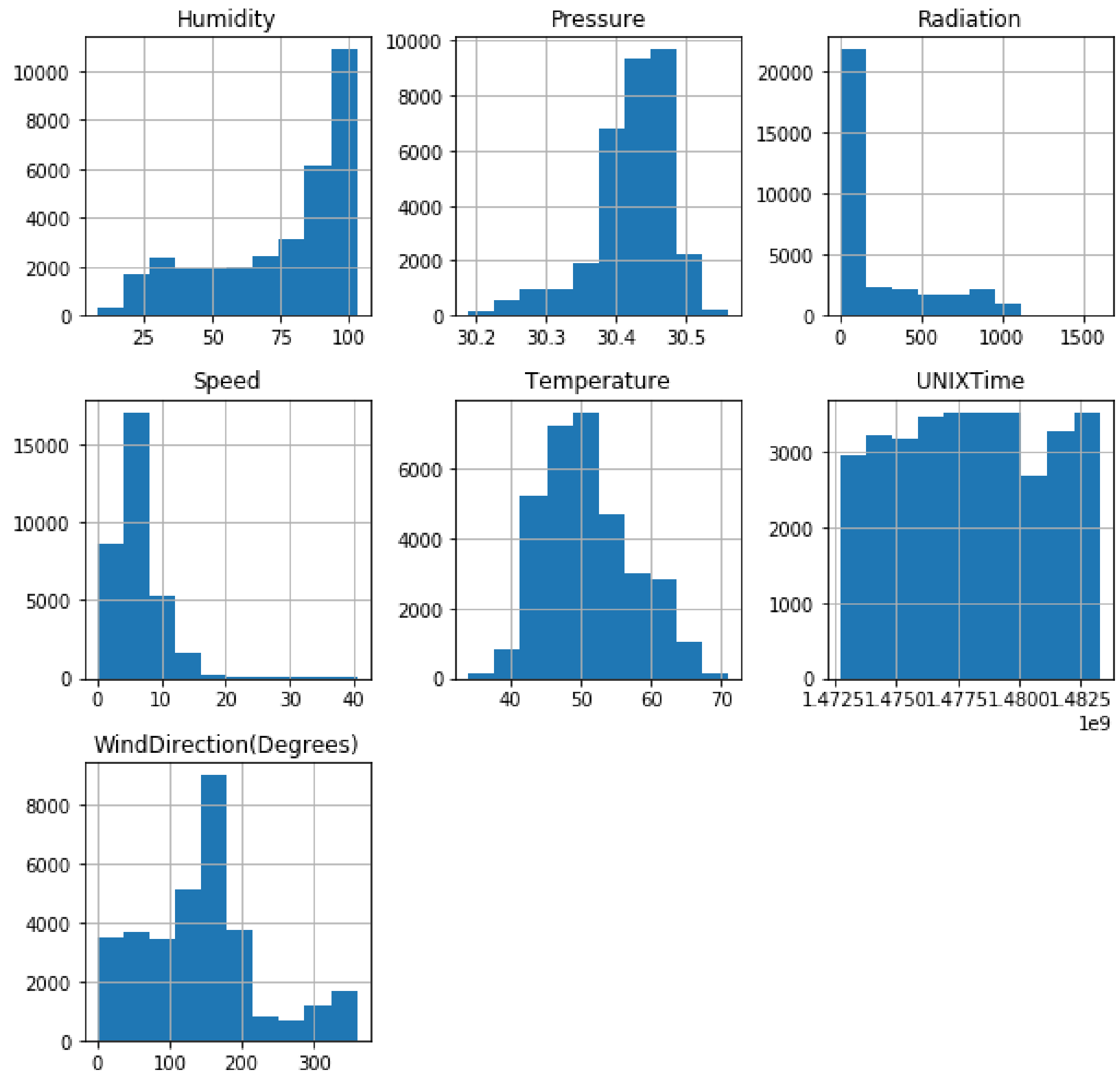
```
           UNIXTime     Radiation   Temperature      Pressure      Humidity  \
count  3.268600e+04  32686.000000  32686.000000  32686.000000  32686.000000
mean   1.478047e+09    207.124697     51.103255     30.422879     75.016307
std    3.005037e+06    315.916387      6.201157      0.054673     25.990219
min    1.472724e+09      1.110000     34.000000     30.190000      8.000000
```

```
25%   1.475546e+09      1.230000    46.000000    30.400000     56.000000
50%   1.478026e+09      2.660000    50.000000    30.430000     85.000000
75%   1.480480e+09    354.235000    55.000000    30.460000     97.000000
max   1.483265e+09   1601.260000    71.000000    30.560000    103.000000

       WindDirection(Degrees)         Speed
count            32686.000000  32686.000000
mean               143.489821      6.243869
std                 83.167500      3.490474
min                  0.090000      0.000000
25%                 82.227500      3.370000
50%                147.700000      5.620000
75%                179.310000      7.870000
max                359.950000     40.500000
```

