```
import pandas as pd
import datetime
import numpy as np
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sn


energy = pd.read_csv(r'C:\Users\derek\Documents\CSE351\HW2\
energy_data.csv')
weather = pd.read_csv(r'C:\Users\derek\Documents\CSE351\HW2\
weather_data.csv')

weather['time'] = weather['time'].apply(lambda x: pd.to_datetime(x,
unit='s'))
# datetime.datetime.fromtimestamp(x)
weather.head()
# weather['time'] = datetime.datetime.fromtimestamp(weather['time'])
```

```
   temperature                 icon  humidity  visibility
summary  \
0        34.98  partly-cloudy-night      0.64       10.00  Partly
Cloudy
1        16.49          clear-night      0.62       10.00
Clear
2        14.63          clear-night      0.68       10.00
Clear
3        13.31          clear-night      0.71       10.00
Clear
4        13.57          clear-night      0.71        9.93
Clear

   pressure  windSpeed  cloudCover                time  windBearing  \
0   1017.69       7.75        0.29 2014-01-01 00:00:00          279
1   1022.76       2.71        0.06 2014-01-01 01:00:00          195
2   1022.32       4.84        0.03 2014-01-01 02:00:00          222
3   1021.64       4.00        0.14 2014-01-01 03:00:00          209
4   1020.73       3.67        0.04 2014-01-01 04:00:00          217

   precipIntensity  dewPoint  precipProbability
0              0.0     23.89                0.0
1              0.0      5.87                0.0
2              0.0      6.17                0.0
3              0.0      5.63                0.0
4              0.0      5.87                0.0
```

Imported all necessary packages, began by parsing all time fields of the weather column. All Unix time values (seconds after 01/01/1970) were converted to YYYY-MM-DD HH:MM:SS format.

```
energy.tail()
```

```
                Date & Time  use [kW]  gen [kW]  Grid [kW]   AC [kW]  \
17515  2014-12-31 21:30:00  1.560890       0.0   1.560890  0.003226
17516  2014-12-31 22:00:00  0.958447       0.0   0.958447  0.000827
17517  2014-12-31 22:30:00  0.834462       0.0   0.834462  0.001438
17518  2014-12-31 23:00:00  0.543863       0.0   0.543863  0.001164
17519  2014-12-31 23:30:00  0.414441       0.0   0.414441  0.000276

       Furnace [kW]  Cellar Lights [kW]  Washer [kW]  First Floor
lights [kW]  \
17515      0.392996            0.006342     0.000872
0.030453
17516      0.027369            0.006326     0.000811
0.030391
17517      0.170561            0.020708     0.000636
0.012631
17518      0.153533            0.008423     0.000553
0.003832
17519      0.009223            0.006619     0.000526
0.003818

       Utility Rm + Basement Bath [kW]  Garage outlets [kW]  \
17515                         0.002248             0.004817
17516                         0.002543             0.004724
17517                         0.002372             0.004711
17518                         0.002353             0.004736
17519                         0.002424             0.004664

       MBed + KBed outlets [kW]  Dryer + egauge [kW]  \
17515                  0.278941             0.000120
17516                  0.243128             0.000139
17517                  0.204744             0.000087
17518                  0.177276             0.000109
17519                  0.154928             0.000190

       Panel GFI (central vac) [kW]  Home Office (R) [kW]  \
17515                      0.000292              0.007983
17516                      0.000334              0.006178
17517                      0.000341              0.005684
17518                      0.000373              0.005160
17519                      0.000363              0.005000

       Dining room (R) [kW]  Microwave (R) [kW]  Fridge (R) [kW]
17515              0.033991            0.003702         0.002906
17516              0.034535            0.004464         0.113162
```

```
17517              0.034484            0.004502         0.051604
17518              0.025601            0.004647         0.039409
17519              0.023976            0.004800         0.117189
```

```
energy['Date & Time'] = energy['Date & Time'].apply(lambda x:
pd.to_datetime(x))
en = energy.set_index('Date & Time').resample('D').sum()
we = weather.set_index('time').resample('D').mean()
#en.resample('D').sum()
# display(we)
```

