Table of Contents

Read & interpret dataset

- Loading some datasets
- Preprocessing missing values and outliers on the datasets

In [1]:
```
# Import modules
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
import pathlib
import glob
import math
import statsmodels.api as sm
import matplotlib.dates as mdates
from matplotlib.dates import DateFormatter
import datetime

# Show all the rows and columns up to 200
pd.set_option('display.max_columns', 200)
pd.set_option('display.max_rows', 200)
```

In [2]:
```
all_data = pd.read_csv('/Users/kenotsu/Documents/master_thesis/Datasets/Master_thesis/all_data.csv', sep=',', header=0)
```

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

Out[3]:

	Date	HH	Open	High	Low	Close	Average	Volume(MWh/h)	Volume(Tick count)	Time	Syster
0	2016-04-01	1	7.69	7.69	7.69	7.69	7.69	0.70	1	00:00:00	
1	2016-04-01	2	7.45	7.45	7.45	7.45	7.45	0.75	0	00:30:00	
2	2016-04-01	3	7.21	7.21	7.21	7.21	7.21	0.80	1	01:00:00	
3	2016-04-01	4	7.06	7.06	7.06	7.06	7.06	0.80	1	01:30:00	
4	2016-04-01	5	7.21	7.21	7.21	7.21	7.21	0.80	1	02:00:00	

Feature Engineering

Moving average/VWAP

[Moving average only for System price]

In [4]:
```
# Moving average for System price (Do not need lag) 1month, 3month, 1year
all_data["Spot_MA25d"] = all_data["System_price(Yen/kWh)"].rolling(1200).mean().r
ound(2)
all_data["Spot_MA75d"] = all_data["System_price(Yen/kWh)"].rolling(3600).mean().r
ound(2)
all_data["Spot_MA200d"] = all_data["System_price(Yen/kWh)"].rolling(9600).mean()
.round(2)
```

[VWAP]

(Reference) MWh/hについて：https://www.jstage.jst.go.jp/article/ieejpes/127/4/127_4_573/_pdf/-char/ja (https://www.jstage.jst.go.jp/article/ieejpes/127/4/127_4_573/_pdf/-char/ja)

In [5]:
```
# Adjust unit from MWh to kWh
all_data['Volume_kWh'] = (all_data['Volume(MWh/h)']/2)*1000
all_data['Cum_Vol'] = all_data['Volume_kWh'].cumsum()
all_data['Cum_Vol_Price'] = (all_data['Volume_kWh'] * all_data['Average'] ).cumsum()
all_data['VWAP'] = all_data['Cum_Vol_Price'] / all_data['Cum_Vol']
all_data = all_data.drop(["Volume_kWh", "Cum_Vol", "Cum_Vol_Price"], axis=1)
```

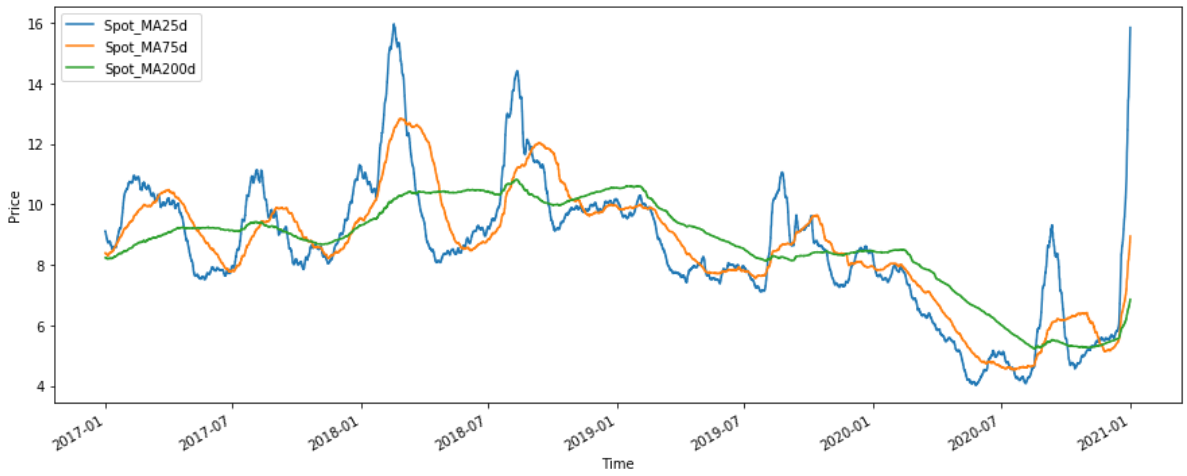
In [6]:
```
all_data = all_data.fillna(0)
all_data.isnull().sum()
```

Out[6]:

Date	0
HH	0
Open	0
High	0
Low	0
Close	0
Average	0
Volume(MWh/h)	0
Volume(Tick count)	0
Time	0
System_price(Yen/kWh)	0
Price_Hokkaido(Yen/kWh)	0
Price_Tokyo(Yen/kWh)	0
Price_Kansai(Yen/kWh)	0
BidExceed_diff	0
HourlyDemand_Hokkaido	0
HourlyDemand_Tokyo	0
HourlyDemand_Kansai	0
HourlyDemand_Okinawa	0
Wind_TOH	0
Geothermal_TOH	0
PumpedStorage_TOH	0
Interconnection_TOH	0
Geothermal_HOK	0
Wind_HOK	0
Interconnection_HOK	0
Wind_TKO	0
Interconnection_TKO	0
Wind_CHB	0
Interconnection_CHB	0
Wind_HKU	0
PumpedStorage_HKU	0
Interconnection_HKU	0
Nuclear_KAN	0
Wind_KAN	0
Interconnection_KAN	0
Thermal_CHG	0
Water_CHG	0
Wind_CHG	0
Interconnection_CHG	0
Nuclear_SHI	0
Wind_SHI	0
Interconnection_SHI	0
Nuclear_KYU	0
Geothermal_KYU	0
PV_KYU	0
PVCurtailment_KYU	0
Wind_KYU	0
WindCurtailment_KYU	0
Interconnection_KYU	0
Thermal_OKI	0
Biomass_OKI	0
Wind_OKI	0
Allarea_TotalDemand	0
Allarea_Water	0
Allarea_Thermal	0
Allarea_Geothermal	0

```
Allarea_Biomass           0
Allarea_PumpedStorage     0
Allarea_Interconnection   0
Water_Ratio               0
Thermal_Ratio             0
Geothermal_Ratio          0
Planned_Min_flag          0
Planned_Max_flag          0
month                     0
dayofweek                 0
holiday                   0
Spot_MA25d                0
Spot_MA75d                0
Spot_MA200d               0
VWAP                      0
dtype: int64
```

In [7]:
```
# plot the moving average
fig, ax = plt.subplots(1, figsize=(15, 6))

graph = all_data.copy()
graph["DateTime"] = pd.to_datetime(graph["Date"].astype(str) + " " + graph["Time"].
astype(str))

# Set index
graph = graph.set_index("DateTime")
start = "2017-01-01 00:00:00"
end = "2020-12-31 23:30:00"

# Plot Close
graph.Spot_MA25d [graph.index > start].plot(ax=ax, label="Spot_MA25d ")
graph.Spot_MA75d[graph.index > start].plot(ax=ax, label="Spot_MA75d")
graph.Spot_MA200d[graph.index > start].plot(ax=ax, label="Spot_MA200d")

# x-axis
plt.gcf().autofmt_xdate()
ax.set(xlabel="Time", ylabel="Price")
plt.legend(loc="upper left");
```



Lag-features (Avoiding data leakage)

※Infinity value will be happen with Downcast preprocessing. ("Total" column)

In [8]:
```
# Check the remaining memory on PC
import gc
gc.collect()
```

Out[8]: 37

In [9]:
```
# This is for generating lag
def generate_lag(train, lag_sizes, cols, lag_sizes_type):

    lag_sizes = np.array(lag_sizes)
    if lag_sizes_type == "HH":
        lag_sizes_adj = lag_sizes * 1 # nothing changes
    elif lag_sizes_type == "Hours":
        lag_sizes_adj = lag_sizes * 2
    elif lag_sizes_type == "Day":
        lag_sizes_adj = lag_sizes * 48

    for ix, lag_sizes_adj_ in enumerate(lag_sizes_adj):
        shifted_df = all_data[cols].shift(lag_sizes_adj_)
        shifted_df.columns = [f"{col_name}_lag_{lag_sizes[ix]}_{lag_sizes_type}" for col
_name in shifted_df.columns]
        if ix == 0:
            shifted_df_return = shifted_df
        else:
            shifted_df_return = shifted_df_return.merge(shifted_df, how="left", left_index
=True, right_index=True)
    return shifted_df_return
```

In [10]:
```
all_data.columns
```

Out[10]:
```
Index(['Date', 'HH', 'Open', 'High', 'Low', 'Close', 'Average',
       'Volume(MWh/h)', 'Volume(Tick count)', 'Time', 'System_price(Yen/kWh)',
       'Price_Hokkaido(Yen/kWh)', 'Price_Tokyo(Yen/kWh)',
       'Price_Kansai(Yen/kWh)', 'BidExceed_diff', 'HourlyDemand_Hokkaido',
       'HourlyDemand_Tokyo', 'HourlyDemand_Kansai', 'HourlyDemand_Okinawa',
       'Wind_TOH', 'Geothermal_TOH', 'PumpedStorage_TOH',
       'Interconnection_TOH', 'Geothermal_HOK', 'Wind_HOK',
       'Interconnection_HOK', 'Wind_TKO', 'Interconnection_TKO', 'Wind_CHB',
       'Interconnection_CHB', 'Wind_HKU', 'PumpedStorage_HKU',
       'Interconnection_HKU', 'Nuclear_KAN', 'Wind_KAN', 'Interconnection_KAN',
       'Thermal_CHG', 'Water_CHG', 'Wind_CHG', 'Interconnection_CHG',
       'Nuclear_SHI', 'Wind_SHI', 'Interconnection_SHI', 'Nuclear_KYU',
       'Geothermal_KYU', 'PV_KYU', 'PVCurtailment_KYU', 'Wind_KYU',
       'WindCurtailment_KYU', 'Interconnection_KYU', 'Thermal_OKI',
       'Biomass_OKI', 'Wind_OKI', 'Allarea_TotalDemand', 'Allarea_Water',
       'Allarea_Thermal', 'Allarea_Geothermal', 'Allarea_Biomass',
       'Allarea_PumpedStorage', 'Allarea_Interconnection', 'Water_Ratio',
       'Thermal_Ratio', 'Geothermal_Ratio', 'Planned_Min_flag',
       'Planned_Max_flag', 'month', 'dayofweek', 'holiday', 'Spot_MA25d',
       'Spot_MA75d', 'Spot_MA200d', 'VWAP'],
      dtype='object')
```

- Prediction point is at 17:00 on a day before the delivery date.
- At least, 2day-lag is necessary to avoid data leakage.