Step 1 Pre Process

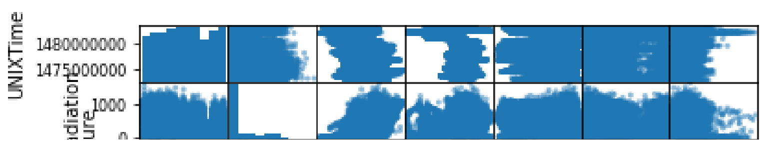
In [9]:

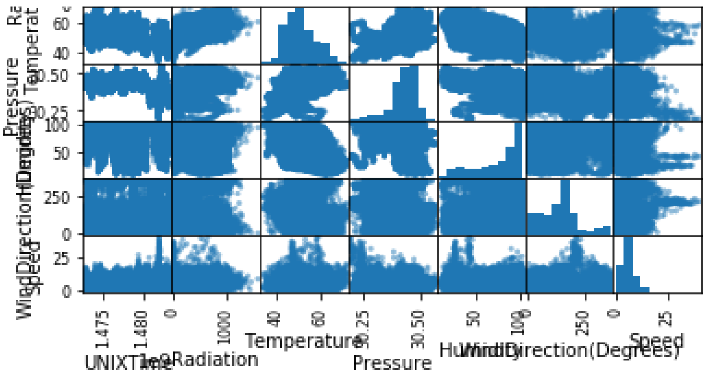
```
df.hist(figsize=(10,10))
plt.show()
```



In [9]:

```
# scatter plot matrix
from pandas.plotting import scatter_matrix
scatter_matrix(df)
plt.show()
```





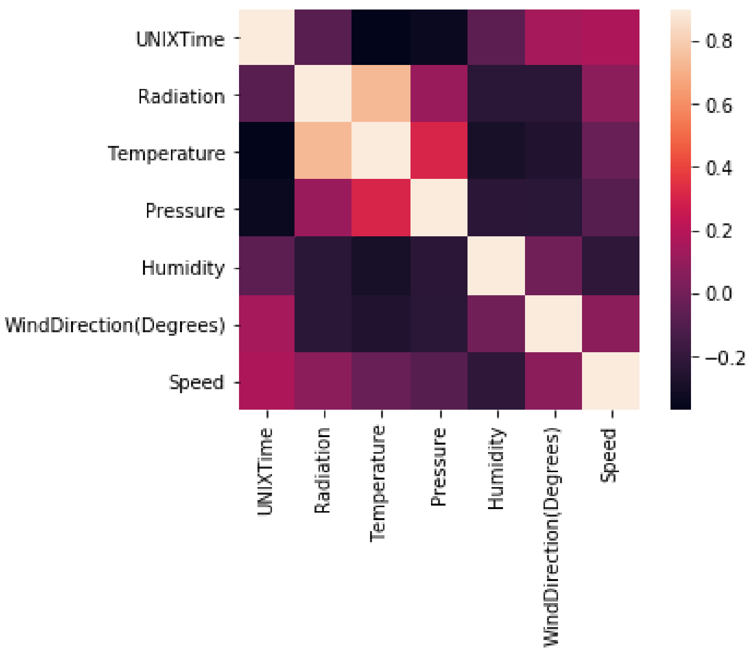
In [10]:

```
#step 6
c=df.corr(method='pearson')
print("The correlation matrix: ",c)
```

```
The correlation matrix:                            UNIXTime  Radiation  Temperature  Press
ure  Humidity  \
UNIXTime                 1.000000  -0.081286    -0.369169 -0.332016 -0.063117
Radiation               -0.081286   1.000000     0.734955  0.119016 -0.226171
Temperature             -0.369169   0.734955     1.000000  0.311173 -0.285055
Pressure                -0.332016   0.119016     0.311173  1.000000 -0.223973
Humidity                -0.063117  -0.226171    -0.285055 -0.223973  1.000000
WindDirection(Degrees)   0.152613  -0.230324    -0.259421 -0.229010 -0.001833
Speed                    0.173860   0.073627    -0.031458 -0.083639 -0.211624

                        WindDirection(Degrees)     Speed
UNIXTime                              0.152613  0.173860
Radiation                            -0.230324  0.073627
Temperature                          -0.259421 -0.031458
Pressure                             -0.229010 -0.083639
Humidity                             -0.001833 -0.211624
WindDirection(Degrees)                1.000000  0.073092
Speed                                 0.073092  1.000000
```