Next, I did the same with the energy dataset's 'Date & Time' Column, converting all cells in the column to a datetime object. Now that the dates in both datasets are represented as datetime objects, we can now set the indices of each data set as the date/time column, resampling the data from half-hourly/hourly intervals to daily intervals. I took the sum when resampling the energy dataset because energy usage is certainly cumulative, but took the mean for the resampling of the weather dataset, because variables like cloud cover and pressure are not cumulative.

```
list(en)
#en.rename(columns = {'Date & Time':'time'}, inplace = False)
en.head()
# merged = pd.merge(we, en, on='time', how='outer')
```

```
              use [kW]  gen [kW]  Grid [kW]   AC [kW]  Furnace [kW]  \
Date & Time
2014-01-01   65.013592       0.0  65.013592  0.042977      8.814319
2014-01-02   32.305336       0.0  32.305336  0.047452     10.830045
2014-01-03   31.164468       0.0  31.164468  0.055865     12.417151
2014-01-04   45.287782       0.0  45.287782  0.048827     11.147332
2014-01-05   36.316643       0.0  36.316643  0.039831      9.301135

             Cellar Lights [kW]  Washer [kW]  First Floor lights [kW]
\
Date & Time

2014-01-01             1.137579     0.750298                 0.567603

2014-01-02             0.600321     0.323182                 0.506440

2014-01-03             0.442453     0.004276                 0.507426

2014-01-04             0.674477     1.046294                 0.515988

2014-01-05             0.686189     0.235143                 0.519449


             Utility Rm + Basement Bath [kW]  Garage outlets [kW]  \
Date & Time
2014-01-01                         0.178529            0.261094
```

```
2014-01-02                          0.178024             0.282479
2014-01-03                          0.176649             0.279159
2014-01-04                          0.180056             0.344005
2014-01-05                          0.178556             0.348489

             MBed + KBed outlets [kW]  Dryer + egauge [kW]  \
Date & Time
2014-01-01                  0.254839            31.938131
2014-01-02                  0.798316             5.423866
2014-01-03                  0.746972             0.005554
2014-01-04                  0.640721            19.994908
2014-01-05                  0.584570             9.493912

             Panel GFI (central vac) [kW]  Home Office (R) [kW]  \
Date & Time
2014-01-01                      0.350291              3.272944
2014-01-02                      0.346679              3.475469
2014-01-03                      0.344061              3.615520
2014-01-04                      0.346872              3.700408
2014-01-05                      0.346070              3.699178

             Dining room (R) [kW]  Microwave (R) [kW]  Fridge (R) [kW]

Date & Time

2014-01-01              0.200970            4.997037         4.639598

2014-01-02              0.207041            1.534426         3.881399

2014-01-03              0.201975            1.667553         3.671391

2014-01-04              0.203913            1.029198         3.357907

2014-01-05              0.197897            1.619991         4.373730
```

```
merged = pd.merge(en, we, left_index = True, right_index = True,
how='outer')
merged.head()
# I merged the data on the index of Date and Time after making both
datasets compatible for merging.
```

```
              use [kW]  gen [kW]  Grid [kW]   AC [kW]  Furnace [kW]  \
Date & Time
2014-01-01   65.013592       0.0  65.013592  0.042977      8.814319
2014-01-02   32.305336       0.0  32.305336  0.047452     10.830045
2014-01-03   31.164468       0.0  31.164468  0.055865     12.417151
2014-01-04   45.287782       0.0  45.287782  0.048827     11.147332
2014-01-05   36.316643       0.0  36.316643  0.039831      9.301135

             Cellar Lights [kW]  Washer [kW]  First Floor lights [kW]
```

```
\
Date & Time

2014-01-01             1.137579     0.750298                 0.567603

2014-01-02             0.600321     0.323182                 0.506440

2014-01-03             0.442453     0.004276                 0.507426

2014-01-04             0.674477     1.046294                 0.515988

2014-01-05             0.686189     0.235143                 0.519449


             Utility Rm + Basement Bath [kW]  Garage outlets [kW]  ...
\
Date & Time                                                        ...

2014-01-01                         0.178529             0.261094  ...

2014-01-02                         0.178024             0.282479  ...

2014-01-03                         0.176649             0.279159  ...

2014-01-04                         0.180056             0.344005  ...

2014-01-05                         0.178556             0.348489  ...


             temperature  humidity  visibility     pressure  windSpeed
\
Date & Time

2014-01-01     20.110833  0.556667    9.970000  1025.395000   6.820417

2014-01-02     16.382500  0.784583    3.834583  1023.465833   7.433750

2014-01-03      6.256667  0.680833    4.509167  1014.428750  12.828333

2014-01-04      2.711667  0.617083    9.822917  1030.096250   5.248333

2014-01-05     17.654167  0.682083    9.134583  1025.275000   3.417083


             cloudCover  windBearing  precipIntensity   dewPoint  \
Date & Time
2014-01-01     0.031304   252.291667         0.000000   6.362083
2014-01-02     0.354444    53.458333         0.002004  10.737083
```

```
2014-01-03     0.186364   207.333333         0.002029  -2.337500
2014-01-04     0.001667   240.166667         0.000000  -8.352083
2014-01-05     0.010952   208.958333         0.000033   8.615000

             precipProbability
Date & Time
2014-01-01            0.000000
2014-01-02            0.074583
2014-01-03            0.080000
2014-01-04            0.000000
2014-01-05            0.000417

[5 rows x 27 columns]
```

```
merged = merged.dropna()
# Droppign null rows (none to begin with, but used for safety)

# merged.plot(x='precipIntensity', y = 'use [kW]', style = 'o')

train = merged[:'2014-11-30']
#Data up until December
test = merged['2014-12-01':]
# December Data

# Removing outliers
q_low = train["temperature"].quantile(0.01)
q_hi  = train["temperature"].quantile(0.99)
train = train[(train["temperature"] < q_hi) & (train["temperature"] >
q_low)]

X_train = train[['temperature']].values
y_train = train['use [kW]'].values



X_test = test[['temperature']].values
y_test = test['use [kW]'].values

# X_train, X_test, y_train, y_test = train_test_split(X, Y,
test_size=0.2, random_state=0)
regressor = LinearRegression()
regressor.fit(X_train, y_train)

LinearRegression()
```