In [11]:
```
# Drop columns that are not necessary to generate lag features
lag_columns = all_data.columns.drop(['Date', 'Time', 'HH', 'System_price(Yen/kWh)', 'Price_Hokkaido(Yen/kWh)', 'Price_Tokyo(Yen/kWh)',
       'Price_Kansai(Yen/kWh)', 'BidExceed_diff', 'Planned_Min_flag', 'Planned_Max_flag', 'month',
       'dayofweek', 'holiday', 'Spot_MA25d', 'Spot_MA75d', 'Spot_MA200d'])

# Generate lag features and drop original columns
# all_data_lagged_HH = generate_lag(all_data, [49, 97], lag_columns, "HH")
# all_data_lagged_Hour = generate_lag(all_data, [2], lag_columns, "Hours")
all_data_lagged_Day = generate_lag(all_data, [2, 3], lag_columns, "Day")

# join everything
# all_data_lagged = pd.merge(all_data, all_data_lagged_HH, how="left", left_index=True, right_index=True)
# all_data = pd.merge(all_data, all_data_lagged_Hour, how="left", left_index=True, right_index=True)
all_data_lagged = pd.merge(all_data, all_data_lagged_Day, how="left", left_index=True, right_index=True)

# Drop lag_columns which can be data leakage
all_data_lagged = all_data_lagged.drop(lag_columns, axis=1)

# Keep both the original and lagged "Close" --> Original: target / Lagged: feature
all_data_lagged["Close"] = all_data["Close"]
```

In [12]:
```
# Check the lag columns
# temp_col = [item for item in all_data.columns if item.find('Day') != -1]

# print(temp_col)
```

In [13]:
```
all_data_lagged.shape
```

Out[13]: (83237, 129)

In [14]:
```
all_data_lagged.fillna(0, inplace=True)
print(all_data_lagged.isnull().sum())
```

Date	0
HH	0
Time	0
System_price(Yen/kWh)	0
Price_Hokkaido(Yen/kWh)	0
Price_Tokyo(Yen/kWh)	0
Price_Kansai(Yen/kWh)	0
BidExceed_diff	0
Planned_Min_flag	0
Planned_Max_flag	0
month	0
dayofweek	0
holiday	0
Spot_MA25d	0
Spot_MA75d	0
Spot_MA200d	0
Open_lag_2_Day	0
High_lag_2_Day	0
Low_lag_2_Day	0
Close_lag_2_Day	0
Average_lag_2_Day	0
Volume(MWh/h)_lag_2_Day	0
Volume(Tick count)_lag_2_Day	0
HourlyDemand_Hokkaido_lag_2_Day	0
HourlyDemand_Tokyo_lag_2_Day	0
HourlyDemand_Kansai_lag_2_Day	0
HourlyDemand_Okinawa_lag_2_Day	0
Wind_TOH_lag_2_Day	0
Geothermal_TOH_lag_2_Day	0
PumpedStorage_TOH_lag_2_Day	0
Interconnection_TOH_lag_2_Day	0
Geothermal_HOK_lag_2_Day	0
Wind_HOK_lag_2_Day	0
Interconnection_HOK_lag_2_Day	0
Wind_TKO_lag_2_Day	0
Interconnection_TKO_lag_2_Day	0
Wind_CHB_lag_2_Day	0
Interconnection_CHB_lag_2_Day	0
Wind_HKU_lag_2_Day	0
PumpedStorage_HKU_lag_2_Day	0
Interconnection_HKU_lag_2_Day	0
Nuclear_KAN_lag_2_Day	0
Wind_KAN_lag_2_Day	0
Interconnection_KAN_lag_2_Day	0
Thermal_CHG_lag_2_Day	0
Water_CHG_lag_2_Day	0
Wind_CHG_lag_2_Day	0
Interconnection_CHG_lag_2_Day	0
Nuclear_SHI_lag_2_Day	0
Wind_SHI_lag_2_Day	0
Interconnection_SHI_lag_2_Day	0
Nuclear_KYU_lag_2_Day	0
Geothermal_KYU_lag_2_Day	0
PV_KYU_lag_2_Day	0
PVCurtailment_KYU_lag_2_Day	0
Wind_KYU_lag_2_Day	0
WindCurtailment_KYU_lag_2_Day	0

```
Interconnection_KYU_lag_2_Day       0
Thermal_OKI_lag_2_Day               0
Biomass_OKI_lag_2_Day               0
Wind_OKI_lag_2_Day                  0
Allarea_TotalDemand_lag_2_Day       0
Allarea_Water_lag_2_Day             0
Allarea_Thermal_lag_2_Day           0
Allarea_Geothermal_lag_2_Day        0
Allarea_Biomass_lag_2_Day           0
Allarea_PumpedStorage_lag_2_Day     0
Allarea_Interconnection_lag_2_Day   0
Water_Ratio_lag_2_Day               0
Thermal_Ratio_lag_2_Day             0
Geothermal_Ratio_lag_2_Day          0
VWAP_lag_2_Day                      0
Open_lag_3_Day                      0
High_lag_3_Day                      0
Low_lag_3_Day                       0
Close_lag_3_Day                     0
Average_lag_3_Day                   0
Volume(MWh/h)_lag_3_Day             0
Volume(Tick count)_lag_3_Day        0
HourlyDemand_Hokkaido_lag_3_Day     0
HourlyDemand_Tokyo_lag_3_Day        0
HourlyDemand_Kansai_lag_3_Day       0
HourlyDemand_Okinawa_lag_3_Day      0
Wind_TOH_lag_3_Day                  0
Geothermal_TOH_lag_3_Day            0
PumpedStorage_TOH_lag_3_Day         0
Interconnection_TOH_lag_3_Day       0
Geothermal_HOK_lag_3_Day            0
Wind_HOK_lag_3_Day                  0
Interconnection_HOK_lag_3_Day       0
Wind_TKO_lag_3_Day                  0
Interconnection_TKO_lag_3_Day       0
Wind_CHB_lag_3_Day                  0
Interconnection_CHB_lag_3_Day       0
Wind_HKU_lag_3_Day                  0
PumpedStorage_HKU_lag_3_Day         0
Interconnection_HKU_lag_3_Day       0
Nuclear_KAN_lag_3_Day               0
Wind_KAN_lag_3_Day                  0
Interconnection_KAN_lag_3_Day       0
Thermal_CHG_lag_3_Day               0
Water_CHG_lag_3_Day                 0
Wind_CHG_lag_3_Day                  0
Interconnection_CHG_lag_3_Day       0
Nuclear_SHI_lag_3_Day               0
Wind_SHI_lag_3_Day                  0
Interconnection_SHI_lag_3_Day       0
Nuclear_KYU_lag_3_Day               0
Geothermal_KYU_lag_3_Day            0
PV_KYU_lag_3_Day                    0
PVCurtailment_KYU_lag_3_Day         0
Wind_KYU_lag_3_Day                  0
WindCurtailment_KYU_lag_3_Day       0
Interconnection_KYU_lag_3_Day       0
```

```
Thermal_OKI_lag_3_Day              0
Biomass_OKI_lag_3_Day              0
Wind_OKI_lag_3_Day                 0
Allarea_TotalDemand_lag_3_Day      0
Allarea_Water_lag_3_Day            0
Allarea_Thermal_lag_3_Day          0
Allarea_Geothermal_lag_3_Day       0
Allarea_Biomass_lag_3_Day          0
Allarea_PumpedStorage_lag_3_Day    0
Allarea_Interconnection_lag_3_Day  0
Water_Ratio_lag_3_Day              0
Thermal_Ratio_lag_3_Day            0
Geothermal_Ratio_lag_3_Day         0
VWAP_lag_3_Day                     0
Close                              0
dtype: int64
```