In [11]:

```
#step -7

#Correlation map to see how features are correlated with radiation
corrmat = df.corr()
plt.subplots()
#figsize=(12,9)
sns.heatmap(corrmat, vmax=0.9, square=True)
plt.show()
```



In [12]:

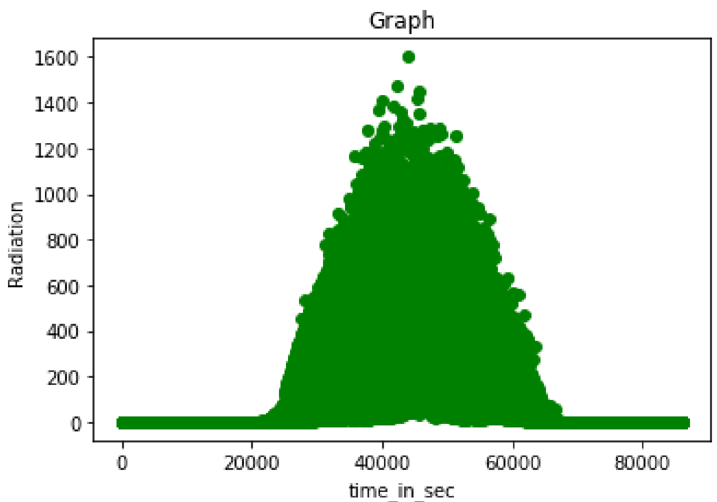
```
# step-8
# TimeSunRise and TimeSunSet columns are used to find length of the day.
#It is then converted into seconds
# ie the length of the day is measured in seconds
time1=df[['TimeSunRise']].values
time2=df[['TimeSunSet']].values
i=0
DayLen=[]
for i in range(len(time1)):
    temp1=(int(time1[i][0][0:2])*3600+int(time1[i][0][3:5])*60+int(time1[i][0][6:8]))
    temp2=(int(time2[i][0][0:2])*3600+int(time2[i][0][3:5])*60+int(time2[i][0][6:8]))
    DayLen.append(temp2-temp1)

DayLen
df['DayLengthinsec']=DayLen
```

In [14]:

```
# step-9
# The time variable is converted into seconds.
#the time at which data was collected
time=df[['Time']].values
#print(time[0][0][0:2]) #hour
#print(time[0][0][3:5]) #min
#print(time[0][0][6:8]) #second

i=0
TimeX=[]
for i in range(len(time)):
    temp=(int(time[i][0][0:2])*3600+int(time[i][0][3:5])*60+int(time[i][0][6:8]))
    TimeX.append(temp)

TimeX
df['time_in_sec']=TimeX
```

In [16]:

```
# step-10
# graph is plotted between time and radiation
# it comes out as perfectly skewed

plt.scatter(df.time_in_sec,df.Radiation,color='green')
plt.xlabel("time_in_sec")
plt.ylabel("Radiation")
plt.title("Graph")
plt.show()
```



In [17]:

```
# step-12

model=smf.ols('Radiation ~ Temperature+ Humidity +Humidity*Temperature', df)
```

```
Fitting_results=model.fit()
print(Fitting_results.summary().tables[1])
```

```
==========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
-
Intercept             -2336.4971     27.626    -84.575      0.000   -2390.646   -2282.349
Temperature              49.7311      0.515     96.473      0.000      48.721      50.741
Humidity                  9.8844      0.386     25.588      0.000       9.127      10.642
Humidity:Temperature     -0.1952      0.007    -26.356      0.000      -0.210      -0.181
==========================================================================================
```

In [18]:

```
## step-13
# therefore we make it a new data frame
Temp_multiply_humid=df.Humidity *df.Temperature
df['Temp_multiply_humid']=Temp_multiply_humid
```

In [24]:

```
#step 14
df['Month']=[d.split('/')[0] for d in df.Data]
df['Day_of_month']=[d.split('/')[1] for d in df.Data]
```

In [19]:

```
#step 15
df['wind_dir'] = df['WindDirection(Degrees)']
```

In [26]:

```
#step 16
#We drop the following columns
df = df.drop(['UNIXTime','Data','TimeSunRise','TimeSunSet','WindDirection(Degrees)'], ax
is=1)
```

