Intel Data Analysis

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
import datetime as dt
from datetime import datetime
import os
```

In [2]:

```
path = "C:\\Users\\PS\\Desktop"
os.getcwd()
os.chdir(path)

pd.set_option('display.max_columns',100) #display upto 100 columns
pd.set_option('display.float_format', lambda x: '%.3f' % x) #convert scientific notation
```

In [3]:

```
headers = ['Date','Time','Epoch','Mote','Temp','Humidity','Light','Voltage']
data = pd.read_csv('./data.csv', sep=' ', header=None, names=headers,
                    parse_dates=True)

print('Count of missing values:')
print(data.isnull().sum())
data.describe(include='all')
```

```
Count of missing values:
Date            0
Time            0
Epoch           0
Mote          526
Temp          901
Humidity      902
Light       93878
Voltage       526
dtype: int64
```

Out[3]:

	Date	Time	Epoch	Mote	Temp	Humidity	L
count	2313682	2313682	2313682.000	2313156.000	2312781.000	2312780.000	2219804
unique	38	2313649	nan	nan	nan	nan	
top	2004-03-08	02:33:10.775785	nan	nan	nan	nan	
freq	101208	2	nan	nan	nan	nan	
mean	NaN	NaN	33039.931	28.544	39.207	33.908	407
std	NaN	NaN	18368.524	50.624	37.419	17.322	539
min	NaN	NaN	0.000	1.000	-38.400	-8983.130	0
25%	NaN	NaN	17572.000	17.000	20.410	31.878	39
50%	NaN	NaN	33327.000	29.000	22.438	39.280	158
75%	NaN	NaN	47789.000	41.000	27.025	43.586	537
max	NaN	NaN	65535.000	65407.000	385.568	137.512	1847

After observing the minimum and maximum values of all variables, data is filtered based on given range of sensor readings

In [4]:

```
countRaw = data['Date'].count() #store number of rows in the original file

#Remove rows with Mote ID greater than 54
dataC = data[data.Mote < 55]

#Remove rows with temperature below 10 and above 35 degrees Celsius
dataC = dataC[dataC.Temp < 35]
dataC = dataC[dataC.Temp > 10]

#Humidity between 20% and 70%
dataC = dataC[dataC.Humidity > 20] #count=1396508
dataC = dataC[dataC.Humidity < 75] #count=1396508

#Light with Lux less than 100000
dataC = dataC[dataC.Light > 0] #count=1347379
dataC = dataC[dataC.Light < 100000] #count=1347379

#Voltage readings between 1.5V and 3.5V
dataC = dataC[dataC.Voltage > 1.5] #count=1347379
dataC = dataC[dataC.Voltage < 3.5] #count=1347379

count1 = dataC['Date'].count() #Store number of rows in cleansed data
loss1 = countRaw - count1
print("Data points lost after first cleanup: ", loss1)
print("Missing Values after cleanup:", '\n', dataC.isnull().sum())
```

```
Data points lost after first cleanup:  528198
Missing Values after cleanup:
 Date        0
Time        0
Epoch       0
Mote        0
Temp        0
Humidity    0
Light       0
Voltage     0
dtype: int64
```

In [5]:

```
DateC = dataC['Date'].unique() #storing date values from cleansed data

DateOG = data['Date'].unique() #storing date values from Raw file

U_MoteNew = dataC['Mote'].unique() #Storing Mote IDs from cleansed data

U_MoteOld = data['Mote'].unique() #Storing Mote IDs from Raw file


set(DateOG) - set(DateC)
```

Out[5]:

```
{'2004-03-26',
 '2004-03-27',
 '2004-03-28',
 '2004-03-29',
 '2004-03-30',
 '2004-03-31',
 '2004-04-03',
 '2004-04-04',
 '2004-04-05'}
```

The above dates have missing values for sensor readings.

In [6]:

```
set(U_MoteOld) - set(U_MoteNew)
```

Out[6]:

```
{nan, 5.0, 28.0, 55.0, 56.0, 57.0, 58.0, 6485.0, 33117.0, 65407.0}
```

Mote 5 and Mote 28 have been eliminated after cleansing. We investigate data from these Motes.

In [7]:

```
data5 = data[data.Mote == 5]
data28 = data[data.Mote == 28]

data5.head()
#Values missing for Light, Temperature and Humidity
```

Out[7]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage
180389	2004-02-28	02:21:16.59372	167	5.000	nan	nan	nan	2.700
180390	2004-02-28	03:42:46.678899	330	5.000	nan	nan	nan	2.675
180391	2004-02-28	05:20:16.549645	525	5.000	nan	nan	nan	2.651
180392	2004-02-28	09:32:47.471012	1030	5.000	nan	nan	nan	2.651
180393	2004-02-28	13:05:48.430632	1456	5.000	nan	nan	nan	2.687

In [8]:

```
data5.tail()
```

Out[8]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage
180419	2004-03-02	22:48:56.59882	11262	5.000	nan	nan	nan	2.276
180420	2004-03-03	02:02:26.487083	11649	5.000	nan	nan	nan	2.250
180421	2004-03-03	04:53:29.437907	11991	5.000	nan	nan	nan	2.216
180422	2004-03-03	06:52:58.11797	12230	5.000	nan	nan	nan	2.200
180423	2004-03-03	17:10:56.993959	13466	5.000	nan	nan	nan	2.168

In [9]:

```
#Checking values above and below Mote_Id Nans
data.iloc[180385:180391]
```

Out[9]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage
180385	2004-03-21	19:01:56.585115	65527	4.000	85.305	46.230	5.520	2.302
180386	2004-03-21	19:02:26.792489	65528	4.000	87.383	45.440	5.520	2.311
180387	2004-03-21	19:04:09.330906	65531	4.000	87.314	45.176	5.520	2.311
180388	2004-03-21	19:05:07.402885	65533	4.000	89.147	45.176	5.060	2.311
180389	2004-02-28	02:21:16.59372	167	5.000	nan	nan	nan	2.700
180390	2004-02-28	03:42:46.678899	330	5.000	nan	nan	nan	2.675

In [10]:

```
data.iloc[180421:180426]
```

Out[10]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage
180421	2004-03-03	04:53:29.437907	11991	5.000	nan	nan	nan	2.216
180422	2004-03-03	06:52:58.11797	12230	5.000	nan	nan	nan	2.200
180423	2004-03-03	17:10:56.993959	13466	5.000	nan	nan	nan	2.168
180424	2004-02-28	00:58:46.657464	2	6.000	20.420	36.612	121.440	2.651
180425	2004-02-28	01:00:46.525723	6	6.000	19.900	37.574	121.440	2.640

No Nans found under column Mote_Id around Mote 5

In [11]:

```
data28.head(5)
data28.tail(5)
#Values missing for Light
```

Out[11]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage
1125087	2004-03-21	19:01:06.65973	65525	28.000	20.018	49.549	nan	2.464
1125088	2004-03-21	19:01:55.92762	65527	28.000	20.008	49.581	nan	2.464
1125089	2004-03-21	19:03:56.19482	65531	28.000	19.988	49.614	nan	2.464
1125090	2004-03-21	19:04:55.269209	65533	28.000	19.988	49.614	nan	2.464
1125091	2004-03-21	19:05:26.077055	65534	28.000	19.979	49.646	nan	2.464

Motes 5 and 28 are very much present with incomplete readings. We now locate rows where Mote id is missing

In [12]:

```
nan_rows = data[data['Mote'].isnull()]
nan_rows.head()
```

Out[12]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage
2313156	2004-02-28	00:58:15.315133	1	nan	nan	nan	nan	nan
2313157	2004-03-31	18:37:46.785947	2	nan	nan	nan	nan	nan
2313158	2004-03-31	18:40:46.949392	3	nan	nan	nan	nan	nan
2313159	2004-03-31	18:43:46.657166	4	nan	nan	nan	nan	nan
2313160	2004-03-31	18:46:46.417537	5	nan	nan	nan	nan	nan

In [13]:

```
nan_rows.tail()
```

Out[13]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage
2313677	2004-04-02	01:14:54.164318	61274	nan	nan	nan	nan	nan
2313678	2004-04-02	01:17:53.670524	61275	nan	nan	nan	nan	nan
2313679	2004-04-02	01:20:52.807972	61276	nan	nan	nan	nan	nan
2313680	2004-04-02	01:26:53.950342	61278	nan	nan	nan	nan	nan
2313681	2004-04-02	01:35:53.897412	61280	nan	nan	nan	nan	nan

In [14]:

```
data.iloc[2313152:2313157]
```

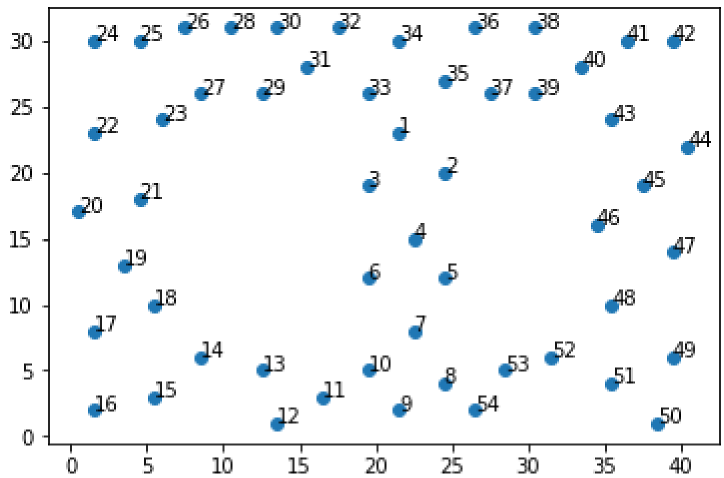
Out[14]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage
2313152	2004-04-02	09:09:22.206544	62427	58.000	24.104	21.437	1729.600	2.788
2313153	2004-03-23	21:32:16.223693	35112	6485.000	262.656	nan	nan	0.393
2313154	2004-03-09	15:04:42.202647	30493	33117.000	-36.205	nan	nan	0.145
2313155	2004-03-05	08:29:04.505813	18182	65407.000	294.251	nan	nan	0.013
2313156	2004-02-28	00:58:15.315133	1	nan	nan	nan	nan	nan

We can observe, the missing values for column Mote appear after Mote 54, which are irrelevant.

In [15]:

```
#Visualizing Mote locations to verify neighbors for Mote 5 and Mote 28
heads = ['Mote', 'X', 'Y']
m_coords = pd.read_csv('./Mote_coords.csv', header=None, names=heads)

x = m_coords.iloc[:,]['X']
y = m_coords.iloc[:,]['Y']
m = m_coords.iloc[:,]['Mote']

fig, ax = plt.subplots()
ax.scatter(x,y)
for i, txt in enumerate(m):
    ax.annotate(txt, (x[i], y[i]))
#We can verify that Mote 5 is closest to Mote 4, and Mote 28 closest to Mote 26
#Therefore missing values can be imputed with medians
```



In [16]:

```
medG = data.groupby('Mote')[['Light']].median()
#Find median Light for all motes
#medG.iloc[3]['G']

data.loc[data['Mote'] == 28, "Light"] = medG.iloc[25]['Light']
#Replace for mote 28 with Light median for mote 26 as they are close
#this makes mote 28 have all the columns filled, hence no need to drop mote 28

#Although Mote 4 is closly placed to Mote 5, readings for humidity, temperature cannot be
#substituted as there can be considerable differences. Also missing out values from Mote 5
#dropping 35 rows of information, which does not have a considerable impact on 300000+ rows
```

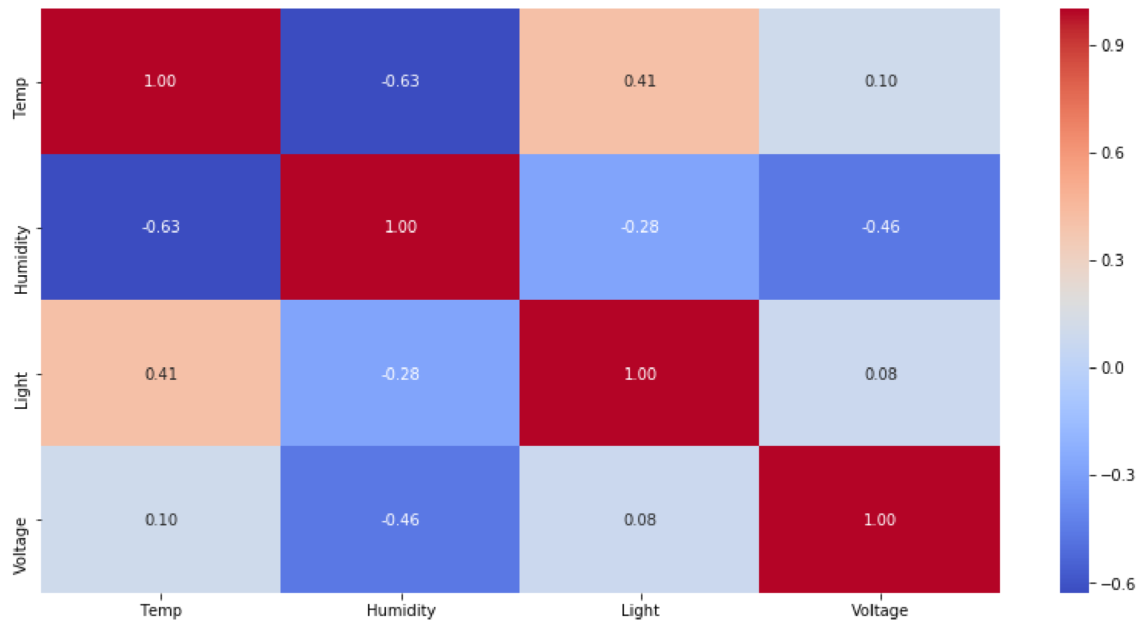
In [17]:

```
#Second Cleanup after including Mote 28:
dataC = data[data.Mote < 55]
dataC['Date'].count() #

dataC = dataC[dataC.Temp < 35]
dataC = dataC[dataC.Temp > 10]

dataC = dataC[dataC.Humidity > 20]
dataC = dataC[dataC.Humidity < 75]

dataC = dataC[dataC.Light > 0]
dataC = dataC[dataC.Light < 100000]

dataC = dataC[dataC.Voltage > 1.5]
dataC = dataC[dataC.Voltage < 3.5]


print("Missing values after second cleanup: ",'\n',  dataC.isnull().sum())
#check for missing values

count2 = dataC['Date'].count()
loss2 = countRaw - count2
print("Data points lost after second cleanup : ", loss2)
print("Data points retained after second cleanup: ", loss1 - loss2)
```

