In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn as skl
import statsmodels.formula.api as smf
#from stargazer.stargazer import Stargazer
```

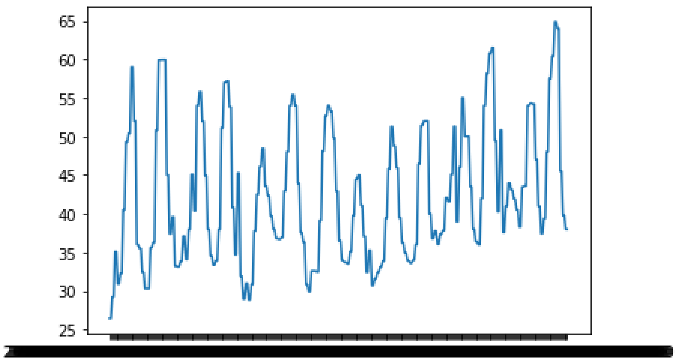
In [2]:
```
epex = pd.read_csv('epex_day_ahead_price.csv')
```

In [3]:
```
epex.head()
```

Out[3]:

	timestamp	apx_da_hourly
0	2019-03-31 23:00:00+00:00	26.43
1	2019-03-31 23:30:00+00:00	26.43
2	2019-04-01 00:00:00+00:00	29.24
3	2019-04-01 00:30:00+00:00	29.24
4	2019-04-01 01:00:00+00:00	35.10

In [4]:
```
# price over a couple of days in 2019
plt.plot(epex.head(48*7)['timestamp'], epex.head(48*7)['apx_da_hourly'])
plt.show()
```



In [5]:
```
# data cleaning - changing timestamp to y, m, d, h, m, s
epex[['date','time']] = epex['timestamp'].str.split(' ', expand=True)
epex[['time','z']] = epex['time'].str.split('+', expand=True)
epex[['h','m', 's']] = epex['time'].str.split(':', expand=True)
epex[['y','mth', 'd']] = epex['date'].str.split('-', expand=True)
epex.drop(['timestamp', 'date', 'time', 'z', 's'], axis=1, inplace=True)
epex
```

0	26.43	23	00	2019	03	31
1	26.43	23	30	2019	03	31
2	29.24	00	00	2019	04	01
3	29.24	00	30	2019	04	01
4	35.10	01	00	2019	04	01
...	...	...	...	...	...	...
47853	315.00	21	30	2021	12	22
47854	276.85	22	00	2021	12	22
47855	276.85	22	30	2021	12	22
47856	325.40	23	00	2021	12	22
47857	325.40	23	30	2021	12	22

47858 rows × 6 columns

In [6]:
```
# drop duplicate prices every 30 mins
epex = epex.drop(epex[epex.m == '30'].index)
epex.drop('m', axis=1, inplace=True)
epex
```

Out[6]:

	apx_da_hourly	h	y	mth	d
0	26.43	23	2019	03	31
2	29.24	00	2019	04	01
4	35.10	01	2019	04	01
6	30.91	02	2019	04	01
8	32.26	03	2019	04	01
...	...	...	...	...	...
47848	360.60	19	2021	12	22
47850	318.40	20	2021	12	22
47852	315.00	21	2021	12	22
47854	276.85	22	2021	12	22
47856	325.40	23	2021	12	22

In [7]:
```
#seasonality: we split year in four seasons:
#spring: MAR-APR-MAI, summer: JUN-JUL-AUG, automn: SEP-OKT-NOV, winter: DEC-JAN-FEB
epex_yr = list()
epex_spr = epex
epex_spr =  epex_spr.drop(epex_spr[epex_spr.mth == '01'].index)
epex_spr =  epex_spr.drop(epex_spr[epex_spr.mth == '02'].index)
epex_spr =  epex_spr.drop(epex_spr[epex_spr.mth == '06'].index)
epex_spr =  epex_spr.drop(epex_spr[epex_spr.mth == '07'].index)
epex_spr =  epex_spr.drop(epex_spr[epex_spr.mth == '08'].index)
epex_spr =  epex_spr.drop(epex_spr[epex_spr.mth == '09'].index)
epex_spr =  epex_spr.drop(epex_spr[epex_spr.mth == '10'].index)
epex_spr =  epex_spr.drop(epex_spr[epex_spr.mth == '11'].index)
epex_spr =  epex_spr.drop(epex_spr[epex_spr.mth == '12'].index)