In [24]:

```
#step 18
#We now check the data-set
print(df.columns)
```

```
Index(['UNIXTime', 'Data', 'Time', 'Radiation', 'Temperature', 'Pressure',
       'Humidity', 'WindDirection(Degrees)', 'Speed', 'TimeSunRise',
       'TimeSunSet', 'DayLengthinsec', 'time_in_sec', 'Temp_multiply_humid',
       'wind_dir'],
      dtype='object')
```

In [29]:

```
#step 19
c=df.corr(method='pearson')
print("The correlation matrix: ",c)
```

```
The correlation matrix:                        Radiation  Temperature  Pressure  Humidity
Speed  \
Radiation             1.000000     0.734955  0.119016 -0.226171  0.073627
Temperature           0.734955     1.000000  0.311173 -0.285055 -0.031458
Pressure              0.119016     0.311173  1.000000 -0.223973 -0.083639
Humidity             -0.226171    -0.285055 -0.223973  1.000000 -0.211624
Speed                 0.073627    -0.031458 -0.083639 -0.211624  1.000000
DayLengthinsec        0.073456     0.355509  0.278614  0.087356 -0.174944
time_in_sec           0.013143     0.204372  0.090749  0.077038 -0.057445
Temp_multiply_humid  -0.020549     0.011732 -0.124006  0.947963 -0.225835
Month                -0.035496    -0.010335 -0.199199  0.072388 -0.035145
Day_of_month         -0.025539    -0.070179 -0.062723  0.052788 -0.075062
wind_dir             -0.230324    -0.259421 -0.229010 -0.001833  0.073092

                     DayLengthinsec  time_in_sec  Temp_multiply_humid  \
```

Radiation	0.073456	0.013143	-0.020549
Temperature	0.355509	0.204372	0.011732
Pressure	0.278614	0.090749	-0.124006
Humidity	0.087356	0.077038	0.947963
Speed	-0.174944	-0.057445	-0.225835
DayLengthinsec	1.000000	0.007510	0.225333
time_in_sec	0.007510	1.000000	0.146242
Temp_multiply_humid	0.225333	0.146242	1.000000
Month	0.268679	0.002507	0.080076
Day_of_month	0.015016	-0.000756	0.034480
wind_dir	-0.129434	-0.080159	-0.081217

	Month	Day_of_month	wind_dir
Radiation	-0.035496	-0.025539	-0.230324
Temperature	-0.010335	-0.070179	-0.259421
Pressure	-0.199199	-0.062723	-0.229010
Humidity	0.072388	0.052788	-0.001833
Speed	-0.035145	-0.075062	0.073092
DayLengthinsec	0.268679	0.015016	-0.129434
time_in_sec	0.002507	-0.000756	-0.080159
Temp_multiply_humid	0.080076	0.034480	-0.081217
Month	1.000000	-0.041591	0.106103
Day_of_month	-0.041591	1.000000	0.039874
wind_dir	0.106103	0.039874	1.000000

In [25]:

```
c=df['Pressure'].corr(df['Speed'])
print("The correlation matrix: ",c)
```

The correlation matrix: -0.08363929418151313

In [26]:

```
Presssure_multiply_speed=df.Pressure *df.Speed
df['Presssure_multiply_speed']=Presssure_multiply_speed
```

In [32]:

```
c=df['Month'].corr(df['Humidity'])
print("The correlation matrix: ",c)
```

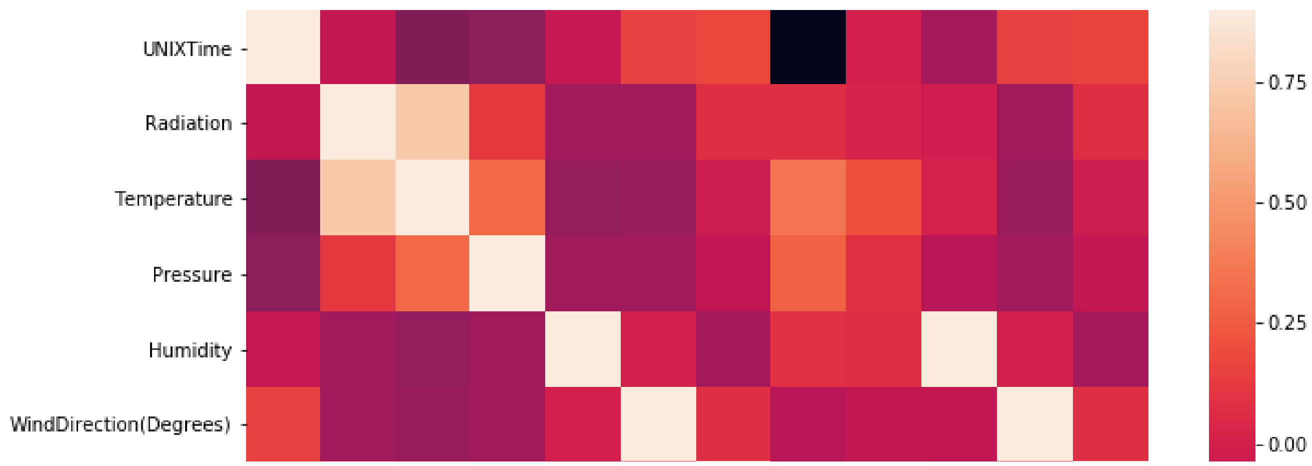
The correlation matrix: 0.07238769376476024