For this model, I split the train test into all data before December, and test set became all data after December. Then, I removed outliers from ONLY the train data. Then, I used temperature to predict use [kW] with the Linear Regression package.

```
merged['use [kW]'].describe()
# Viewing the mean and std of the use [kW] column will be useful in
gauging the success of our model.
```

```
count    365.000000
mean      31.819442
std       14.466709
min       10.572219
25%       21.660309
50%       27.108372
75%       37.879129
max       96.443073
Name: use [kW], dtype: float64
```

```
y_pred = regressor.predict(X_test)
df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df

# df2 = pd.DataFrame({'Date': energy['Date & Time'], 'Predicted':
y_pred})
```

	Actual	Predicted
0	30.550010	30.302844
1	31.748857	27.079370
2	28.773233	27.709034
3	39.484491	27.671397
4	33.342503	25.129264
5	36.470153	27.280021
6	26.486585	26.883319
7	23.013980	22.821907
8	27.954351	26.144858
9	37.422625	27.814684
10	35.182712	26.400573
11	24.209088	25.898100
12	20.455440	26.461203
13	19.821203	26.720911
14	41.912526	27.473773
15	20.712163	25.951106
16	21.802123	28.718336
17	19.836075	27.974430
18	32.802819	26.713892
19	34.296287	25.039830
20	21.058376	26.072852
21	27.362027	27.085058
22	19.387136	28.429221
23	27.682246	28.958318
24	40.268132	30.988177
25	44.563400	29.358529
26	35.046127	27.459613
27	37.695824	29.320166
28	28.675929	27.239237

```
29  31.514313  24.369141
30  28.674498  22.822875
```

This dataframe shows the actual use values vs the estimated use in kilowatts values for the month of December. Some predicted values are closer to the actual value than others.

```
print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Root Mean Squared Error: 7.378317412210945
```

My linear regression model takes the data from the first 11 months of 2014 to train, and the month of December as the test data. The root mean squared error of this model is ~7, which is around 25% of the mean of use [kW] across the entire year. Therefore, the model is somewhat adequate at predicting December's use [kW].