# calculates spring average price
expec_yr.append(epex_spr['apx_da_hourly'].mean())
```

Out[7]: 44.81351300799187

In [8]:
```
#summer
epex_sum = epex

epex_sum =  epex_sum.drop(epex_sum[epex_sum.mth == '01'].index)
epex_sum =  epex_sum.drop(epex_sum[epex_sum.mth == '02'].index)
epex_sum =  epex_sum.drop(epex_sum[epex_sum.mth == '03'].index)
epex_sum =  epex_sum.drop(epex_sum[epex_sum.mth == '04'].index)
epex_sum =  epex_sum.drop(epex_sum[epex_sum.mth == '05'].index)
epex_sum =  epex_sum.drop(epex_sum[epex_sum.mth == '09'].index)
epex_sum =  epex_sum.drop(epex_sum[epex_sum.mth == '10'].index)
epex_sum =  epex_sum.drop(epex_sum[epex_sum.mth == '11'].index)
epex_sum =  epex_sum.drop(epex_sum[epex_sum.mth == '12'].index)

# calculates summer average price
expec_yr.append(epex_sum['apx_da_hourly'].mean())
```

Out[8]: 54.26209692028977

In [9]:
```
#automn
epex_aut = epex

epex_aut =  epex_aut.drop(epex_aut[epex_aut.mth == '01'].index)
epex_aut =  epex_aut.drop(epex_aut[epex_aut.mth == '02'].index)
epex_aut =  epex_aut.drop(epex_aut[epex_aut.mth == '03'].index)
epex_aut =  epex_aut.drop(epex_aut[epex_aut.mth == '04'].index)
epex_aut =  epex_aut.drop(epex_aut[epex_aut.mth == '05'].index)
epex_aut =  epex_aut.drop(epex_aut[epex_aut.mth == '06'].index)
epex_aut =  epex_aut.drop(epex_aut[epex_aut.mth == '07'].index)
epex_aut =  epex_aut.drop(epex_aut[epex_aut.mth == '08'].index)
epex_aut =  epex_aut.drop(epex_aut[epex_aut.mth == '12'].index)

# calculates autumn average price
expec_yr.append(epex_aut['apx_da_hourly'].mean())
```

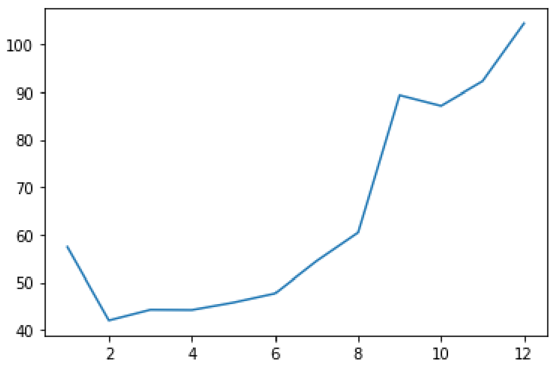
Out[9]: 89.5184065934067

In [34]:
```
#winter
epex_win = epex

epex_win =  epex_win.drop(epex_win[epex_win.mth == '03'].index)
epex_win =  epex_win.drop(epex_win[epex_win.mth == '04'].index)
epex_win =  epex_win.drop(epex_win[epex_win.mth == '05'].index)
epex_win =  epex_win.drop(epex_win[epex_win.mth == '06'].index)
epex_win =  epex_win.drop(epex_win[epex_win.mth == '07'].index)
epex_win =  epex_win.drop(epex_win[epex_win.mth == '08'].index)
epex_win =  epex_win.drop(epex_win[epex_win.mth == '09'].index)
epex_win =  epex_win.drop(epex_win[epex_win.mth == '10'].index)
epex_win =  epex_win.drop(epex_win[epex_win.mth == '11'].index)

# calculates winter average price
expec_yr.append(epex_win['apx_da_hourly'].mean())
plt.plot(['spring','summer','automn','winter'], epex_month_mean)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-34-a91ad0755a51> in <module>
     13 
     14 # calculates winter average price
---> 15 expec_yr.append(epex_win['apx_da_hourly'].mean())
     16 plt.plot(['spring','summer','automn','winter'], epex_month_mean)