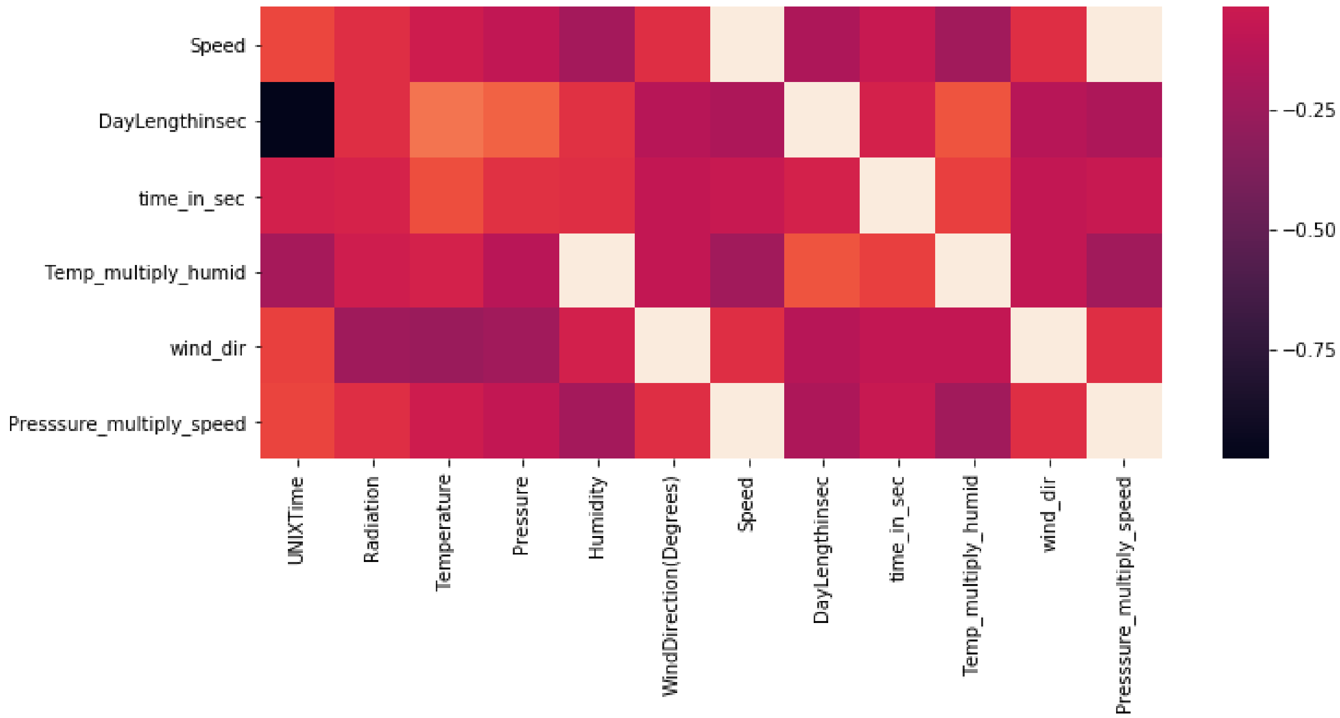
In [33]:

```
Month_multiply_Temperature=df.Temperature *df.Month
df['Month_multiply_Temperature']=Month_multiply_Temperature
```

In [27]:

```
#Correlation map to see how features are correlated with Radiation
corrmat = df.corr()
plt.subplots(figsize=(12,9))
sns.heatmap(corrmat, vmax=0.9, square=True)
plt.show()
```