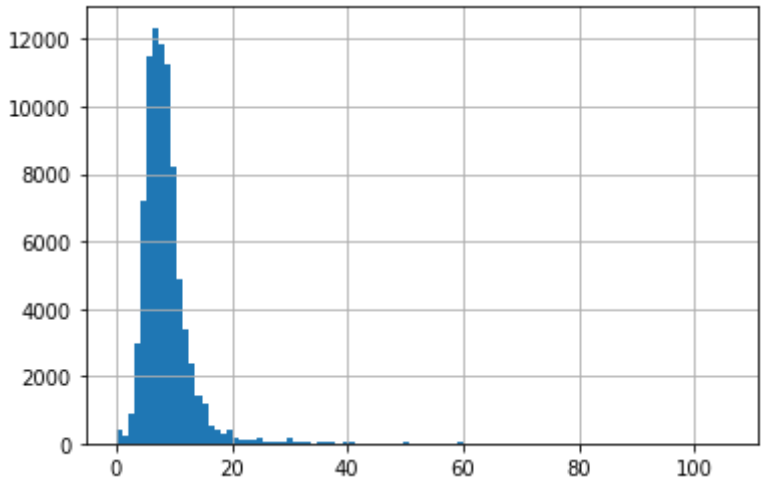
In [15]:
```
all_data_lagged.tail()
```

Out[15]:

	Date	HH	Time	System_price(Yen/kWh)	Price_Hokkaido(Yen/kWh)	Price_Tokyo(Yen/kW
83232	2020-12-31	44	21:30:00	35.0	35.0	3
83233	2020-12-31	45	22:00:00	45.0	40.0	4
83234	2020-12-31	46	22:30:00	40.0	40.0	4
83235	2020-12-31	47	23:00:00	35.0	35.0	3
83236	2020-12-31	48	23:30:00	25.0	25.0	2

Standardise (log-transformation)

In [17]:
```
all_data_lagged["Close"].hist(bins=100);
```



Features seem to be positive skew, and have different scale. --> Need to standardise

In [18]:
```
all_data_lagged.columns
```

Out[18]:
```
Index(['Date', 'HH', 'Time', 'System_price(Yen/kWh)',
       'Price_Hokkaido(Yen/kWh)', 'Price_Tokyo(Yen/kWh)',
       'Price_Kansai(Yen/kWh)', 'BidExceed_diff', 'Planned_Min_flag',
       'Planned_Max_flag',
       ...
       'Allarea_Thermal_lag_3_Day', 'Allarea_Geothermal_lag_3_Day',
       'Allarea_Biomass_lag_3_Day', 'Allarea_PumpedStorage_lag_3_Day',
       'Allarea_Interconnection_lag_3_Day', 'Water_Ratio_lag_3_Day',
       'Thermal_Ratio_lag_3_Day', 'Geothermal_Ratio_lag_3_Day',
       'VWAP_lag_3_Day', 'Close'],
      dtype='object', length=129)
```

In [19]:
```
all_data_lagged1 = all_data_lagged[['Date', 'Time', 'HH', 'month', 'dayofweek', 'holida
y', 'Planned_Min_flag', 'Planned_Max_flag']]
all_data_lagged2 = all_data_lagged.drop(['Date', 'Time', 'HH', 'month', 'dayofweek', 'h
oliday', 'Planned_Min_flag', 'Planned_Max_flag'], axis=1)
```

In [20]:
```
# PowerTransformer() with Yeo-Johnson
from sklearn.preprocessing import PowerTransformer
def trans_yeo_johnson(df, df2):
    pt = PowerTransformer() #default: Yeo-Johnson (this allow also 0-value to transform t
o logarithmic value)
    pt.fit_transform(df)
    return pt.transform(df2)

def inverse_trans_yeo_johnson(df, df2):
    pt = PowerTransformer() #default: Yeo-Johnson (this allow also 0-value to transform t
o logarithmic value)
    pt.fit_transform(df)
    return pt.inverse_transform(df2)
```

In [21]:
```
# Transformation
all_data_log2_transformed = all_data_lagged2.copy()
cols = all_data_log2_transformed.columns

all_data_log2_transformed = trans_yeo_johnson(all_data_lagged2, all_data_log2_tran
sformed)
all_data_log2_transformed = pd.DataFrame(all_data_log2_transformed)
all_data_log2_transformed.columns = cols
```

In [22]:
```
all_data_log = pd.concat([all_data_lagged1, all_data_log2_transformed], axis=1)
```

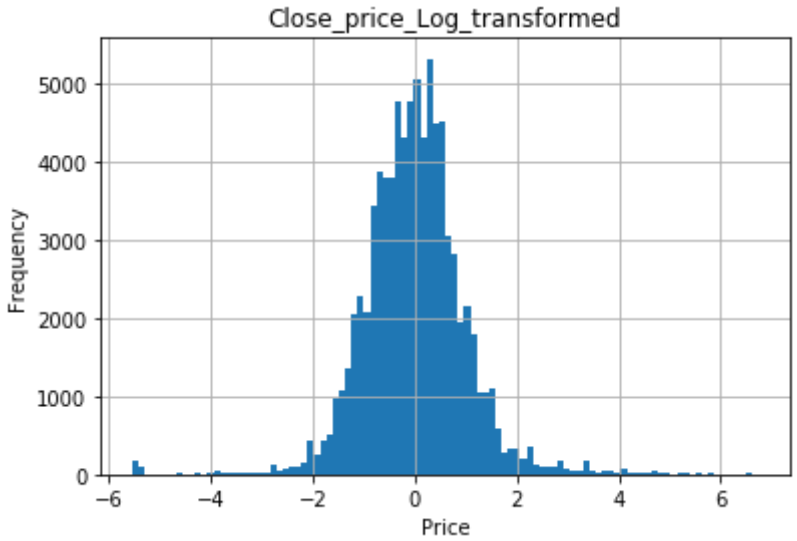
In [23]:
```
all_data_log.tail()
```

Out[23]:

	Date	Time	HH	month	dayofweek	holiday	Planned_Min_flag	Planned_Max_flag	S
83232	2020-12-31	21:30:00	44	12	3	0	0.0	0.0	
83233	2020-12-31	22:00:00	45	12	3	0	0.0	0.0	
83234	2020-12-31	22:30:00	46	12	3	0	0.0	0.0	
83235	2020-12-31	23:00:00	47	12	3	0	0.0	0.0	
83236	2020-12-31	23:30:00	48	12	3	0	0.0	0.0	

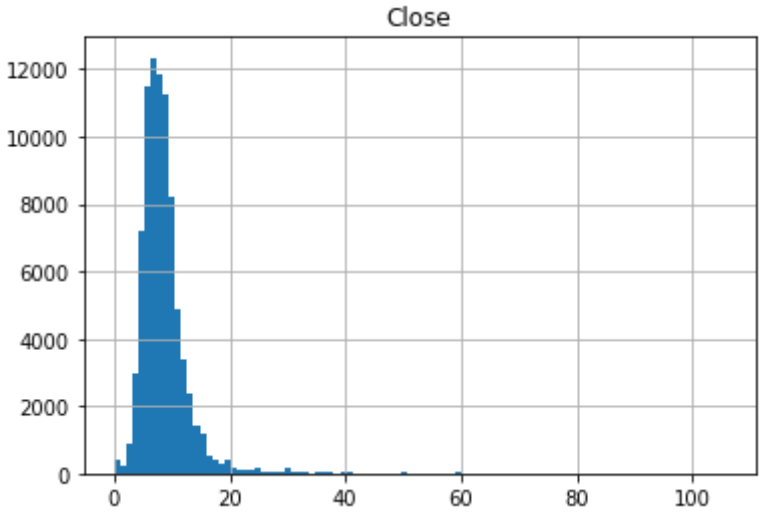
In [24]:
```
fig, ax = plt.subplots(1, figsize=plt.figaspect(.65))

all_data_log["Close"].hist(bins=100);
print("Skew: %f" % all_data_log["Close"].skew())
print("Kurt: %f" % all_data_log["Close"].kurt())
print("Mean: %f" % all_data_log["Close"].mean())
print("Std: %f" % all_data_log["Close"].std())
ax.set(title="Close_price_Log_transformed", ylabel="Frequency", xlabel="Price");
```

```
Skew: 0.018881
Kurt: 5.002006
Mean: 0.000000
Std: 1.000006
```