NameError: name 'expec_yr' is not defined
```

In [11]:
```
#mean price per month
epex_month_mean = list()
month = [1,2,3,4,5,6,7,8,9,10,11,12]
epex_month_mean.append(epex[epex.mth=='01']['apx_da_hourly'].mean()) #jan
epex_month_mean.append(epex[epex.mth=='02']['apx_da_hourly'].mean()) #feb
epex_month_mean.append(epex[epex.mth=='03']['apx_da_hourly'].mean()) #mar
epex_month_mean.append(epex[epex.mth=='04']['apx_da_hourly'].mean()) #apr
epex_month_mean.append(epex[epex.mth=='05']['apx_da_hourly'].mean()) #mai
epex_month_mean.append(epex[epex.mth=='06']['apx_da_hourly'].mean()) #jun
epex_month_mean.append(epex[epex.mth=='07']['apx_da_hourly'].mean()) #jul
epex_month_mean.append(epex[epex.mth=='08']['apx_da_hourly'].mean()) #aug
epex_month_mean.append(epex[epex.mth=='09']['apx_da_hourly'].mean()) #sep
epex_month_mean.append(epex[epex.mth=='10']['apx_da_hourly'].mean()) #oct
epex_month_mean.append(epex[epex.mth=='11']['apx_da_hourly'].mean()) #nov
epex_month_mean.append(epex[epex.mth=='12']['apx_da_hourly'].mean()) #dec

epex_month_mean

plt.plot(month, epex_month_mean)
```

Out[11]: [<matplotlib.lines.Line2D at 0x127df0cd0>]

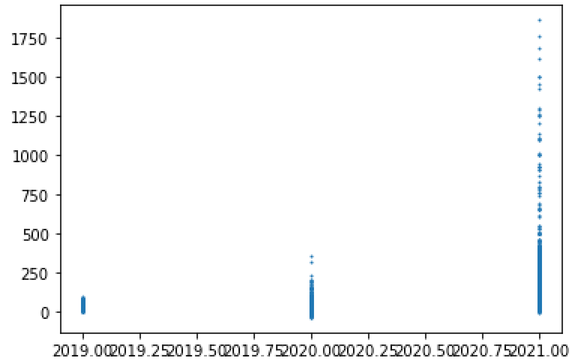


Here we clearly see that the average prices is much higher in the winter months than the other months. The low is in spring.

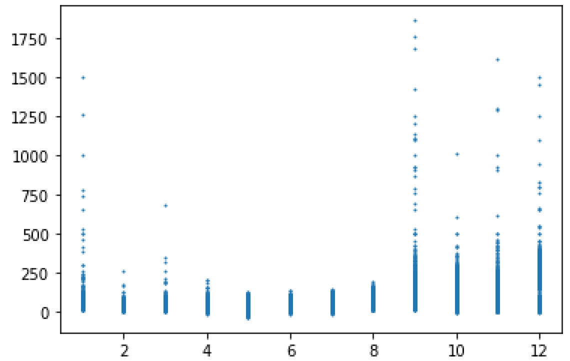
In [12]:
```
# changing data types to feed into model
epex['y'] = epex['y'].astype(int)
epex['mth'] = epex['mth'].astype(int)
epex['d'] = epex['d'].astype(int)
epex['h'] = epex['h'].astype(int)
epex.dtypes
```

Out[12]:
```
apx_da_hourly    float64
h                  int64
y                  int64
mth                int64
d                  int64
dtype: object
```

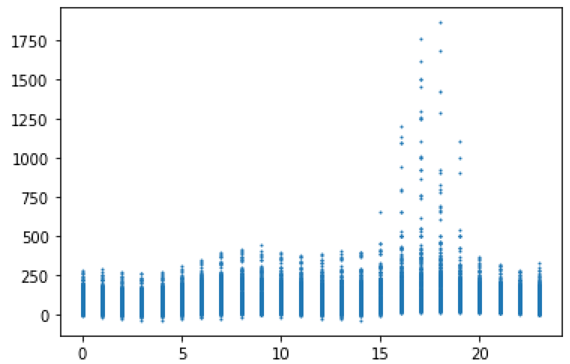
In [13]:
```
# prices per year
plt.scatter(epex['y'], epex['apx_da_hourly'], s=1)
#plt.figure(figsize=(100,100))
plt.show()
```



In [14]:
```
# prices per month
plt.scatter(epex['mth'], epex['apx_da_hourly'], s=1)
#plt.figure(figsize=(100,100))
plt.show()
```



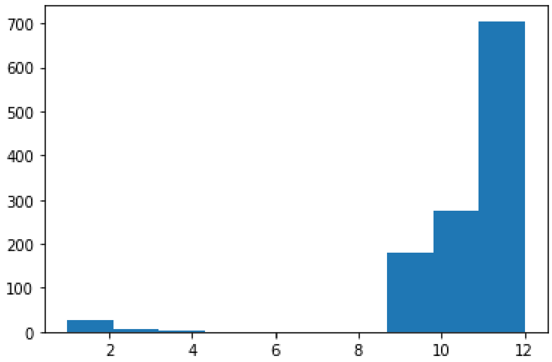
In [15]:
```
# prices per hour
plt.scatter(epex['h'], epex['apx_da_hourly'], s=1)
#plt.figure(figsize=(100,100))
plt.show()
```



We see that a lot of the extreme price jumps occur in the evening hours between 4pm and 8pm.

In [33]:
```
#extreme values - we look at 95% quartile
extr = []
epex.quantile([0.95]) #5% of values ar elarger than 187.4, these are considered as extreme value