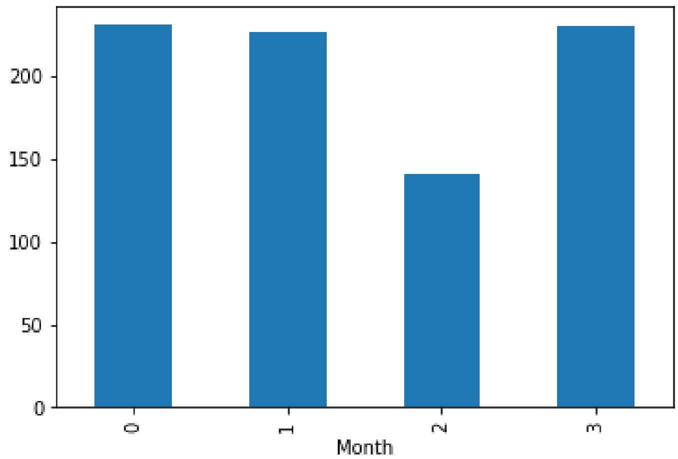
In [35]:

```
pclass_group=df.groupby(['Month']).mean()
print(pclass_group)
```

```
         Radiation  Temperature   Pressure   Humidity     Speed  \
Month
0       230.582292    52.468654  30.438463  78.946378  5.880243
1       226.727750    50.785007  30.445780  62.384959  6.852886
2       141.283240    47.608893  30.374428  79.526458  6.733328
3       229.804828    53.681138  30.432098  79.485776  5.457367

        DayLengthinsec  time_in_sec  Temp_multiply_humid  Day_of_month  \
Month
0         42065.502777  4211.301666          4083.771454     15.006008
1         40351.122646  4148.892685          3099.453404     14.366731
2         39428.098971  4200.959946          3760.574351     13.842479
3         44096.076581  4214.919240          4233.860725     14.134556

          wind_dir  Presssure_multiply_speed  Month_multiply_Temperature
Month
0       126.036855                178.987805                    0.000000
1       135.261972                208.637605                   50.785007
2       177.431927                204.486391                   95.217785
3       136.075603                166.073007                  161.043414
```

In [36]:

```
pclass_group['Radiation'].plot.bar()
plt.show()
```



In [37]:

```
#We drop the following columns
df = df.drop(['Time'], axis=1)
```

Train and Test

In [29]:

```
from sklearn.model_selection import train_test_split
X=df[['Temperature', 'Pressure', 'Humidity', 'Speed',
     'DayLengthinsec', 'time_in_sec', 'Temp_multiply_humid',
       'wind_dir',]]


Y=df.Radiation

X_train, X_test, Y_train, Y_test= train_test_split(X, Y, random_state= 0)
```

In [30]:

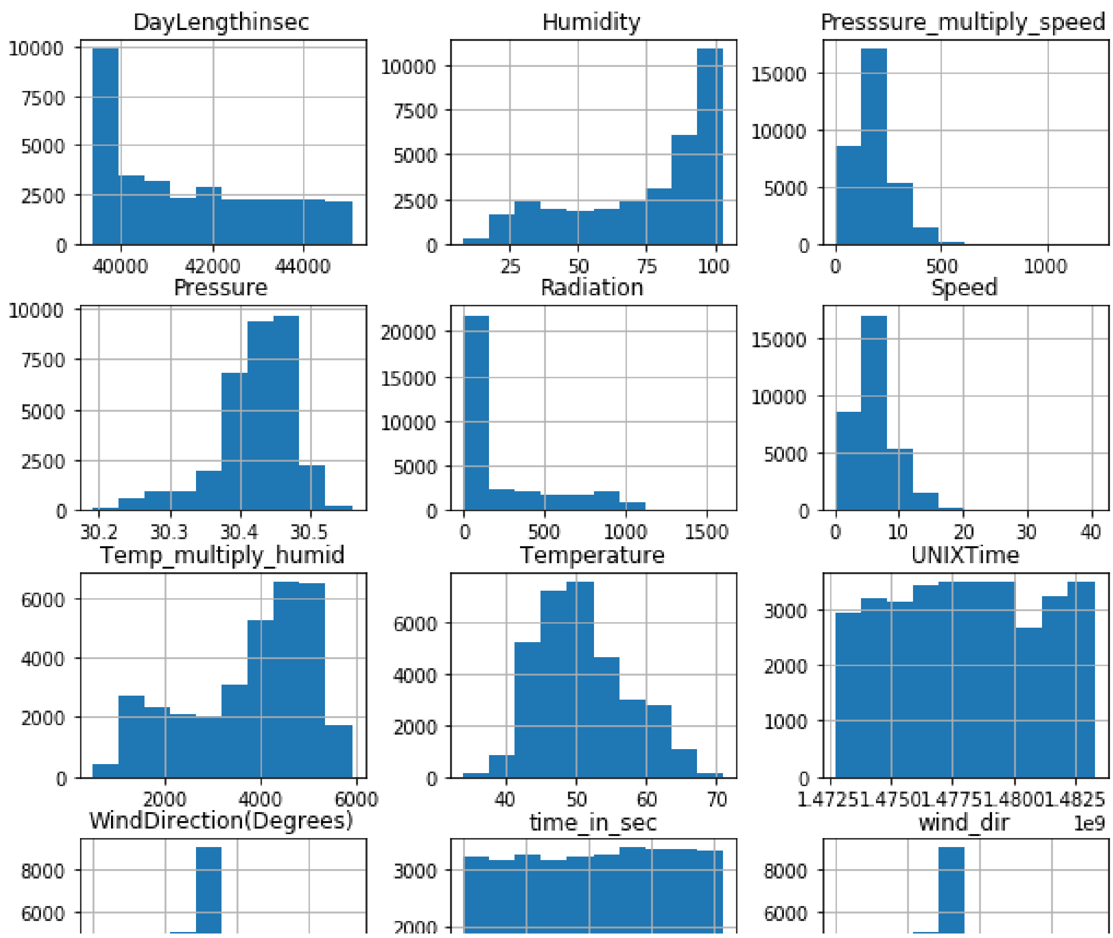
```
linreg= LinearRegression().fit(X_train, Y_train)
print("Score: ",linreg.score(X,Y))
from sklearn.metrics import mean_squared_error
Target_predicted= linreg.predict(X_test)
MSE=mean_squared_error(Y_test,Target_predicted)
print('mean square error', MSE)
```