Included in the homework ZIP is the CSV dump for this data, as well as included below.

```
df = pd.DataFrame({'Date': test.index, 'Predicted': y_pred})
df
```

```
         Date  Predicted
0  2014-12-01  30.302844
1  2014-12-02  27.079370
2  2014-12-03  27.709034
3  2014-12-04  27.671397
4  2014-12-05  25.129264
5  2014-12-06  27.280021
6  2014-12-07  26.883319
7  2014-12-08  22.821907
8  2014-12-09  26.144858
9  2014-12-10  27.814684
10 2014-12-11  26.400573
11 2014-12-12  25.898100
12 2014-12-13  26.461203
13 2014-12-14  26.720911
14 2014-12-15  27.473773
15 2014-12-16  25.951106
16 2014-12-17  28.718336
17 2014-12-18  27.974430
18 2014-12-19  26.713892
19 2014-12-20  25.039830
20 2014-12-21  26.072852
21 2014-12-22  27.085058
22 2014-12-23  28.429221
23 2014-12-24  28.958318
24 2014-12-25  30.988177
25 2014-12-26  29.358529
26 2014-12-27  27.459613
27 2014-12-28  29.320166
28 2014-12-29  27.239237
```

```
29 2014-12-30  24.369141
30 2014-12-31  22.822875
```

This dataframe shows the predicted energy use [kW] based on temperature for the month of December. This was achieved by training the linear regression model with data from the first 11 months of the year.

```
# compression_opts = dict(method='zip',
#                         archive_name='part3.csv')
#df.to_csv('part3.zip', index=False,
#          compression=compression_opts)
```

This kernel creates the csv dump but is commented out because it will be included in submission ZIP regardless.

```
weather.head()
```

```
   temperature                 icon  humidity  visibility
summary  \
0        34.98  partly-cloudy-night      0.64       10.00  Partly
Cloudy
1        16.49          clear-night      0.62       10.00
Clear
2        14.63          clear-night      0.68       10.00
Clear
3        13.31          clear-night      0.71       10.00
Clear
4        13.57          clear-night      0.71        9.93
Clear

   pressure  windSpeed  cloudCover                time  windBearing  \
0   1017.69       7.75        0.29 2014-01-01 00:00:00          279
1   1022.76       2.71        0.06 2014-01-01 01:00:00          195
2   1022.32       4.84        0.03 2014-01-01 02:00:00          222
3   1021.64       4.00        0.14 2014-01-01 03:00:00          209
4   1020.73       3.67        0.04 2014-01-01 04:00:00          217

   precipIntensity  dewPoint  precipProbability
0              0.0     23.89                0.0
1              0.0      5.87                0.0
2              0.0      6.17                0.0
3              0.0      5.63                0.0
4              0.0      5.87                0.0
```

```
weather2 =  weather.set_index('time').resample('D').mean()
weather2['temperature']= weather2['temperature'].apply(lambda x: 1 if
x >= 35 else 0)
```

```
logtrain = weather2[:'2014-11-30']
#Data up until December
logtest = weather2['2014-12-01':]
```

```
# December Data

X_train2 = logtrain[['dewPoint', 'pressure']].values
y_train2 = logtrain['temperature'].values

X_test2 = logtest[['dewPoint', 'pressure']].values
y_test2 = logtest['temperature'].values

# X_train, X_test, y_train, y_test = train_test_split(X, Y,
test_size=0.2, random_state=0)
log = LogisticRegression()
log.fit(X_train2, y_train2)

LogisticRegression()
```