for i in range(0,47856,2):
    if epex['apx_da_hourly'][i] >= 187.4:
        extr.append(epex['mth'][i])
#print(extr)
plt.hist(extr)
```

Out[33]:
```
(array([ 27.,   7.,   2.,   0.,   0.,   0.,   1., 181., 274., 705.]),
 array([ 1. ,  2.1,  3.2,  4.3,  5.4,  6.5,  7.6,  8.7,  9.8, 10.9, 12. ]),
 <BarContainer object of 10 artists>)
```



We investigated when the big price jumps occured. We notice that the big price jumps usually occur in the winter.

In [16]:
```
# initial regression model with all combinations of variables
epexm1 = smf.ols(formula = 'apx_da_hourly ~ y*mth^2 + y*mth + mth*d^2 + mth*d + d*h^2 + d*h', data=ep
print(epexm1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          apx_da_hourly   R-squared:                       0.399
Model:                            OLS   Adj. R-squared:                  0.399
Method:                 Least Squares   F-statistic:                     1224.
Date:                Sun, 13 Mar 2022   Prob (F-statistic):               0.00
Time:                        11:05:18   Log-Likelihood:            -1.3006e+05
No. Observations:               23929   AIC:                         2.601e+05
Df Residuals:                   23915   BIC:                         2.603e+05
Df Model:                          13
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   2.009e+04   2441.669      8.226      0.000    1.53e+04    2.49e+04
y             -9.9370      1.209     -8.222      0.000     -12.306      -7.568
mth ^ 2    -4161.4201    461.758     -9.012      0.000   -5066.495   -3256.345
y:mth ^ 2      2.0610      0.229      9.016      0.000       1.613       2.509
mth        -1.133e+04    528.359    -21.435      0.000   -1.24e+04   -1.03e+04
y:mth          5.6084      0.262     21.443      0.000       5.096       6.121
d ^ 2         -1.1599      0.417     -2.782      0.005      -1.977      -0.343
mth:d ^ 2      0.1372      0.055      2.508      0.012       0.030       0.244
d              0.9339      0.430      2.170      0.030       0.090       1.777
mth:d         -0.0904      0.056     -1.621      0.105      -0.200       0.019
h ^ 2          1.0077      0.371      2.719      0.007       0.281       1.734
d:h ^ 2       -0.0032      0.021     -0.154      0.878      -0.044       0.037
h              0.2356      0.371      0.636      0.525      -0.491       0.962
d:h           -0.0057      0.021     -0.275      0.783      -0.046       0.035
==============================================================================
Omnibus:                    41300.666   Durbin-Watson:                   0.350
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         64323949.415
Skew:                          11.950   Prob(JB):                         0.00
Kurtosis:                     255.871   Cond. No.                     1.51e+08
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.51e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [17]:
```
# forward stepwise regression to drop variables
epexm1 = smf.ols(formula = 'apx_da_hourly ~ y*mth^2 + y*mth + mth*d^2 + mth*d + h^2', data=epex).fit(
print(epexm1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          apx_da_hourly   R-squared:                       0.399
Model:                            OLS   Adj. R-squared:                  0.399
Method:                 Least Squares   F-statistic:                     1591.
Date:                Sun, 13 Mar 2022   Prob (F-statistic):               0.00