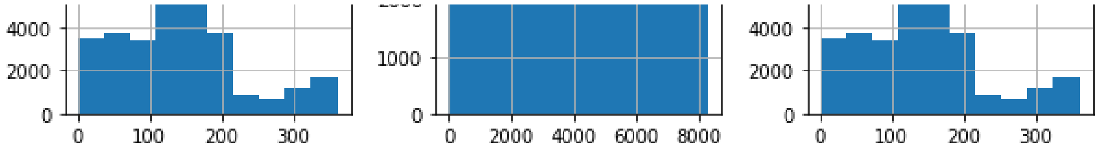
```
Score:  0.6204710002875158
mean square error 37504.873939162055
```

Step 2 Data Visualization

In [31]:

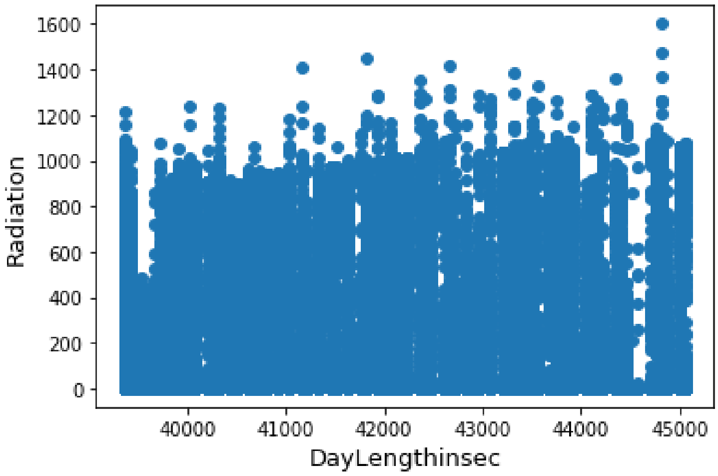
```
df.hist(figsize=(10,10))
plt.show()
```





In [43]:

```
fig, ax = plt.subplots()
ax.scatter(x = df['DayLengthinsec'], y = df['Radiation'])
plt.ylabel('Radiation', fontsize=13)
plt.xlabel('DayLengthinsec', fontsize=13)
plt.show()
```



In [44]:

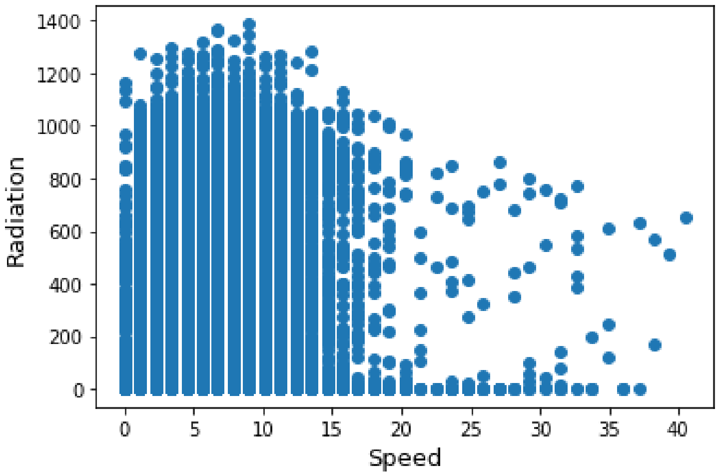
```
df= df.drop(df[(df['Radiation']>1400)].index)
```