※ Confirm whether inverse transform works for Close price appropriately, or not

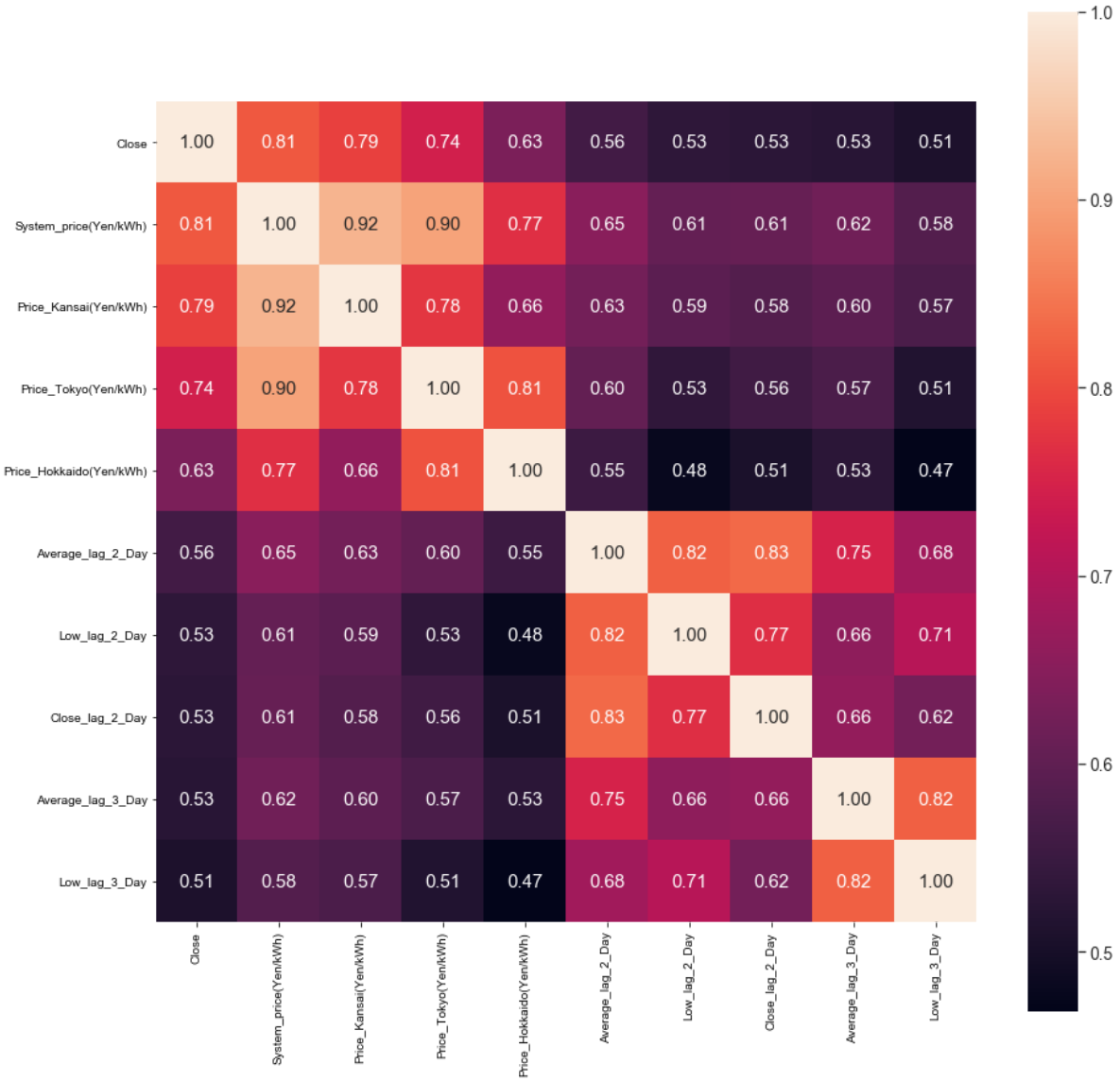
In [25]:
```
# inverse only for Close (Target)
y_log_inversed = inverse_trans_yeo_johnson(all_data_lagged2["Close"].values.reshape(-1,1), all_data_log["Close"].values.reshape(-1, 1))
y_log_inversed = pd.DataFrame(y_log_inversed)
y_log_inversed.columns = ["Close"]
y_log_inversed.hist(bins=100);
```



EDA (for all_data)

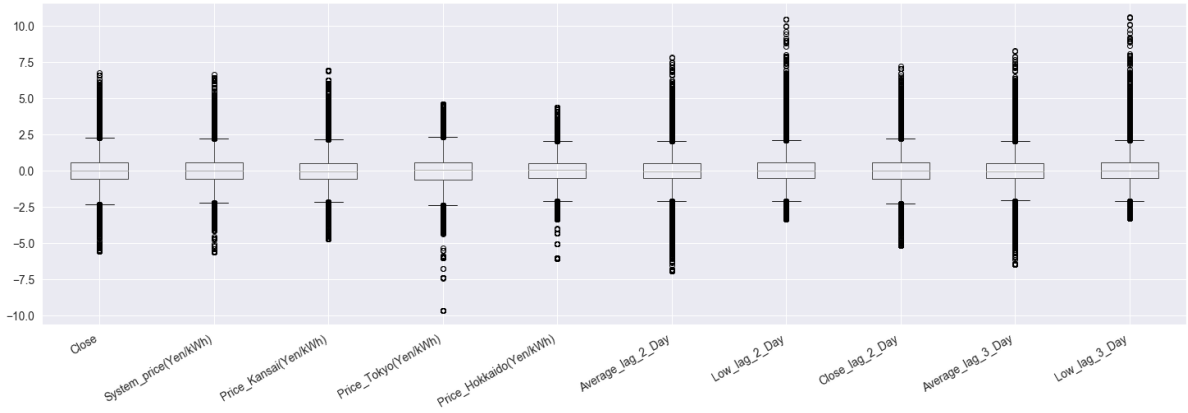
Check the correlation of features with the target

In [26]:
```
# correlation matrix
corrmat = all_data_log.corr()

# revenue correlation matrix
k = 10 # The number of variables on the heatmap
cols = corrmat.nlargest(k, 'Close')['Close'].index
cm = np.corrcoef(all_data_log[cols].values.T)
f, ax = plt.subplots(figsize=(15, 15))
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size': 15}, yticklabels=cols.values, xticklabels=cols.values)
plt.show()
```



※ In the case of Day1_lag, Ave=0.65, Low=0.62, Open=0.57, Low_HHlag=0.57,HIgh=0.56,Ave_HHlag=0.55

In [28]:
```
plt.figure(figsize = (25,8))
all_data_log[cols].boxplot()
plt.gcf().autofmt_xdate()

plt.show()
```



Feature scaling is also completed.

In [99]:
```
# all_data after pre-processing
all_data_log.tail()
```

Out[99]:

	Date	Time	HH	month	dayofweek	holiday	Planned_Min_flag	Planned_Max_flag	S
83232	2020-12-31	21:30:00	44	12	3	0	0.0	0.0	
83233	2020-12-31	22:00:00	45	12	3	0	0.0	0.0	
83234	2020-12-31	22:30:00	46	12	3	0	0.0	0.0	
83235	2020-12-31	23:00:00	47	12	3	0	0.0	0.0	
83236	2020-12-31	23:30:00	48	12	3	0	0.0	0.0	

Model training and evaluation

Preparation

In [30]:
```
all_data_log.shape
```

Out[30]: (83237, 129)

In [31]:
```
X = all_data_log.drop(['Close', 'Date', 'Time'], axis=1)
y = all_data_log.Closey = all_data_log.Close
```

Split all_data into train and valid for validation

In [32]:
```
# Rolling/Walk forward validation (Timeseries validation with the parameter of "max_trai
n_size")
from sklearn.model_selection import TimeSeriesSplit

n_splits=10
train_ratio=8
test_ratio=2
max_train_size=int(round((len(X)*train_ratio)/(train_ratio+test_ratio*n_splits), 0))
test_size=int(round((len(X)*test_ratio)/(train_ratio+test_ratio*n_splits), 0))

tscv = TimeSeriesSplit(n_splits=n_splits, test_size=test_size
#                       , max_train_size=max_train_size
                      )
Min_valid_index = len(X) - (n_splits * test_size)

print(tscv)
print('Minimum of valid_index: %.0f' % Min_valid_index)

# Confirming the split logic
for train_index, valid_index in tscv.split(X):
    # Divide the train/valid set  into 10 folds and pick up it.
    X_train, X_valid = X.iloc[train_index], X.iloc[valid_index]
    y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]
    print("TRAIN:", train_index, "Valid:", valid_index)
```

```
TimeSeriesSplit(gap=0, max_train_size=None, n_splits=10, test_size=5946)
Minimum of valid_index: 23777
TRAIN: [    0     1     2 ... 23774 23775 23776] Valid: [23777 23778 23779 ... 29720 2
9721 29722]
TRAIN: [    0     1     2 ... 29720 29721 29722] Valid: [29723 29724 29725 ... 35666 3
5667 35668]
TRAIN: [    0     1     2 ... 35666 35667 35668] Valid: [35669 35670 35671 ... 41612 4
1613 41614]
TRAIN: [    0     1     2 ... 41612 41613 41614] Valid: [41615 41616 41617 ... 47558 4
7559 47560]
TRAIN: [    0     1     2 ... 47558 47559 47560] Valid: [47561 47562 47563 ... 53504 5
3505 53506]
TRAIN: [    0     1     2 ... 53504 53505 53506] Valid: [53507 53508 53509 ... 59450 5
9451 59452]
TRAIN: [    0     1     2 ... 59450 59451 59452] Valid: [59453 59454 59455 ... 65396 6
5397 65398]
TRAIN: [    0     1     2 ... 65396 65397 65398] Valid: [65399 65400 65401 ... 71342 7
1343 71344]
TRAIN: [    0     1     2 ... 71342 71343 71344] Valid: [71345 71346 71347 ... 77288 7
7289 77290]
TRAIN: [    0     1     2 ... 77288 77289 77290] Valid: [77291 77292 77293 ... 83234 8
3235 83236]
```

Make the tables for graph visualisation and for evaluation results

In [33]:
```
# DataTable for graph_log
graph_data_log = all_data_log[["Date", "Time", "Close"]]
graph_data_log["DateTime"] = pd.to_datetime(graph_data_log["Date"].astype(str) +
" " + graph_data_log["Time"].astype(str))
prediction_point = graph_data_log["DateTime"][graph_data_log.index==Min_valid_ind
ex].iat[-1]
graph_data_log = graph_data_log.drop(["Date", "Time"], axis=1)
print("Prediction_point: {}".format(prediction_point))

# DataTable for Evaluation results_log
Eval_table_log = pd.DataFrame()
Eval_table_log["EvalFunc"] = pd.Series(["RMSE_log", "MAE_log"])
Eval_table_log
```

Prediction_point: 2017-08-09 08:30:00

Out[33]:

	EvalFunc
0	RMSE_log
1	MAE_log

In [34]:
```
# DataTable for graph_original
graph_data_original = all_data_lagged[["Date", "Time", "Close"]]
graph_data_original["DateTime"] = pd.to_datetime(graph_data_original["Date"].astyp
e(str) + " " + graph_data_original["Time"].astype(str))
prediction_point = graph_data_original["DateTime"][graph_data_original.index==Min_
valid_index].iat[-1]
graph_data_original = graph_data_original.drop(["Date", "Time"], axis=1)
print("Prediction_point: {}".format(prediction_point))

# DataTable for Evaluation functions_original
Eval_table_original = pd.DataFrame()
Eval_table_original["EvalFunc"] = pd.Series(["RMSE_Yen/kWh", "MAE_Yen/kWh"])
Eval_table_original
```