Time:                        11:05:18   Log-Likelihood:            -1.3006e+05
No. Observations:               23929   AIC:                         2.601e+05
Df Residuals:                   23918   BIC:                         2.602e+05
Df Model:                          10
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   2.009e+04   2441.662      8.226      0.000    1.53e+04    2.49e+04
y             -9.9365      1.209     -8.222      0.000     -12.305      -7.568
mth ^ 2    -4161.3161    461.757     -9.012      0.000   -5066.389   -3256.243
y:mth ^ 2      2.0609      0.229      9.016      0.000       1.613       2.509
mth        -1.133e+04    528.358    -21.435      0.000   -1.24e+04   -1.03e+04
y:mth          5.6084      0.262     21.443      0.000       5.096       6.121
d ^ 2         -1.1599      0.417     -2.781      0.005      -1.977      -0.343
mth:d ^ 2      0.1372      0.055      2.508      0.012       0.030       0.244
d              0.8319      0.425      1.958      0.050      -0.001       1.665
mth:d         -0.0904      0.056     -1.621      0.105      -0.200       0.019
h ^ 2          1.0986      0.052     21.194      0.000       0.997       1.200
==============================================================================
Omnibus:                    41298.696   Durbin-Watson:                   0.350
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         64297943.524
Skew:                          11.949   Prob(JB):                         0.00
Kurtosis:                     255.819   Cond. No.                     1.51e+08
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.51e+08. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [18]:
```
# adding interaction terms and square terms as columns to epex
epex['y^2'] = epex['y'] ** 2
epex['mth^2'] = epex['mth'] ** 2
epex['d^2'] = epex['d'] ** 2
epex['h^2'] = epex['h'] ** 2
epex['y:mth'] = epex['y'] * epex['mth']
epex['mth:d'] = epex['y'] * epex['mth']
epex['y:mth^2'] = (epex['y'] * epex['mth']) ** 2
epex['mth:d^2'] = (epex['mth'] * epex['d']) ** 2
epex['d:h^2'] = (epex['d'] * epex['h']) ** 2
epex
```

Out[18]:

	apx_da_hourly	h	y	mth	d	y^2	mth^2	d^2	h^2	y:mth	mth:d	y:mth^2	mth:d^2	d:h^2
0	26.43	23	2019	3	31	4076361	9	961	529	6057	6057	36687249	8649	508369
2	29.24	0	2019	4	1	4076361	16	1	0	8076	8076	65221776	16	0
4	35.10	1	2019	4	1	4076361	16	1	1	8076	8076	65221776	16	1
6	30.91	2	2019	4	1	4076361	16	1	4	8076	8076	65221776	16	4
8	32.26	3	2019	4	1	4076361	16	1	9	8076	8076	65221776	16	9
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
47848	360.60	19	2021	12	22	4084441	144	484	361	24252	24252	588159504	69696	174724
47850	318.40	20	2021	12	22	4084441	144	484	400	24252	24252	588159504	69696	193600
47852	315.00	21	2021	12	22	4084441	144	484	441	24252	24252	588159504	69696	213444
47854	276.85	22	2021	12	22	4084441	144	484	484	24252	24252	588159504	69696	234256
47856	325.40	23	2021	12	22	4084441	144	484	529	24252	24252	588159504	69696	256036

23929 rows × 14 columns

In [19]:
```
#80-20 splits of data training and test dataset
from sklearn.model_selection import train_test_split
X_columns = ['y', 'y:mth^2', 'y:mth', 'd^2', 'mth:d^2', 'd', 'mth:d', 'h^2']
X_train, X_test, y_train, y_test = train_test_split(epex[X_columns], epex['apx_da_hourly'], test_size
```

In [20]:
```
#trains model
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[20]:
```
LinearRegression()
```