I split the original weather dataframe into new train and test sets, and trained the model using two columns, dewPoint and pressure, instead of just one column. I did trial and error to see which datapoints produced better F1 scores, which would indicate a better logistic regression model.

```
#y_pred = regressor.predict(X_test)
#df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
#df
y_pred2 = log.predict(X_test2)
print('Accuracy of logistic regression classifier on test set:
{:.2f}'.format(metrics.f1_score(y_test2, y_pred2)))

Accuracy of logistic regression classifier on test set: 0.70
```

The accuracy of our logistic regression is 0.70, which indicates it is better than randomly guessing, but still shows room for improvement.

```
df = pd.DataFrame({'Date': logtest.index, 'Predicted': y_pred2})
df
```

	Date	Predicted
0	2014-12-01	1
1	2014-12-02	1
2	2014-12-03	1
3	2014-12-04	1
4	2014-12-05	1
5	2014-12-06	1
6	2014-12-07	1
7	2014-12-08	0
8	2014-12-09	1
9	2014-12-10	1
10	2014-12-11	1
11	2014-12-12	0
12	2014-12-13	1
13	2014-12-14	1
14	2014-12-15	1

```
15 2014-12-16          1
16 2014-12-17          1
17 2014-12-18          1
18 2014-12-19          0
19 2014-12-20          0
20 2014-12-21          1
21 2014-12-22          1
22 2014-12-23          1
23 2014-12-24          1
24 2014-12-25          1
25 2014-12-26          1
26 2014-12-27          1
27 2014-12-28          1
28 2014-12-29          0
29 2014-12-30          0
30 2014-12-31          0
```

This dataframe shows the predicted binary classifier for temperature for the month of December based on our Logistic regression.

```
# df.to_csv('part4.csv', index=False)
```

```
energy2 = energy
energy2['Date & Time'] = pd.to_datetime(energy2['Date & Time'],
errors='coerce', format='%Y-%m-%d %H:%M:%S')
for index, cell in enumerate(energy2['Date & Time']):
        #energy2['Date & Time'][index] = "Day"
        energy2.loc[index, 'Date & Time'] = "Day" if cell.hour >= 19
else "Night"


energy2.rename(columns= {'Date & Time' : "Time of Day"}, inplace =
True)
energy2.head()
#display(energy2["Date & Time"][17518].hour)
```

```
  Time of Day  use [kW]  gen [kW]  Grid [kW]   AC [kW]  Furnace
[kW]  \
0       Night  0.304439       0.0   0.304439  0.000058      0.009531

1       Night  0.656771       0.0   0.656771  0.001534      0.364338

2       Night  0.612895       0.0   0.612895  0.001847      0.417989

3       Night  0.683979       0.0   0.683979  0.001744      0.410653

4       Night  0.197809       0.0   0.197809  0.000030      0.017152


   Cellar Lights [kW]  Washer [kW]  First Floor lights [kW]  \
```

```
0            0.005336     0.000126                 0.011175
1            0.005522     0.000043                 0.003514
2            0.005504     0.000044                 0.003528
3            0.005556     0.000059                 0.003499
4            0.005302     0.000119                 0.003694

   Utility Rm + Basement Bath [kW]  Garage outlets [kW]  \
0                         0.003836             0.004836
1                         0.003512             0.004888
2                         0.003484             0.004929
3                         0.003476             0.004911
4                         0.003865             0.004876

   MBed + KBed outlets [kW]  Dryer + egauge [kW]  \
0                  0.002132             0.000009
1                  0.002137             0.000107
2                  0.002052             0.000170
3                  0.002068             0.000121
4                  0.002087             0.000052

   Panel GFI (central vac) [kW]  Home Office (R) [kW]  Dining room (R)
[kW]  \
0                      0.007159              0.063666
0.004299
1                      0.007221              0.064698
0.003589
2                      0.007197              0.065109
0.003522
3                      0.007236              0.065032
0.003404
4                      0.007133              0.062451
0.003915

   Microwave (R) [kW]  Fridge (R) [kW]
0            0.004733         0.042589
1            0.004445         0.096008
2            0.004396         0.025928
3            0.004262         0.105472
4            0.004407         0.016798
```