Prediction_point: 2017-08-09 08:30:00

Out[34]:

	EvalFunc
0	RMSE_Yen/kWh
1	MAE_Yen/kWh

Linear model

Linear regression

In [35]:
```
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn import linear_model
from sklearn.metrics import mean_squared_error, mean_absolute_error
from numpy import sqrt
import itertools

training_accuracy = []
valid_accuracy = []
rmse = []
mae = []
prediction_Line = []

for train_index, valid_index in tscv.split(X):
    # Divide the train/valid set  into 10 folds and pick up it.
    X_train, X_valid = X.iloc[train_index], X.iloc[valid_index]
    y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]

    #Fit train set to the model (Chooose one model)
    modelLine = LinearRegression().fit(X_train, y_train)

    # Generate prediction results
    y_pred = modelLine.predict(X_valid)
    true_values = y_valid.values
    # Save prediction results
    prediction_Line.append(y_pred)
    # Save evaluation results for each 10 validation and get mean
    training_accuracy.append(modelLine.score(X_train, y_train))
    valid_accuracy.append(modelLine.score(X_valid, y_valid))
    rmse.append(sqrt(mean_squared_error(true_values, y_pred)))
    mae.append(mean_absolute_error(true_values, y_pred))

# print("Training_accuracy: {}".format(training_accuracy))
print("Training_accuracy: {}".format(np.mean(training_accuracy)))
# print("Valid_accuracy: {}".format(valid_accuracy))
print("Valid_accuracy: {}".format(np.mean(valid_accuracy)))

# print("RMSE: {}".format(rmse))
print("RMSE: {}".format(np.mean(rmse)))
# print("MAE: {}".format(mae))
print("MAE: {}".format(np.mean(mae)))

# Convert prediction results with valid data from 2D list to 1D list
prediction_Line = list(itertools.chain.from_iterable(prediction_Line))
# Prediction with train data
y_pred_train = list(modelLine.predict(X_train)[:Min_valid_index])
# Store the prediction into the "graph data" table
graph_data_log["Close_pred_Linear"] = pd.Series(y_pred_train + prediction_Line)
# Store the result of evaluation into the "Eval_table"
Eval_table_log["Linear"] = pd.Series([np.mean(rmse), np.mean(mae)])
rmse_10fold_Linear = pd.Series(rmse)
mae_10fold_Linear = pd.Series(mae)
```

```
Training_accuracy: 0.6502979830020057
Valid_accuracy: 0.5386248140546919
RMSE: 0.6080416855716432
MAE: 0.4309379445757787
```

In [36]:
```
rmse
```

Out[36]:
```
[0.5546641390621865,
 0.5238936006243287,
 0.5666275248199817,
 0.5280543569632954,
 0.6466499812700253,
 0.5688303359047185,
 0.6023519276276659,
 0.6966468323780556,
 0.7715093389779504,
 0.6211888180882228]
```

In [37]:
```
mae
```

Out[37]:
```
[0.38910165797859186,
 0.3805094959640819,
 0.4196649497804815,
 0.4026892358952931,
 0.47686943820131933,
 0.39786071304430687,
 0.4265245934852403,
 0.47701706665332855,
 0.5285878920535734,
 0.4105544027015704]
```

Ridge

In [38]:
```
# Searching the optimal alpha
for train_index, valid_index in tscv.split(X):
    # Divide the train/valid set  into 10 folds and pick up it.
    X_train, X_valid = X.iloc[train_index], X.iloc[valid_index]
    y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]

    # For the test of alpha
    for alpha in [0.1, 1, 3, 7, 10]: # alphaで特に結果の違いなし (0.1, 1, 3, 7, 10)
        modelRidge = Ridge(alpha=alpha).fit(X_train, y_train)
        print("\n alpha={}".format(str(alpha)))
        print("Train set score: {:.2f}".format(modelRidge.score(X_train, y_train)))
        print("Test set score: {:.2f}".format(modelRidge.score(X_valid, y_valid)))
        y_pred = modelRidge.predict(X_valid)
        print("RMSE: {:.2f}".format(sqrt(mean_squared_error(y_valid, y_pred))) )
        print("MAE: {:.2f}".format(mean_absolute_error(y_valid, y_pred)))
        print("Number of features used:{}".format(np.sum(modelRidge.coef_ != 0)))
```

alpha=0.1
Train set score: 0.66
Test set score: 0.52
RMSE: 0.55
MAE: 0.39
Number of features used:123

alpha=1
Train set score: 0.66
Test set score: 0.52
RMSE: 0.55
MAE: 0.39
Number of features used:123

alpha=3
Train set score: 0.66
Test set score: 0.52
RMSE: 0.55
MAE: 0.39
Number of features used:123

alpha=7
Train set score: 0.66
Test set score: 0.52
RMSE: 0.55
MAE: 0.39
Number of features used:123

alpha=10
Train set score: 0.66
Test set score: 0.52
RMSE: 0.55
MAE: 0.39
Number of features used:123

alpha=0.1
Train set score: 0.63
Test set score: 0.66
RMSE: 0.52
MAE: 0.38
Number of features used:120

alpha=1
Train set score: 0.63
Test set score: 0.66
RMSE: 0.52
MAE: 0.38
Number of features used:120

alpha=3
Train set score: 0.63
Test set score: 0.66
RMSE: 0.52
MAE: 0.38
Number of features used:120

alpha=7

Train set score: 0.63
Test set score: 0.66
RMSE: 0.52
MAE: 0.38
Number of features used:120

alpha=10
Train set score: 0.63
Test set score: 0.66
RMSE: 0.52
MAE: 0.38
Number of features used:120

alpha=0.1
Train set score: 0.67
Test set score: 0.57
RMSE: 0.57
MAE: 0.42
Number of features used:125

alpha=1
Train set score: 0.67
Test set score: 0.57
RMSE: 0.57
MAE: 0.42
Number of features used:125

alpha=3
Train set score: 0.67
Test set score: 0.57
RMSE: 0.57
MAE: 0.42
Number of features used:125

alpha=7
Train set score: 0.67
Test set score: 0.57
RMSE: 0.57
MAE: 0.42
Number of features used:125

alpha=10
Train set score: 0.67
Test set score: 0.57
RMSE: 0.57
MAE: 0.42
Number of features used:125

alpha=0.1
Train set score: 0.67
Test set score: 0.38
RMSE: 0.53
MAE: 0.40
Number of features used:125

alpha=1
Train set score: 0.67

Test set score: 0.38
RMSE: 0.53
MAE: 0.40
Number of features used:125

alpha=3
Train set score: 0.67
Test set score: 0.38
RMSE: 0.53
MAE: 0.40
Number of features used:125

alpha=7
Train set score: 0.67
Test set score: 0.39
RMSE: 0.53
MAE: 0.40
Number of features used:125

alpha=10
Train set score: 0.67
Test set score: 0.39
RMSE: 0.53
MAE: 0.40
Number of features used:125

alpha=0.1
Train set score: 0.66
Test set score: 0.38
RMSE: 0.65
MAE: 0.48
Number of features used:126

alpha=1
Train set score: 0.66
Test set score: 0.38
RMSE: 0.65
MAE: 0.48
Number of features used:126

alpha=3
Train set score: 0.66
Test set score: 0.38
RMSE: 0.65
MAE: 0.48
Number of features used:126

alpha=7
Train set score: 0.66
Test set score: 0.38
RMSE: 0.65
MAE: 0.48
Number of features used:126

alpha=10
Train set score: 0.66
Test set score: 0.38

RMSE: 0.65
MAE: 0.48
Number of features used:126

alpha=0.1
Train set score: 0.64
Test set score: 0.55
RMSE: 0.57
MAE: 0.40
Number of features used:126

alpha=1
Train set score: 0.64
Test set score: 0.55
RMSE: 0.57
MAE: 0.40
Number of features used:126

alpha=3
Train set score: 0.64
Test set score: 0.55
RMSE: 0.57
MAE: 0.40
Number of features used:126

alpha=7
Train set score: 0.64
Test set score: 0.55
RMSE: 0.57
MAE: 0.40
Number of features used:126

alpha=10
Train set score: 0.64
Test set score: 0.55
RMSE: 0.57
MAE: 0.40
Number of features used:126

alpha=0.1
Train set score: 0.64
Test set score: 0.47
RMSE: 0.60
MAE: 0.43
Number of features used:126

alpha=1
Train set score: 0.64
Test set score: 0.47
RMSE: 0.60
MAE: 0.43
Number of features used:126

alpha=3
Train set score: 0.64
Test set score: 0.47
RMSE: 0.60

MAE: 0.43
Number of features used:126

alpha=7
Train set score: 0.64
Test set score: 0.47
RMSE: 0.60
MAE: 0.43
Number of features used:126

alpha=10
Train set score: 0.64
Test set score: 0.47
RMSE: 0.60
MAE: 0.43
Number of features used:126

alpha=0.1
Train set score: 0.63
Test set score: 0.49
RMSE: 0.70
MAE: 0.48
Number of features used:126

alpha=1
Train set score: 0.63
Test set score: 0.49
RMSE: 0.70
MAE: 0.48
Number of features used:126

alpha=3
Train set score: 0.63
Test set score: 0.49
RMSE: 0.70
MAE: 0.48
Number of features used:126