In [21]:
```
# retrieves coefficient and intercept values for each regressor variable
Coeff = pd.DataFrame({
    'variable': X_train.columns,
    'coefficient': model.coef_,
    'intercept': model.intercept_
})
Coeff
```

Out[21]:

	variable	coefficient	intercept
0	y	4.534060e+01	-91580.338661
1	y:mth^2	1.136437e-07	-91580.338661
2	y:mth	4.715160e-04	-91580.338661
3	d^2	-4.596944e-02	-91580.338661
4	mth:d^2	-4.635079e-05	-91580.338661
5	d	1.509731e+00	-91580.338661
6	mth:d	4.715159e-04	-91580.338661
7	h^2	3.268667e-02	-91580.338661

In [22]:
```
#prints preview of price predictions made by linear regression model
y_pred = model.predict(X_test)
print(y_pred)
```

```
[ -5.45589106  66.21063328   7.38184886 ...  78.89490877  95.27157541
 167.67577233]
```

In [23]:
```
#calculates R value
model.score(X_test, y_test)
```

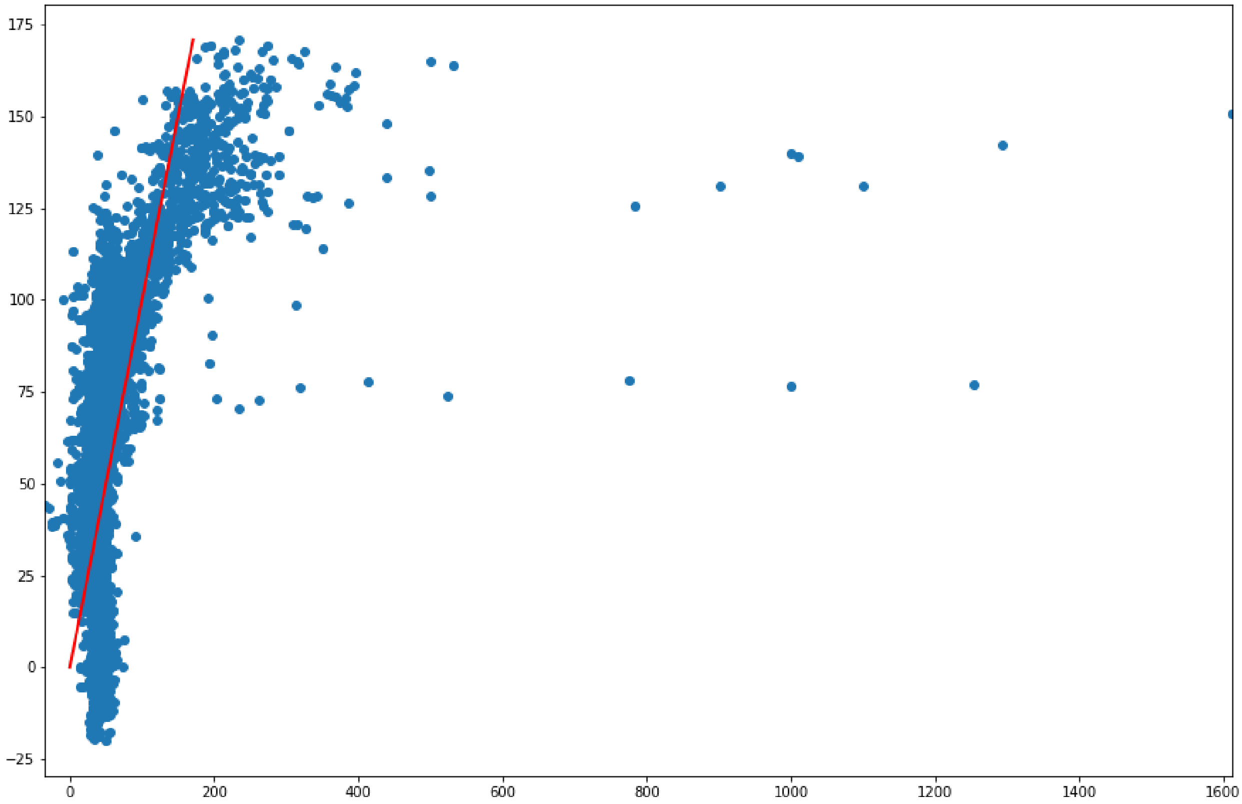
Out[23]:
```
0.31027258408485536
```

In [24]:
```
#calculates intercept of line of best fit
model.intercept_
```

Out[24]:
```
-91580.33866117799
```

In [25]:
```
#sets up plot
plt.figure(figsize=(15,10))
x = np.linspace(0, y_pred.max())
plt.margins(x=0)

#graphs the actual vs prediction
plt.scatter(y_test, y_pred)

#displays line of best fit using model.score and model.intercept
plt.plot(
    x + model.score(X_test, y_test),
    x,
    linewidth=2,
    markersize=12,
    color='r'
)
```

Out[25]: [<matplotlib.lines.Line2D at 0x12918c880>]



In [26]:
```
model.coef_
```

Out[26]:
```
array([ 4.53406000e+01,  1.13643701e-07,  4.71516034e-04, -4.59694377e-02,