In [45]:

```
df= df.drop(df[(df['wind_dir']>8000)].index)
```

In [46]:

```
fig, ax = plt.subplots()
ax.scatter(x = df['Speed'], y = df['Radiation'])
plt.ylabel('Radiation', fontsize=13)
plt.xlabel('Speed', fontsize=13)
plt.show()
```



In [47]:

```
df= df.drop(df[(df['Speed']>35)].index)
```

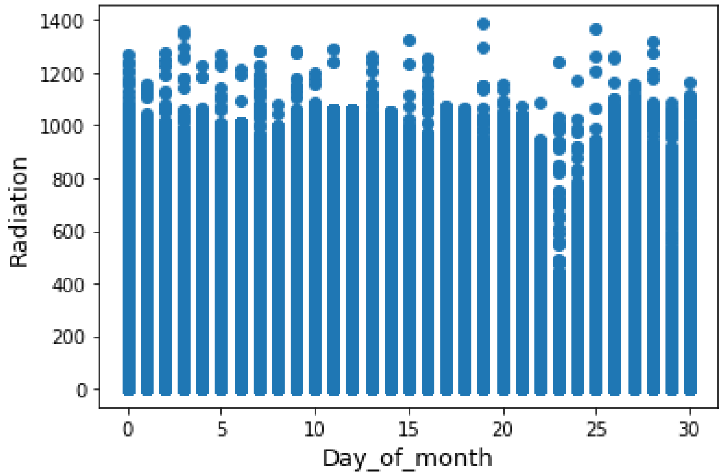
In [48]:

```
print(df.shape)
```

```
(32672, 13)
```

In [49]:

```
fig, ax = plt.subplots()
ax.scatter(x = df['Day_of_month'], y = df['Radiation'])
plt.ylabel('Radiation', fontsize=13)
plt.xlabel('Day_of_month', fontsize=13)
plt.show()
```



In [39]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.linear_model import ElasticNet, Lasso, BayesianRidge, LassoLarsIC
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import RobustScaler
from sklearn.base import BaseEstimator, TransformerMixin, RegressorMixin, clone
from sklearn.model_selection import KFold, cross_val_score, train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.neural_network import MLPRegressor
from sklearn.svm import SVR
```

In [40]:

```
sub = pd.DataFrame()
sub = sub.reset_index()
sub['Radiation'] = Target_predicted
sub.to_csv('SolarPrediction.csv',index=False)
```

In [41]:

```
X=df[['Temperature', 'Pressure', 'Humidity', 'Speed',
       'DayLengthinsec', 'time_in_sec', 'Temp_multiply_humid',
       'wind_dir',]]
Y=df.Radiation

X_train, X_test, Y_train, Y_test= train_test_split(X, Y, random_state= 0)
def model_score_error(model):
    prepared_model=model.fit(X_train, Y_train)
    x=prepared_model.score(X_test,Y_test)
    print('Score: ',x)
    Target_predicted=prepared_model.predict(X_test)
    MSE=mean_squared_error(Y_test,Target_predicted)
    print('mean square error', MSE)
```

Random Forest

In [42]:

```
RandomForest = RandomForestRegressor(n_estimators=300, random_state=0).fit(X_train, Y_tr
```

```
RandomForest = RandomForestRegressor(n_estimators=500, random_state=0).fit(X_train, Y_tr
ain)
```

In [43]:

```
# scores
model_score_error(RandomForest)
```

```
Score:  0.9313959733168413
mean square error 6799.1878187607645
```

Decision Tree

In [44]:

```
DTregressor = DecisionTreeRegressor(random_state=0).fit(X_train, Y_train)
```

In [45]:

```
# scores
model_score_error(DTregressor)
```

```
Score:  0.8654033024590941
mean square error 13339.57014785854
```

Final Result

In [ ]:

```
#Linear Regrassion
Score:  0.6204710002875158
mean square error 37504.873939162055
#RNN
Score:  0.9313959733168413
mean square error 6799.1878187607645
#Decision Tree
Score:  0.8654033024590941
mean square error 13339.57014785854
```