alpha=7
Train set score: 0.63
Test set score: 0.49
RMSE: 0.70
MAE: 0.48
Number of features used:126

alpha=10
Train set score: 0.63
Test set score: 0.49
RMSE: 0.70
MAE: 0.48
Number of features used:126

alpha=0.1
Train set score: 0.64
Test set score: 0.57
RMSE: 0.77
MAE: 0.53

Number of features used:126

alpha=1
Train set score: 0.64
Test set score: 0.57
RMSE: 0.77
MAE: 0.53
Number of features used:126

alpha=3
Train set score: 0.64
Test set score: 0.57
RMSE: 0.77
MAE: 0.53
Number of features used:126

alpha=7
Train set score: 0.64
Test set score: 0.57
RMSE: 0.77
MAE: 0.53
Number of features used:126

alpha=10
Train set score: 0.64
Test set score: 0.57
RMSE: 0.77
MAE: 0.53
Number of features used:126

alpha=0.1
Train set score: 0.67
Test set score: 0.79
RMSE: 0.62
MAE: 0.41
Number of features used:126

alpha=1
Train set score: 0.67
Test set score: 0.79
RMSE: 0.62
MAE: 0.41
Number of features used:126

alpha=3
Train set score: 0.67
Test set score: 0.79
RMSE: 0.62
MAE: 0.41
Number of features used:126

alpha=7
Train set score: 0.67
Test set score: 0.79
RMSE: 0.62
MAE: 0.41
Number of features used:126

alpha=10
Train set score: 0.67
Test set score: 0.79
RMSE: 0.62
MAE: 0.41
Number of features used:126

10 is the optimal

In [39]:
```
training_accuracy = []
valid_accuracy = []
rmse = []
mae = []
prediction_Ridge = []

for train_index, valid_index in tscv.split(X):
    # Divide the train/valid set  into 10 folds and pick up it.
    X_train, X_valid = X.iloc[train_index], X.iloc[valid_index]
    y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]

    #Fit train set to the model
    modelRidge = linear_model.Ridge(alpha=10).fit(X_train, y_train)

    # Generate prediction results
    y_pred = modelRidge.predict(X_valid)
    true_values = y_valid.values
    # Save prediction results
    prediction_Ridge.append(y_pred)
    # Save evaluation results for each 10 validation and get mean
    training_accuracy.append(modelRidge.score(X_train, y_train))
    valid_accuracy.append(modelRidge.score(X_valid, y_valid))
    rmse.append(sqrt(mean_squared_error(true_values, y_pred)))
    mae.append(mean_absolute_error(true_values, y_pred))

# print("Training_accuracy: {}".format(training_accuracy))
print("Training_accuracy: {}".format(np.mean(training_accuracy)))
# print("Valid_accuracy: {}".format(valid_accuracy))
print("Valid_accuracy: {}".format(np.mean(valid_accuracy)))

# print("RMSE: {}".format(rmse))
print("RMSE: {}".format(np.mean(rmse)))
# print("MAE: {}".format(mae))
print("MAE: {}".format(np.mean(mae)))

# Convert prediction results with valid data from 2D list to 1D list
prediction_Ridge = list(itertools.chain.from_iterable(prediction_Ridge))
# Prediction with train data
y_pred_train = list(modelRidge.predict(X_train)[:Min_valid_index])
# Store the prediction into the "graph data" table
graph_data_log["Close_pred_Ridge"] = pd.Series(y_pred_train + prediction_Ridge)
# Store the result of evaluation into the "Eval_table"
Eval_table_log["Ridge"] = pd.Series([np.mean(rmse), np.mean(mae)])
rmse_10fold_Ridge = pd.Series(rmse)
mae_10fold_Ridge = pd.Series(mae)
```

```
Training_accuracy: 0.6502867232547516
Valid_accuracy: 0.5391885427473524
RMSE: 0.6077197748816277
MAE: 0.4305920621715062
```

In [40]:
```
rmse
```

Out[40]:
```
[0.5543652192014195,
 0.5240074925813516,
 0.565856643687398,
 0.5267097621422938,
 0.646446438915108,
 0.5688747458687198,
 0.602317370025118,
 0.6966079151237113,
 0.7713920164281705,
 0.6206201448429867]
```

In [41]:
```
mae
```

Out[41]:
```
[0.3886569287407804,
 0.380566252147163,
 0.418884215877639,
 0.40138943841150865,
 0.4766695222645213,
 0.3978708038210129,
 0.42643623578135403,
 0.47701305689978596,
 0.5284573290776129,
 0.4099768386936842]
```

Lasso

In [42]:
```
for train_index, valid_index in tscv.split(X):
    # Divide the train/valid set  into 10 folds and pick up it.
    X_train, X_valid = X.iloc[train_index], X.iloc[valid_index]
    y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]

    # For the test of alpha
    for alpha in [0.02, 0.5, 1]: #0.02 is the best (0.02, 0.5, 1)
        modelLasso = Lasso(alpha=alpha).fit(X_train, y_train)
        print("\n alpha={}".format(str(alpha)))
        print("Train set score: {:.2f}".format(modelLasso.score(X_train, y_train)))
        print("Test set score: {:.2f}".format(modelLasso.score(X_valid, y_valid)))
        y_pred = modelLasso.predict(X_valid)
        print("RMSE: {:.2f}".format(sqrt(mean_squared_error(y_valid, y_pred))) )
        print("MAE: {:.2f}".format(mean_absolute_error(y_valid, y_pred)))
        print("Number of features used:{}".format(np.sum(modelLasso.coef_ != 0)))
```

alpha=0.02
Train set score: 0.63
Test set score: 0.51
RMSE: 0.56
MAE: 0.38
Number of features used:18

alpha=0.5
Train set score: 0.06
Test set score: 0.04
RMSE: 0.78
MAE: 0.59
Number of features used:1

alpha=1
Train set score: 0.06
Test set score: 0.04
RMSE: 0.78
MAE: 0.59
Number of features used:1

alpha=0.02
Train set score: 0.61
Test set score: 0.63
RMSE: 0.55
MAE: 0.41
Number of features used:17

alpha=0.5
Train set score: 0.06
Test set score: -0.54
RMSE: 1.12
MAE: 0.86
Number of features used:1

alpha=1
Train set score: 0.05
Test set score: -0.54
RMSE: 1.12
MAE: 0.86
Number of features used:1

alpha=0.02
Train set score: 0.66
Test set score: 0.62
RMSE: 0.53
MAE: 0.38
Number of features used:20

alpha=0.5
Train set score: 0.07
Test set score: -0.01
RMSE: 0.87
MAE: 0.60
Number of features used:2

alpha=1

Train set score: 0.04
Test set score: -0.01
RMSE: 0.87
MAE: 0.60
Number of features used:1

alpha=0.02
Train set score: 0.65
Test set score: 0.47
RMSE: 0.49
MAE: 0.37
Number of features used:20

alpha=0.5
Train set score: 0.06
Test set score: 0.00
RMSE: 0.67
MAE: 0.52
Number of features used:2

alpha=1
Train set score: 0.05
Test set score: -0.01
RMSE: 0.67
MAE: 0.52
Number of features used:1

alpha=0.02
Train set score: 0.64
Test set score: 0.45
RMSE: 0.61
MAE: 0.44
Number of features used:23

alpha=0.5
Train set score: 0.05
Test set score: -0.02
RMSE: 0.83
MAE: 0.60
Number of features used:1

alpha=1
Train set score: 0.05
Test set score: -0.02
RMSE: 0.83
MAE: 0.60
Number of features used:1

alpha=0.02
Train set score: 0.62
Test set score: 0.54
RMSE: 0.58
MAE: 0.41
Number of features used:20

alpha=0.5
Train set score: 0.05

Test set score: -0.15
RMSE: 0.91
MAE: 0.66
Number of features used:1

alpha=1
Train set score: 0.04
Test set score: -0.16
RMSE: 0.92
MAE: 0.67
Number of features used:1

alpha=0.02
Train set score: 0.62
Test set score: 0.50
RMSE: 0.59
MAE: 0.40
Number of features used:20

alpha=0.5
Train set score: 0.05
Test set score: -0.07
RMSE: 0.86
MAE: 0.58
Number of features used:1

alpha=1
Train set score: 0.04
Test set score: -0.07
RMSE: 0.86
MAE: 0.58
Number of features used:1

alpha=0.02
Train set score: 0.62
Test set score: 0.48
RMSE: 0.71
MAE: 0.49
Number of features used:18

alpha=0.5
Train set score: 0.05
Test set score: -0.61
RMSE: 1.24
MAE: 0.90
Number of features used:1

alpha=1
Train set score: 0.04
Test set score: -0.61
RMSE: 1.24
MAE: 0.90
Number of features used:1

alpha=0.02
Train set score: 0.63
Test set score: 0.59

RMSE: 0.76
MAE: 0.52
Number of features used:21

alpha=0.5
Train set score: 0.09
Test set score: -0.90
RMSE: 1.63
MAE: 1.32
Number of features used:2

alpha=1
Train set score: 0.03
Test set score: -1.05
RMSE: 1.69
MAE: 1.38
Number of features used:1

alpha=0.02
Train set score: 0.66
Test set score: 0.79
RMSE: 0.62
MAE: 0.41
Number of features used:20

alpha=0.5
Train set score: 0.33
Test set score: 0.32
RMSE: 1.11
MAE: 0.86
Number of features used:3

alpha=1
Train set score: 0.03
Test set score: -0.09
RMSE: 1.40
MAE: 1.10
Number of features used:1