First, I classified every row as either at Night or Day by checking whether or not the hour of the day is >= 19 (7:00PM) and setting the value accordingly. Then, I changed the title of the column as well

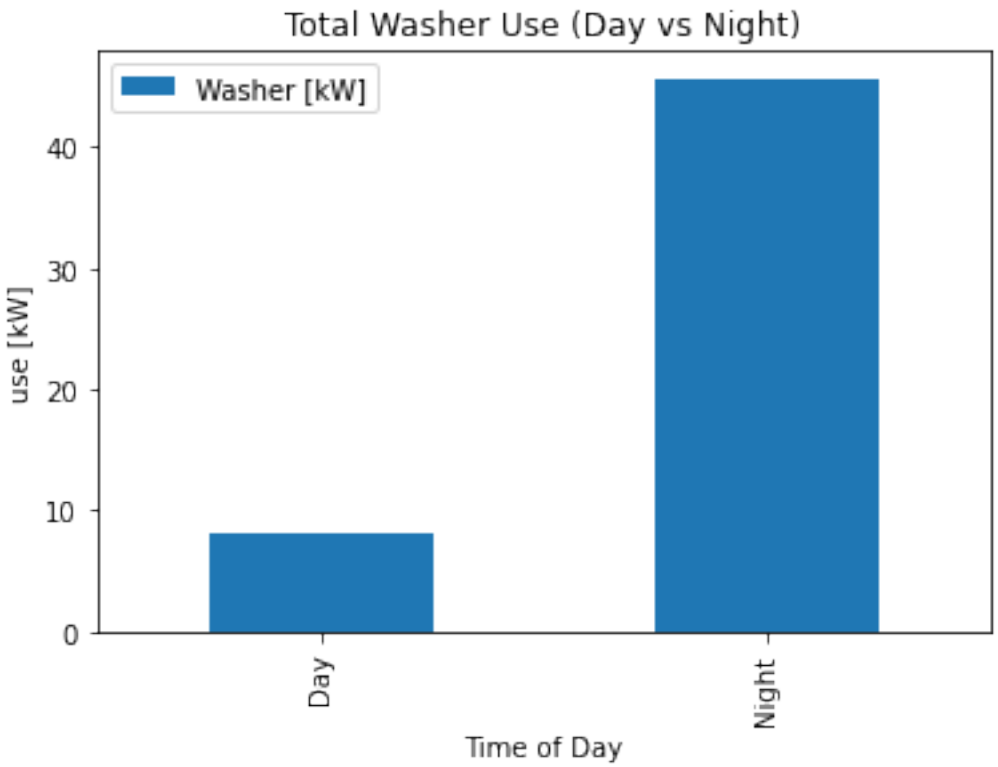
```
energy2=energy2.groupby('Time of Day').sum()
energy2.head()
```

```
                use [kW]  gen [kW]    Grid [kW]     AC [kW]  Furnace
[kW]  \
Time of Day
```

```
Day          3253.106113       0.0  3253.106113  969.154715
418.607244
Night        8360.990284       0.0  8360.990284  590.103678
1086.156111

             Cellar Lights [kW]  Washer [kW]  First Floor lights [kW]
\
Time of Day

Day                   39.719061     8.100475               124.571935

Night                153.623698    45.635419               153.155038


             Utility Rm + Basement Bath [kW]  Garage outlets [kW]  \
Time of Day
Day                                19.172422            20.690776
Night                              70.269197            83.536905

             MBed + KBed outlets [kW]  Dryer + egauge [kW]  \
Time of Day
Day                        219.043097           203.839336
Night                      587.346411          1006.769207

             Panel GFI (central vac) [kW]  Home Office (R) [kW]  \
Time of Day
Day                             17.761923            190.844626
Night                           69.931731            749.972166

             Dining room (R) [kW]  Microwave (R) [kW]  Fridge (R) [kW]

Time of Day

Day                     21.729269           41.540276       289.493202

Night                   51.603253          225.417134       999.303023
```

```
# Utilizing a simple bar graph, we can plot the differences in energy
usage between day and night.
energy2.plot.bar( y ="Washer [kW]", ylabel= "use [kW]", title = 'Total
Washer Use (Day vs Night)')
```