       -4.63507912e-05,  1.50973063e+00,  4.71515917e-04,  3.26866734e-02])
```

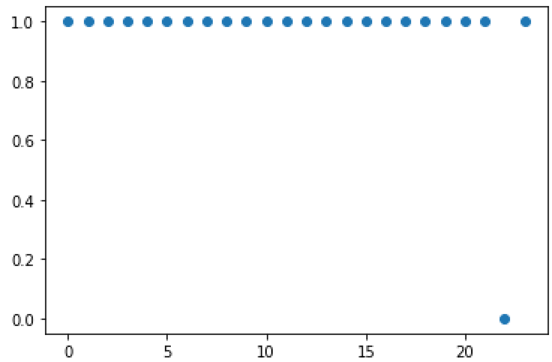
In [27]:
```
# Price prediction for 2022-03-13
date_y = 2022
date_m = 3
date_d = 13
beta_0 = model.coef_[0]*date_y + model.coef_[1]*((date_y*date_m)**2) + model.coef_[2]*(date_y*date_m)
```

In [28]:
```
# price prediction for each hour of the day using regression model apx_da_hourly = 120.887 + 0.0326h^
for i in range(0, 24):
    print(i, round(beta_0 + (model.coef_[-1] * i**2), 3))
```

```
0 125.069
1 125.102
2 125.2
3 125.363
4 125.592
5 125.886
6 126.246
7 126.671
8 127.161
9 127.717
10 128.338
11 129.024
12 129.776
13 130.593
14 131.475
15 132.423
16 133.437
17 134.515
18 135.659
19 136.869
20 138.144
21 139.484
22 140.889
23 142.36
```

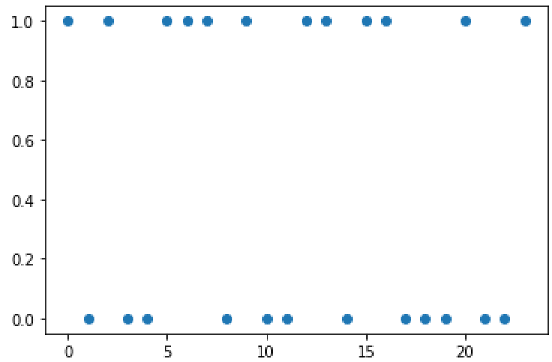
In [29]:
```
# (using AMPL for optimisation code) these are the buy/sell decisions at each hour.
# Using our model we buy at 11pm and sell the next day at 10pm.
hour = [23,0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22]
battery = [1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,0]
plt.scatter(hour, battery)
plt.show
```

Out[29]: `<function matplotlib.pyplot.show(close=None, block=None)>`



In [30]:
```
# Using the real prices on 13/03/2022 the model suggests to buy and sell at these times:
hour = [23,0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22]
battery = [1,1,0,1,0,0,1,1,1,0,1,0,0,1,1,0,1,1,0,0,0,1,0,0]
plt.scatter(hour, battery)
plt.show
```

Out[30]: `<function matplotlib.pyplot.show(close=None, block=None)>`



Thank you for reading.