0.02 is the optimal

In [43]:
```
training_accuracy = []
valid_accuracy = []
rmse = []
mae = []
prediction_Lasso = []

for train_index, valid_index in tscv.split(X):
    # Divide the train/valid set  into 10 folds and pick up it.
    X_train, X_valid = X.iloc[train_index], X.iloc[valid_index]
    y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]

    #Fit train set to the model (Chooose one model)
    modelLasso = linear_model.Lasso(alpha=0.02).fit(X_train, y_train)

    # Generate prediction results
    y_pred = modelLasso.predict(X_valid)
    true_values = y_valid.values
    # Save prediction results
    prediction_Lasso.append(y_pred)
    # Save evaluation results for each 10 validation and get mean
    training_accuracy.append(modelLasso.score(X_train, y_train))
    valid_accuracy.append(modelLasso.score(X_valid, y_valid))
    rmse.append(sqrt(mean_squared_error(true_values, y_pred)))
    mae.append(mean_absolute_error(true_values, y_pred))

# print("Training_accuracy: {}".format(training_accuracy))
print("Training_accuracy: {}".format(np.mean(training_accuracy)))
# print("Valid_accuracy: {}".format(valid_accuracy))
print("Valid_accuracy: {}".format(np.mean(valid_accuracy)))

# print("RMSE: {}".format(rmse))
print("RMSE: {}".format(np.mean(rmse)))
# print("MAE: {}".format(mae))
print("MAE: {}".format(np.mean(mae)))

# Convert prediction results with valid data from 2D list to 1D list
prediction_Lasso = list(itertools.chain.from_iterable(prediction_Lasso))
# Prediction with train data
y_pred_train = list(modelLasso.predict(X_train)[:Min_valid_index])
# Store the prediction into the "graph data" table
graph_data_log["Close_pred_Lasso"] = pd.Series(y_pred_train + prediction_Lasso)
# Store the result of evaluation into the "Eval_table"
Eval_table_log["Lasso"] = pd.Series([np.mean(rmse), np.mean(mae)])
rmse_10fold_Lasso = pd.Series(rmse)
mae_10fold_Lasso = pd.Series(mae)
```

```
Training_accuracy: 0.6345050805298386
Valid_accuracy: 0.5564409977013466
RMSE: 0.5989540442173967
MAE: 0.42022492648322773
```

In [44]:
```
rmse
```

Out[44]:
```
[0.5562744815260185,
 0.5524874081537432,
 0.5348781215865028,
 0.4905191352681698,
 0.6071698984802824,
 0.5759355923547725,
 0.5879139069542589,
 0.707204801025531,
 0.7603265724104851,
 0.616830524414203]
```

In [45]:
```
mae
```

Out[45]:
```
[0.38410674300617736,
 0.41214763567699614,
 0.3756235505691139,
 0.3650921640925861,
 0.4427017829205779,
 0.40896378727702154,
 0.39886362664117075,
 0.48897551508988574,
 0.5171494304378856,
 0.40862502912086196]
```

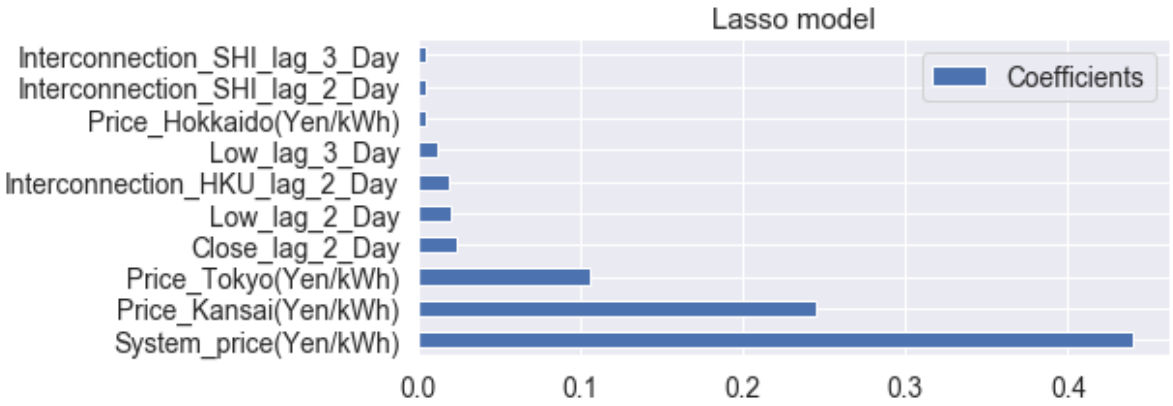
Interpretation of the linear model

https://scikit-learn.org/stable/auto_examples/inspection/plot_linear_model_coefficient_interpretation.html (https://scikit-learn.org/stable/auto_examples/inspection/plot_linear_model_coefficient_interpretation.html)

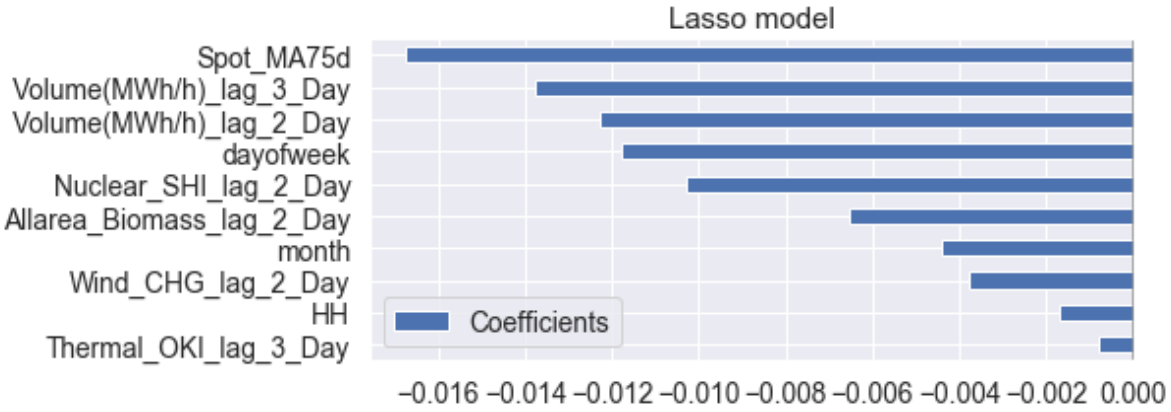
In [46]:
```
print("Intercept: {}".format(modelLine.intercept_))

feature_names = X_train.columns
coefs = pd.DataFrame(modelLasso.coef_, columns=['Coefficients'], index=feature_nam
es
).sort_values('Coefficients', ascending=False)

# Absolute value of coefficients
coef_abs = coefs.abs()
print(coef_abs.head(10))
```

```
Intercept: 0.08408114225644028
                          Coefficients
System_price(Yen/kWh)         0.440287
Price_Kansai(Yen/kWh)         0.245256
Price_Tokyo(Yen/kWh)          0.105903
Close_lag_2_Day               0.023760
Low_lag_2_Day                 0.019909
Interconnection_HKU_lag_2_Day     0.019313
Low_lag_3_Day                 0.011879
Price_Hokkaido(Yen/kWh)       0.005193
Interconnection_SHI_lag_2_Day     0.005121
Interconnection_SHI_lag_3_Day     0.004120
```

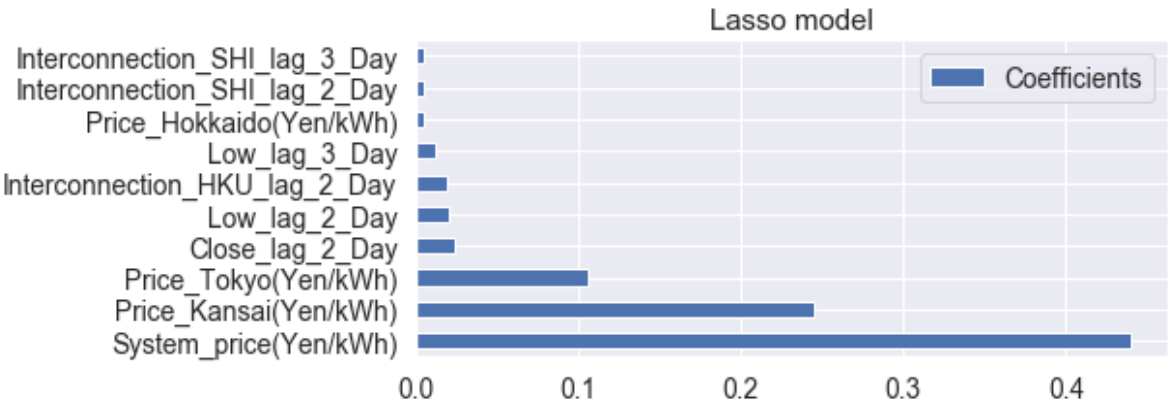
In [47]:
```
# Positive coeficients
coefs[:10].plot(kind='barh', figsize=(9, 3))
plt.title('Lasso model')
plt.axvline(x=0, color='.5')
plt.subplots_adjust(left=.3)
```



In [48]:
```
# Negative coeficients
end = len(coefs)
start = end - 10
coefs[start:end].plot(kind='barh', figsize=(9, 3))
plt.title('Lasso model')
plt.axvline(x=0, color='.5')
plt.subplots_adjust(left=.3)
```



In [49]:
```
# Absolute coeficients
coef_abs[:10].plot(kind='barh', figsize=(9, 3))
plt.title('Lasso model')
plt.axvline(x=0, color='.5')
plt.subplots_adjust(left=.3)
```



Non-linear model

Linear Regression with PolynomialFeatures

In [50]:
```
X.shape
```

Out[50]: (83237, 126)

In [51]:
```
# Make polynominal features
from sklearn.preprocessing import PolynomialFeatures

dimension = 2
polynomial = PolynomialFeatures(degree=dimension)
Poly_X = polynomial.fit_transform(X)
Poly_X = pd.DataFrame(Poly_X)
```

In [52]:
```
Poly_X.shape
```

Out[52]: (83237, 8128)

Skip now because kernel dies due to the spec of my PC. Run the following code only after reducing the number of features sufficiently.