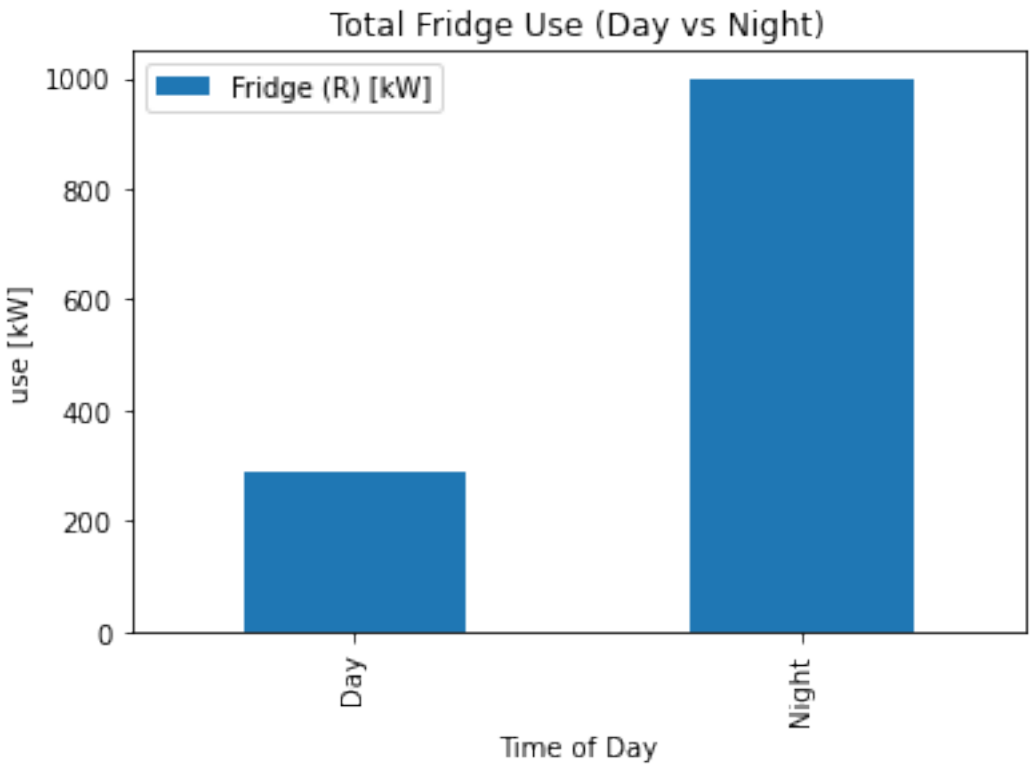
```
<AxesSubplot:title={'center':'Total Washer Use (Day vs Night)'},
xlabel='Time of Day', ylabel='use [kW]'>
```



As shown in the bar graph above, the washer uses significantly more energy at night as opposed to day. This can be attributed to people working jobs and being out the house in the day time, then coming home and utilizing the washer at night.

```
# Utilizing a simple bar graph, we can plot the differences in energy
usage between day and night.
energy2.plot.bar( y ="Fridge (R) [kW]", ylabel = "use [kW]", title =
"Total Fridge Use (Day vs Night)")
```

```
<AxesSubplot:title={'center':'Total Fridge Use (Day vs Night)'},
xlabel='Time of Day', ylabel='use [kW]'>
```



Similarly to the energy usage of the Washer, the fridge uses much more energy at night as people are more likely to be at home at nighttime. Opening and closing the fridge frequently will increase energy usage, and this occurs more often at nightime.