```
Missing values after second cleanup: 
 Date        0
Time        0
Epoch       0
Mote        0
Temp        0
Humidity    0
Light       0
Voltage     0
dtype: int64
Data points lost after second cleanup :  490016
Data points retained after second cleanup:  38182
```

In [18]:

```
#Observe correlations amongst variables:
plt.figure(figsize=(14,7))
sns.heatmap(data=dataC.iloc[:,4:].corr(),annot=True,fmt='.2f',cmap='coolwarm')
plt.show()
```



Humidity is negatively correlated with Voltage, Temperature Temperature is positively correlated with Light

In [19]:

```
#Convert date and time to epoch time, could be used to easily sort data for time-series ana
dataC['period'] = dataC['Date'].map(str) + ' ' + dataC['Time']
dataC['period'] = dataC['period'].str[:19]
dataC['period'] = pd.to_datetime(dataC['period'])
dataC['EpochTime'] = (dataC['period'] - dt.datetime(1970,1,1)).dt.total_seconds()
```

In [20]:

```
dataC.head()
```

Out[20]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage	period	Epocl
1	2004-02-28	00:59:16.02785	3	1.000	19.988	37.093	45.080	2.700	2004-02-28 00:59:16	107792995
2	2004-02-28	01:03:16.33393	11	1.000	19.302	38.463	45.080	2.687	2004-02-28 01:03:16	10779301[illegible]
3	2004-02-28	01:06:16.013453	17	1.000	19.165	38.804	45.080	2.687	2004-02-28 01:06:16	107793037
4	2004-02-28	01:06:46.778088	18	1.000	19.175	38.838	45.080	2.700	2004-02-28 01:06:46	10779304[illegible]
5	2004-02-28	01:08:45.992524	22	1.000	19.146	38.940	45.080	2.687	2004-02-28 01:08:45	10779305[illegible]

In [21]:

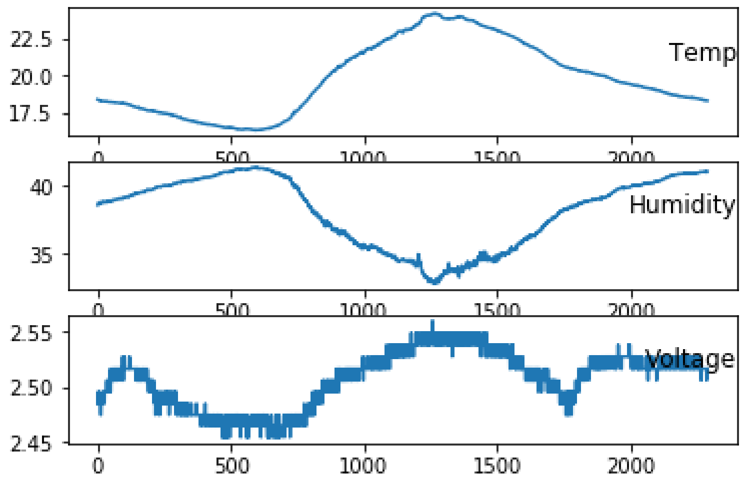
```
#We can check for each desired Mote reading as per given date or between/before/after dates
M_46 = dataC[(dataC.Date == '2004-02-28') & (dataC.Mote == 46)]
M_46.head()
```

Out[21]:

	Date	Time	Epoch	Mote	Temp	Humidity	Light	Voltage	period	
1938258	2004-02-28	01:06:46.232475	18	46.000	18.391	38.599	114.080	2.485	2004-02-28 01:06:46	1
1938259	2004-02-28	01:07:16.327646	19	46.000	18.381	38.667	114.080	2.495	2004-02-28 01:07:16	1
1938260	2004-02-28	01:07:46.088858	20	46.000	18.362	38.667	114.080	2.495	2004-02-28 01:07:46	1
1938261	2004-02-28	01:08:16.813675	21	46.000	18.342	38.736	114.080	2.485	2004-02-28 01:08:16	1
1938262	2004-02-28	01:08:46.125095	22	46.000	18.342	38.736	114.080	2.485	2004-02-28 01:08:46	1

In [22]:

```
#We can check for each desired Mote reading as per given date or between/before/after dates
values = M_46.values
# specify columns to plot
groups = [4, 5, 7]
i = 1
# plot each column
plt.figure()
for g in groups:
    plt.subplot(len(groups), 1, i)
    plt.plot(values[:, g])
    plt.title(M_46.columns[g], y=0.5, loc='right')
    i += 1
plt.show()
```



As per the correlations obtained, we can verify the behavior of these variables with respect to each other. High negative correlation gives almost opposite graphs for Temperature and Humidity.

In [23]:

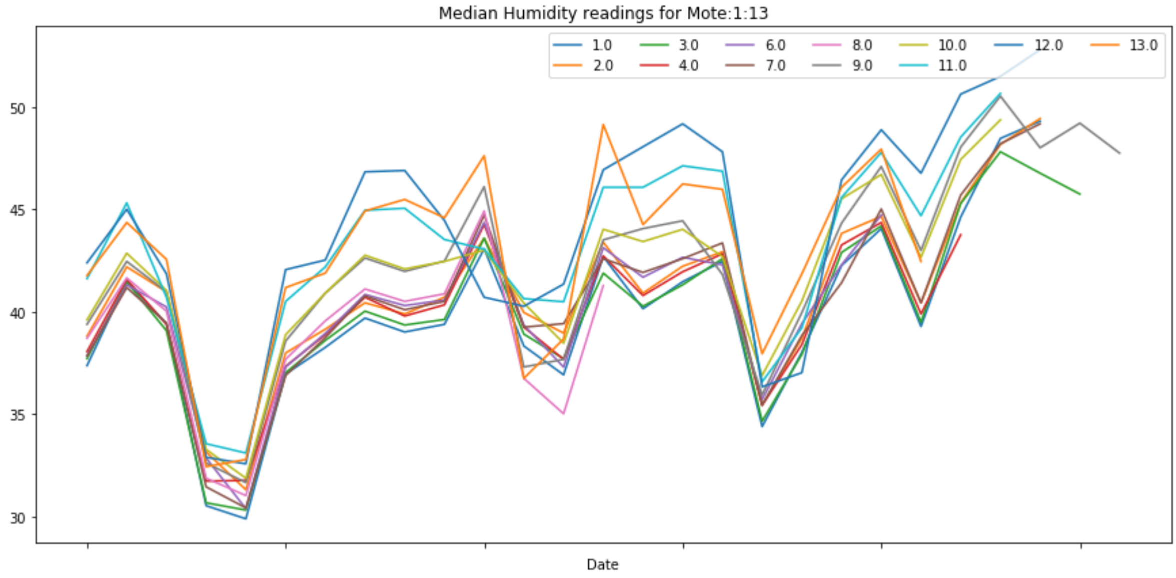
```
#Slicing dataframes by number of Motes, roughly 13 each
Mote13 = dataC[dataC.Mote < 14]
Mote26 = dataC[(dataC.Mote > 13) & (dataC.Mote < 27)]
Mote39 = dataC[(dataC.Mote > 26) & (dataC.Mote < 37)]
Mote54 = dataC[dataC.Mote > 36]
```

In [50]:

```
def plot_figs(dataC, a,b, column):
    fig, ax = plt.subplots(figsize=(15,7))
    plot_title ='Median ' + column + ' readings for Mote:' + str(a + 1)+':'+str(b - 1)
    mote_temp = dataC[(dataC.Mote > a) & (dataC.Mote < b)]
    mote_temp.groupby(['Date','Mote']).median()[column].unstack().plot(ax=ax)
    plt.legend((mote_temp['Mote'].unique()), loc='upper right', ncol = 7)
    plt.title(plot_title)
```

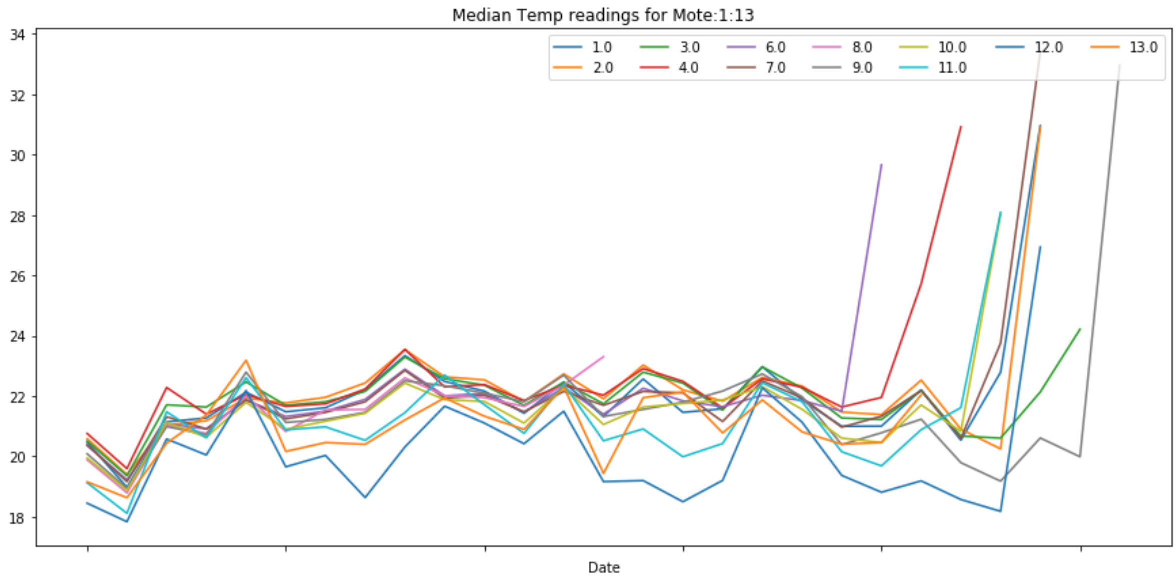
In [51]:

```
plot_figs(dataC, 0,14, 'Humidity')
```



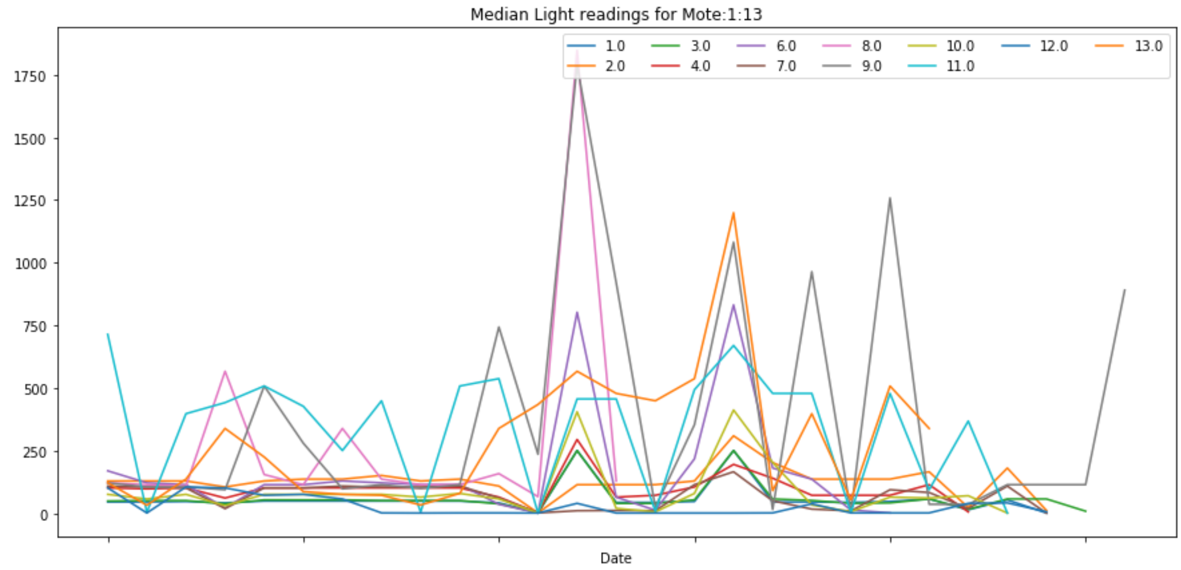
In [52]:

```
plot_figs(dataC, 0,14, 'Temp')
```



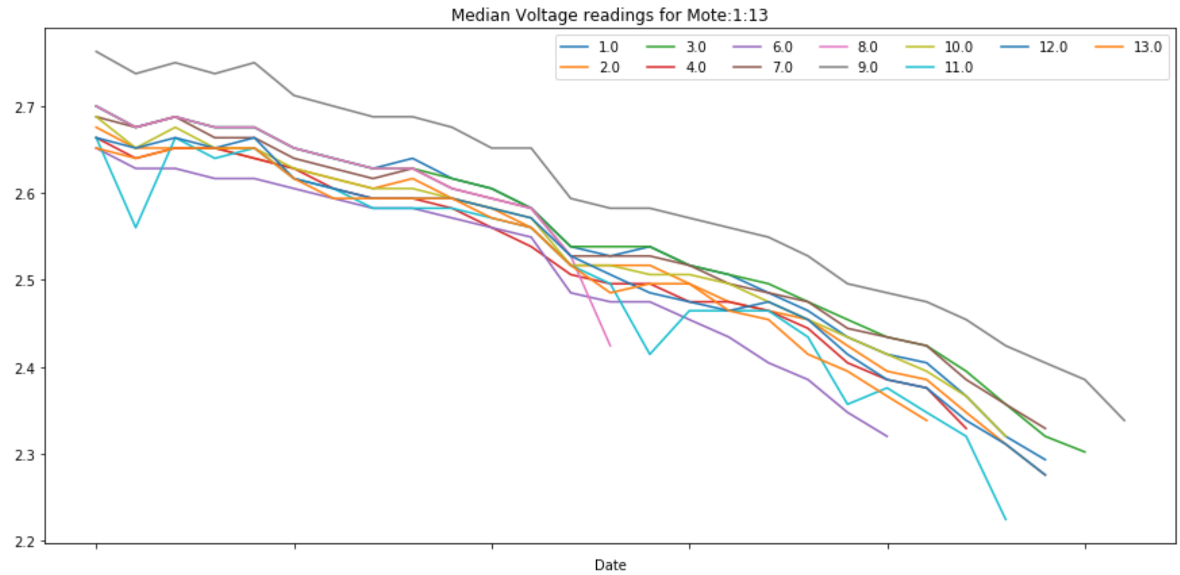
In [53]:

```
plot_figs(dataC, 0,14, 'Light')
```



In [54]:

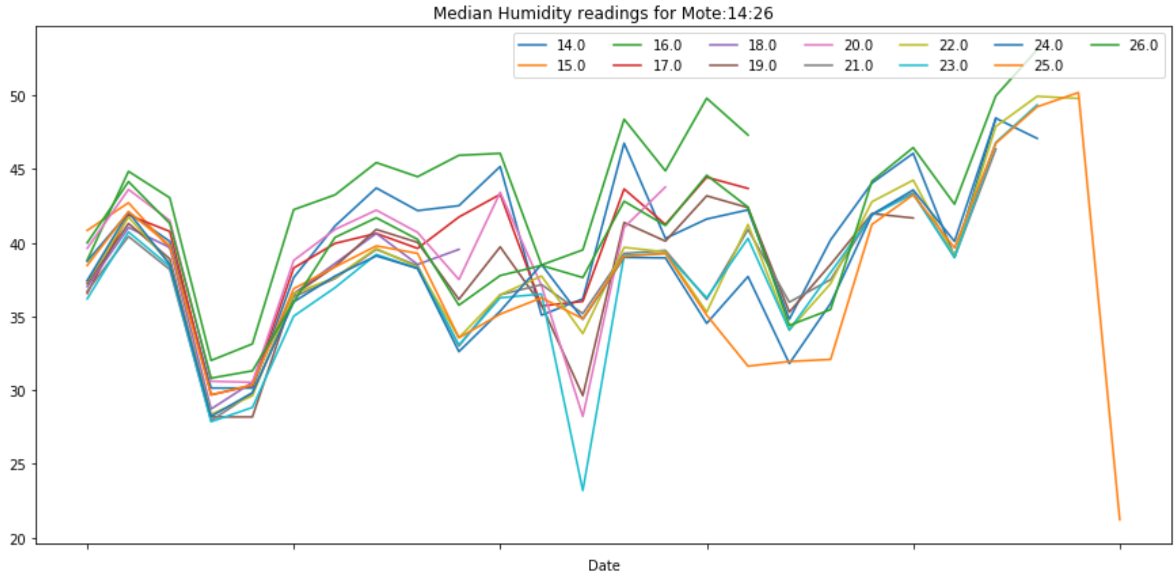
```
plot_figs(dataC, 0,14, 'Voltage')
```



Median readings of Humidity, Temperature, Voltage, Light: Mote 14 - 26

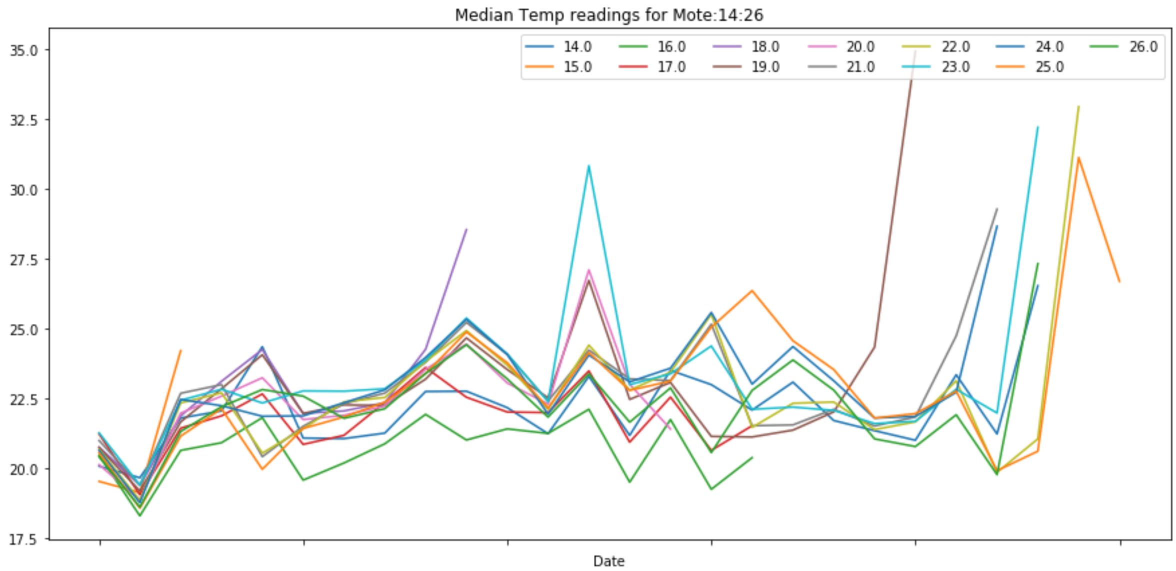
In [55]:

```
plot_figs(dataC, 13,27, 'Humidity')
```



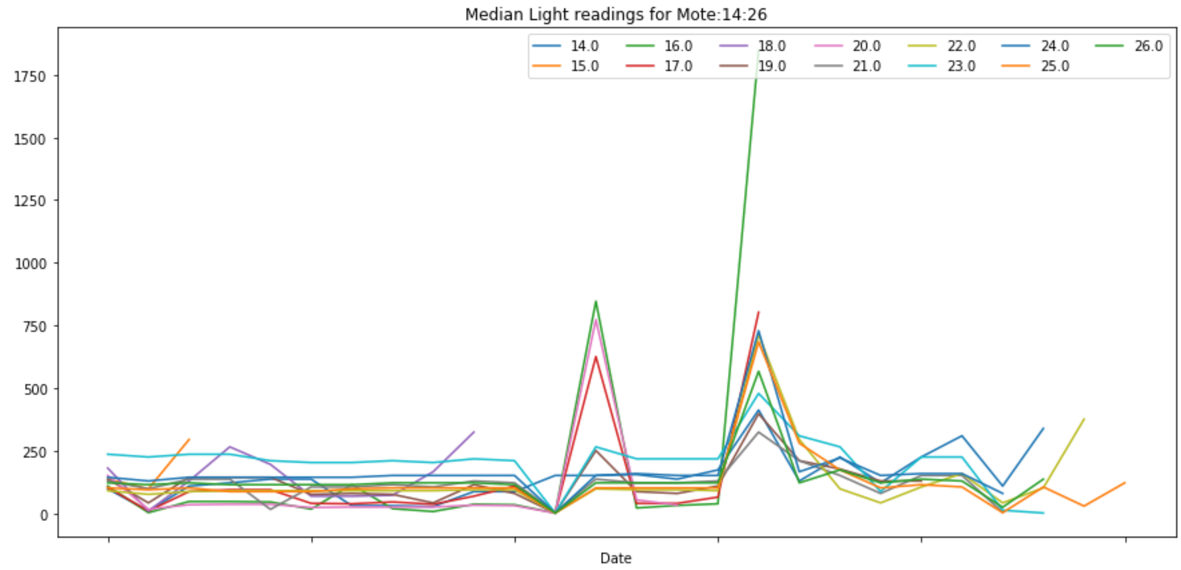
In [56]:

```
plot_figs(dataC, 13,27, 'Temp')
```



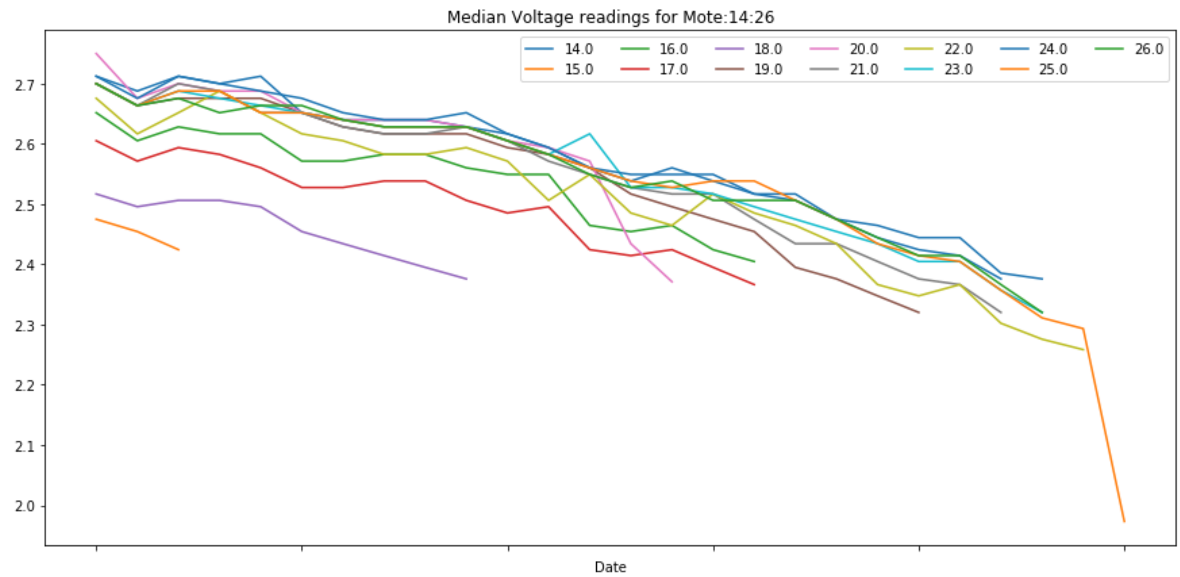
In [57]:

```
plot_figs(dataC, 13,27, 'Light')
```



In [58]:

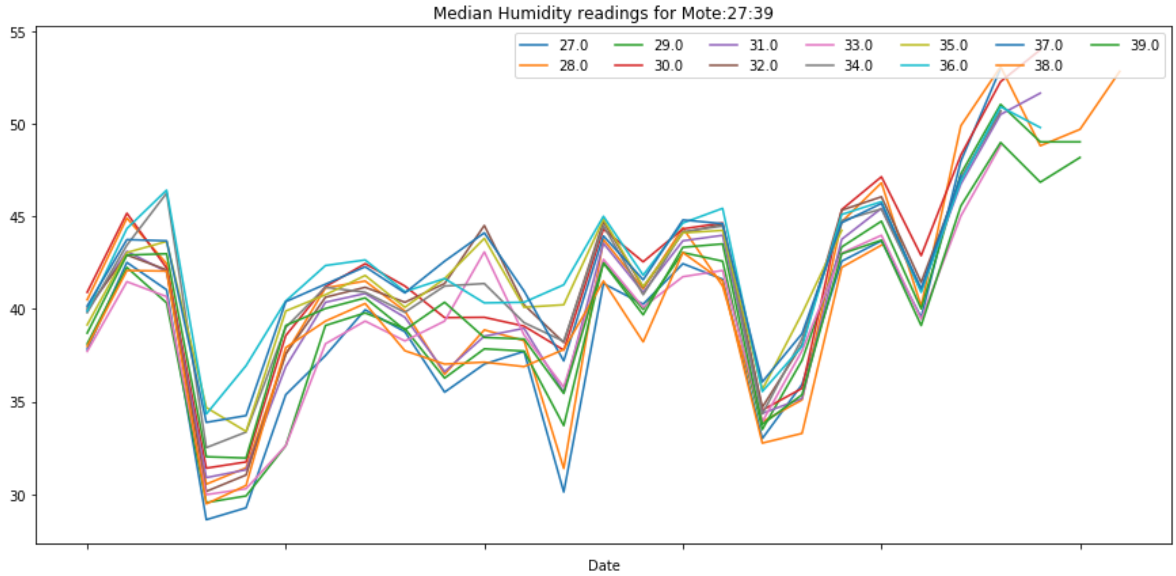
```
plot_figs(dataC, 13,27, 'Voltage')
```



Median readings of Humidity, Temperature, Voltage, Light: Mote 27-39

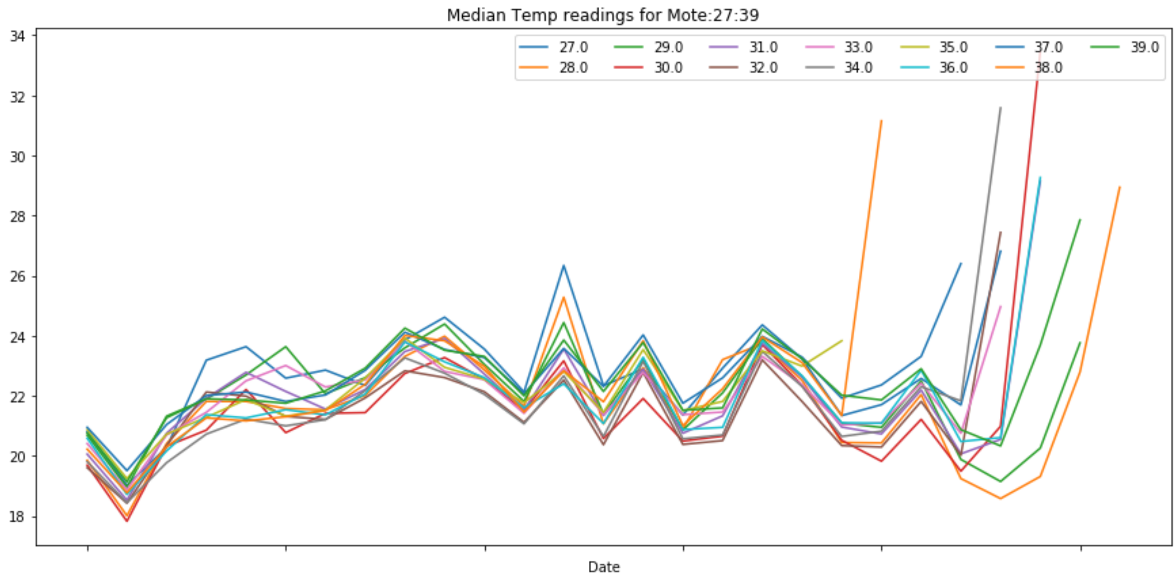
In [59]:

```
plot_figs(dataC, 26,40, 'Humidity')
```



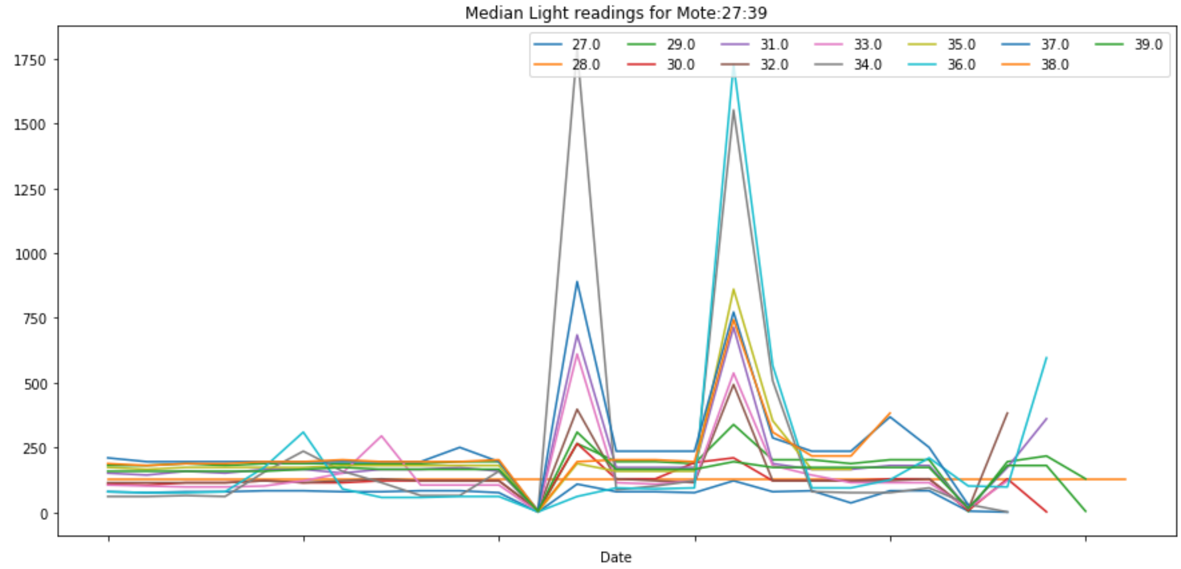
In [60]:

```
plot_figs(dataC, 26,40, 'Temp')
```



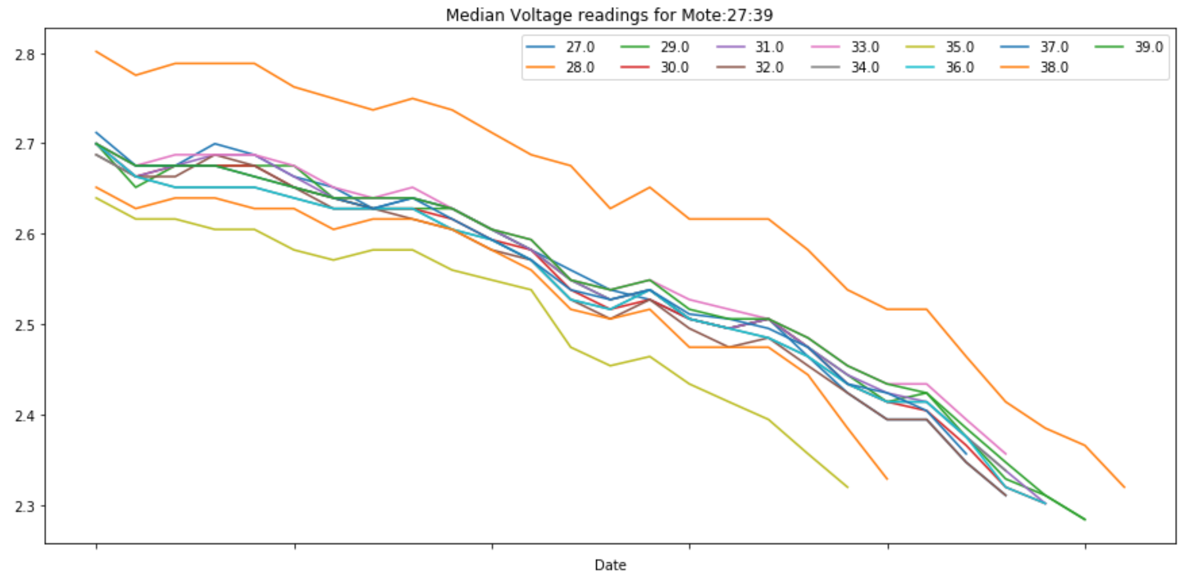
In [61]:

```
plot_figs(dataC, 26,40, 'Light')
```



In [62]:

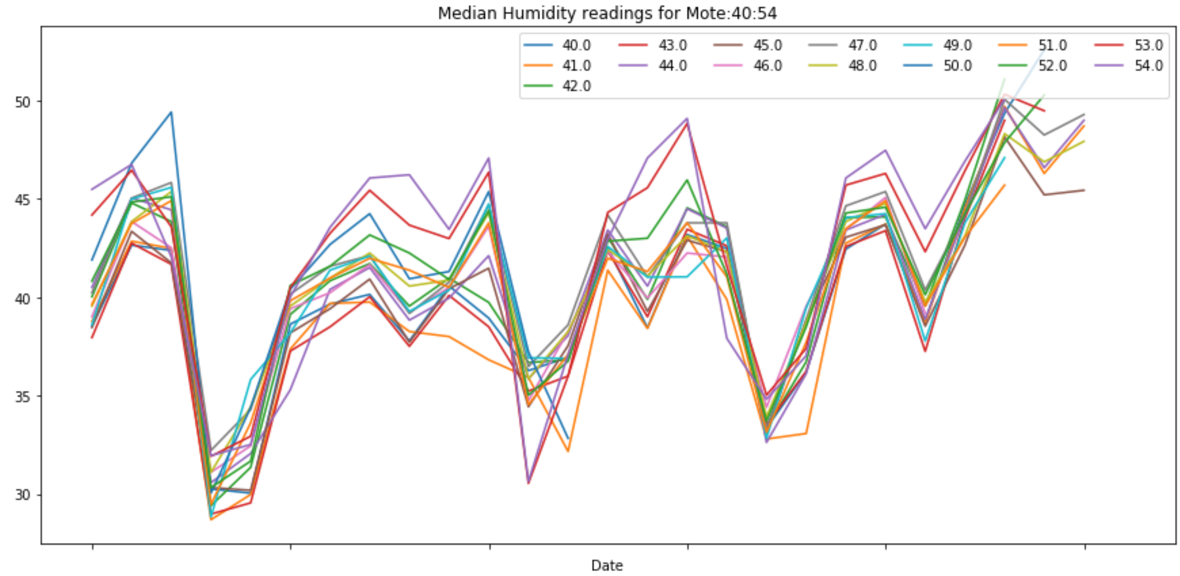
```
plot_figs(dataC, 26,40, 'Voltage')
```



Median readings of Humidity, Temperature, Voltage, Light: Mote 40 - 54

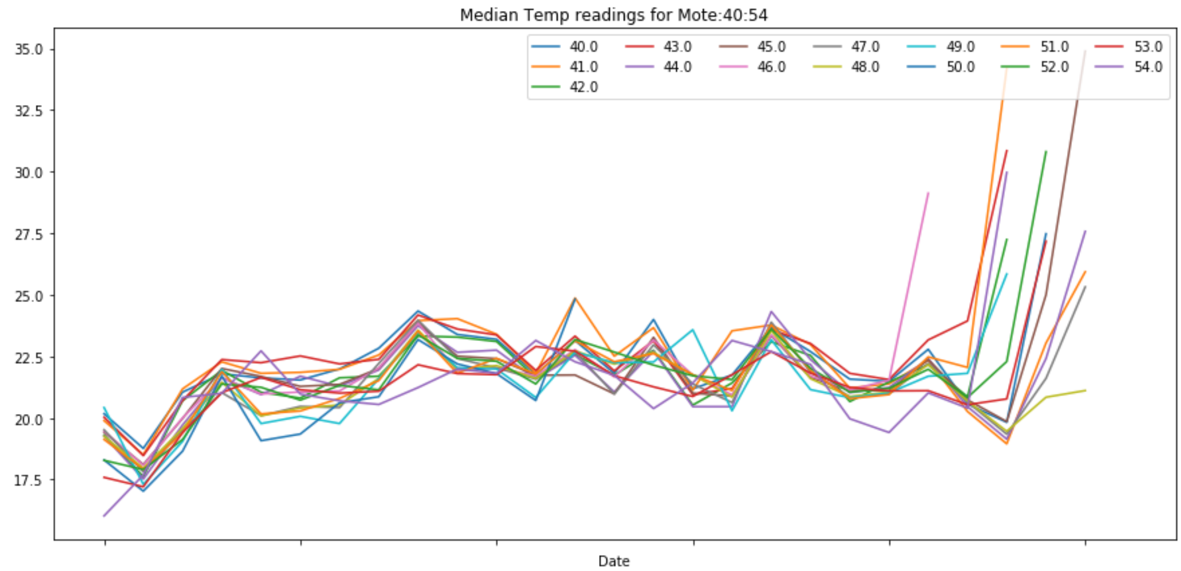
In [63]:

```
plot_figs(dataC, 39,55, 'Humidity')
```



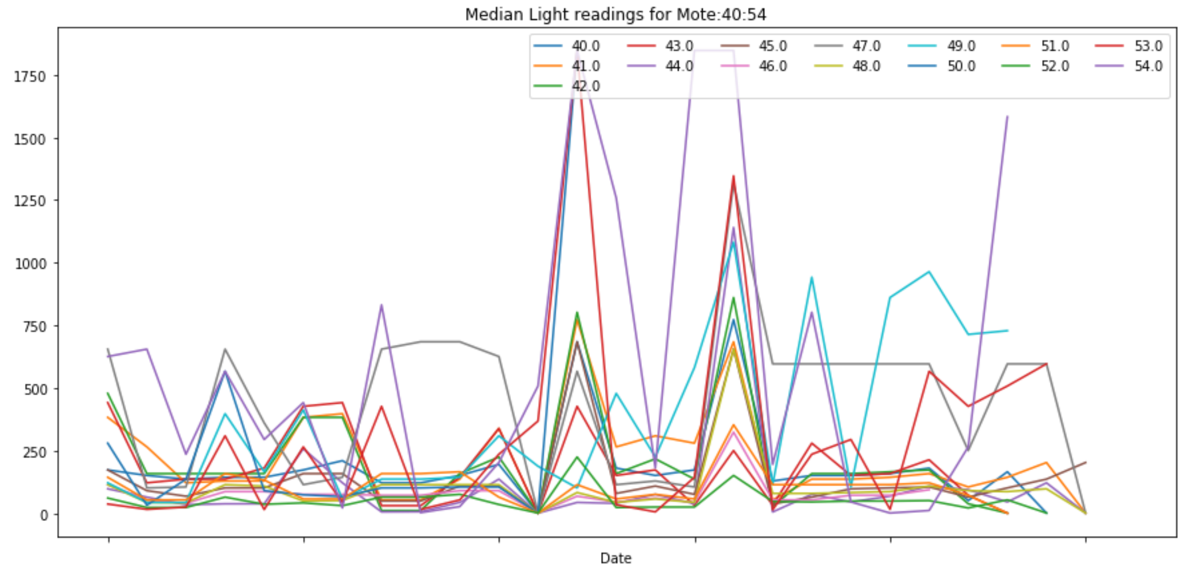
In [64]:

```
plot_figs(dataC, 39,55, 'Temp')
```



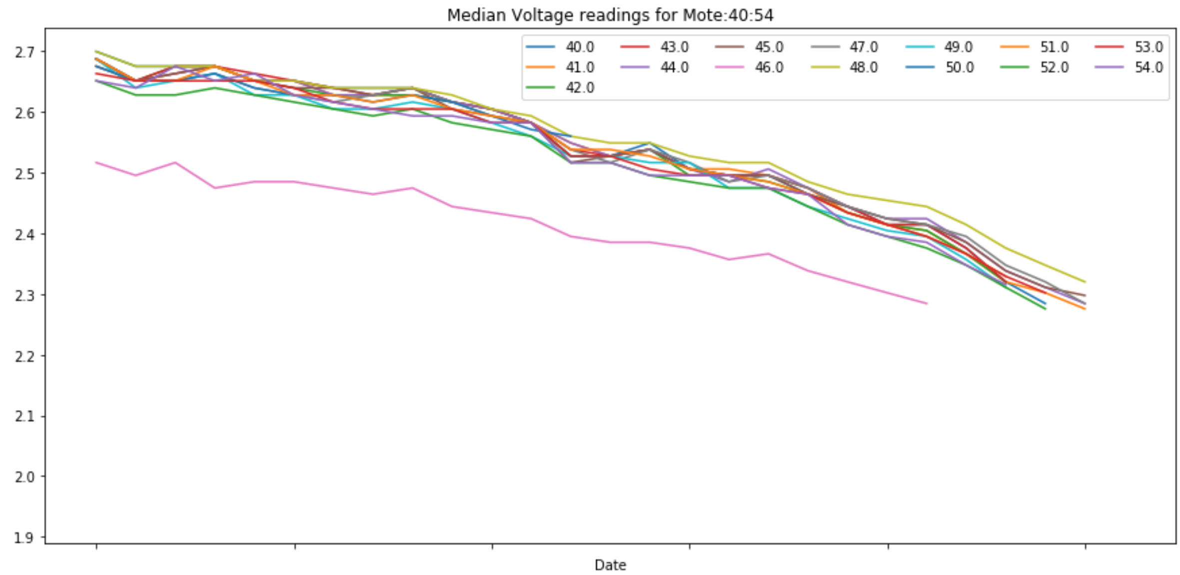
In [65]:

```
plot_figs(dataC, 39,55, 'Light')
```



In [66]:

```
plot_figs(dataC, 39,55, 'Voltage')
```




```
Key Insights:

    Battery life for majority of Motes was about than 15-20 days. The spikes could be
faulty readings due to malfunction
    caused by battery wear-out.

    For almost every Mote which was functioning till March 20 - March 25, we saw
drastically increased temperature readings,
    after which, we had no relevant readings.
    This verifies an earlier observation regarding missing values heavily obtained for
dates after March 25.

    Similar temperature and light spikes were observed across many Motes for March 15.
```

```
    Motes 15 and 18 lost power very early compared to others, the visualized locations prove high proximity suggesting common
    reason for their breakdown. Both experienced high temperatures as well as received higher amounts of Light
    just before they ceased to work.

    Motes located at the left end of the room towards the top left corner (Motes 14-26), is the only group having many motes
    malfunctioning within the first 18 days. The sudden changes in temperature and humidity might indicate reasons for
    their breakdown around March 15.
```