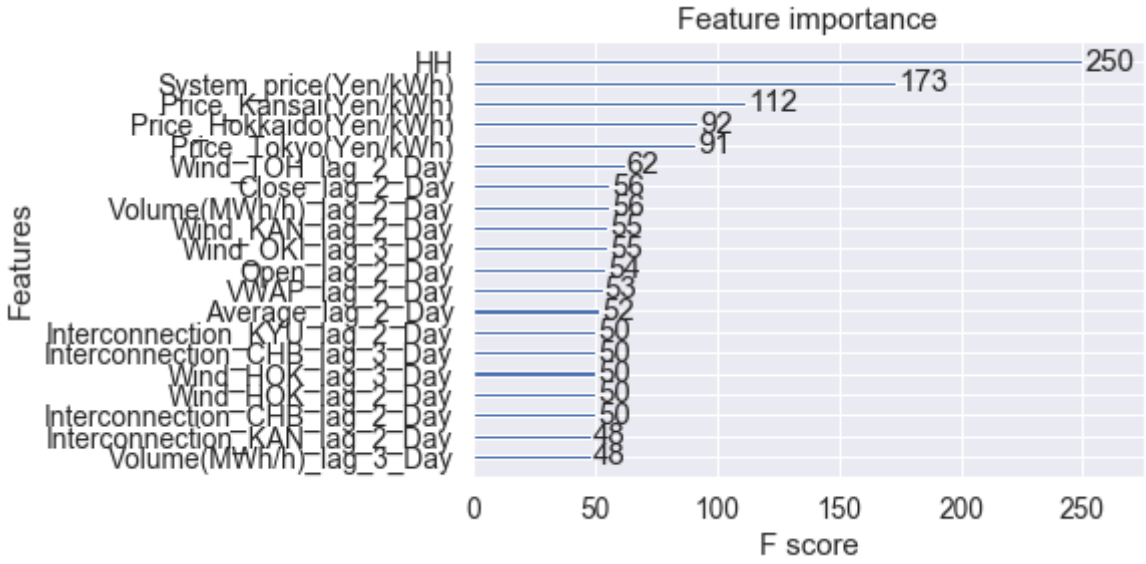
In [53]:
```
# training_accuracy = []
# valid_accuracy = []
# rmse = []
# mae = []
# prediction_PolyLine = []

# for train_index, valid_index in tscv.split(X):
#     # Divide the train/valid set  into 10 folds and pick up it.
#     X_train, X_valid = X.iloc[train_index], X.iloc[valid_index]
#     y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]

#     #Fit train set to the model (Chooose one model)
#     modelPolyLine = LinearRegression().fit(X_train, y_train)

#     # Generate prediction results
#     y_pred = modelPolyLine.predict(X_valid)
#     true_values = y_valid.values
#     # Save prediction results
#     prediction_PolyLine.append(y_pred)
#     # Save evaluation results for each 10 validation and get mean
#     training_accuracy.append(modelPolyLine.score(X_train, y_train))
#     valid_accuracy.append(modelPolyLine.score(X_valid, y_valid))
#     rmse.append(sqrt(mean_squared_error(true_values, y_pred)))
#     mae.append(mean_absolute_error(true_values, y_pred))

# # print("Training_accuracy: {}".format(training_accuracy))
# print("Training_accuracy: {}".format(np.mean(training_accuracy)))
# # print("Valid_accuracy: {}".format(valid_accuracy))
# print("Valid_accuracy: {}".format(np.mean(valid_accuracy)))

# # print("RMSE: {}".format(rmse))
# print("RMSE: {}".format(np.mean(rmse)))
# # print("MAE: {}".format(mae))
# print("MAE: {}".format(np.mean(mae)))

# # Convert prediction results with valid data from 2D list to 1D list
# prediction_PolyLine = list(itertools.chain.from_iterable(prediction_PolyLine))
# # Prediction with train data
# y_pred_train = list(modelPolyLine.predict(X_train)[:Min_valid_index])
# # Store the prediction into the "graph data" table
# #graph_data_log = graph_data_log.reset_index()
# graph_data_log["Close_pred_PolyLinear"] = pd.Series(y_pred_train + prediction_Pol
yLine)
# # Store the result of evaluation into the "Eval_table"
# Eval_table_log["PolyLinear"] = pd.Series([np.mean(rmse), np.mean(mae)])
```

XGBoost

In [54]:
```
from xgboost import XGBRegressor

training_accuracy = []
valid_accuracy = []
rmse = []
mae = []
prediction_XGB = []

for train_index, valid_index in tscv.split(X):
    # Divide the train/valid set  into 10 folds and pick up it.
    X_train, X_valid = X.iloc[train_index], X.iloc[valid_index]
    y_train, y_valid = y.iloc[train_index], y.iloc[valid_index]

    #Fit train set to the model
    modelXGB = XGBRegressor().fit(X_train, y_train)
    # Generate prediction results
    y_pred = modelXGB.predict(X_valid)
    true_values = y_valid.values
    # Save prediction results
    prediction_XGB.append(y_pred)
    # Save evaluation results for each 10 validation and get mean
    training_accuracy.append(modelXGB.score(X_train, y_train))
    valid_accuracy.append(modelXGB.score(X_valid, y_valid))
    rmse.append(sqrt(mean_squared_error(true_values, y_pred)))
    mae.append(mean_absolute_error(true_values, y_pred))

# print("Training_accuracy: {}".format(training_accuracy))
print("Training_accuracy: {}".format(np.mean(training_accuracy)))
# print("Valid_accuracy: {}".format(valid_accuracy))
print("Valid_accuracy: {}".format(np.mean(valid_accuracy)))

# print("RMSE: {}".format(rmse))
print("RMSE: {}".format(np.mean(rmse)))
# print("MAE: {}".format(mae))
print("MAE: {}".format(np.mean(mae)))

# Convert prediction results with valid data from 2D list to 1D list
prediction_XGB = list(itertools.chain.from_iterable(prediction_XGB))
# Prediction with train data
y_pred_train = list(modelXGB.predict(X_train)[:Min_valid_index])
# Store the prediction into the "graph data" table
graph_data_log["Close_pred_XGB"] = pd.Series(y_pred_train + prediction_XGB)
# Store the result of evaluation into the "Eval_table"
Eval_table_log["XGB"] = pd.Series([np.mean(rmse), np.mean(mae)])
rmse_10fold_XGB = pd.Series(rmse)
mae_10fold_XGB = pd.Series(mae)
```

```
Training_accuracy: 0.8335864283141963
Valid_accuracy: 0.35375851599227015
RMSE: 0.7320568012268152
MAE: 0.5376172269659407
```

In [55]:
```
# Feature importance of the last train set
from xgboost import plot_importance

# plot feature importance
plot_importance(modelXGB, max_num_features = 20)
plt.figure(figsize=(10, 5),dpi=100)
plt.show()
```



<Figure size 1000x500 with 0 Axes>

RandomForest ※ Skip for the same reason as polynomial model

In [56]:
```
from sklearn.ensemble import RandomForestRegressor

# training_accuracy = []
# valid_accuracy = []
# rmse = []
# mae = []
# prediction_RF = []

# for train_index, valid_index in zip(Rolling_forward_split_train, Rolling_forward_split_valid):
#     # Divide the train/valid set  into 10 folds and pick up it.
#     X_train, X_valid = X.iloc[:train_index], X.iloc[train_index: valid_index]
#     y_train, y_valid = y.iloc[:train_index], y.iloc[train_index: valid_index]

#     #Fit train set to the model
#     modelRF = RandomForestRegressor(n_jobs = -1).fit(X_train, y_train)
#     # Generate prediction results
#     y_pred = modelRF.predict(X_valid)
#     true_values = y_valid.values
#     # Save prediction results
#     prediction_RF.append(y_pred)
#     # Save evaluation results for each 10 validation and get mean
#     training_accuracy.append(modelRF.score(X_train, y_train))
#     valid_accuracy.append(modelRF.score(X_valid, y_valid))
#     rmse.append(sqrt(mean_squared_error(true_values, y_pred)))
#     mae.append(mean_absolute_error(true_values, y_pred))

# # print("Training_accuracy: {}".format(training_accuracy))
# print("Training_accuracy: {}".format(np.mean(training_accuracy)))
# # print("Valid_accuracy: {}".format(valid_accuracy))
# print("Valid_accuracy: {}".format(np.mean(valid_accuracy)))

# # print("RMSE: {}".format(rmse))
# print("RMSE: {}".format(np.mean(rmse)))
# # print("MAE: {}".format(mae))
# print("MAE: {}".format(np.mean(mae)))

# # Convert prediction results with valid data from 2D list to 1D list
# prediction_RF = list(itertools.chain.from_iterable(prediction_RF))
# # Prediction with train data
# y_pred_train = list(modelRF.predict(X_train)[:Min_valid_index])
# # Store the prediction into the "graph data" table
# graph_data_log["Close_pred_RF"] = pd.Series(y_pred_train + prediction_RF)
# # Store the result of evaluation into the "Eval_table"
# Eval_table_log["RF"] = pd.Series([np.mean(rmse), np.mean(mae)])
```

In [57]:
```
# Feature importance of the last train set
# # plot feature importance
# df_feature_importance = pd.DataFrame(modelRF.feature_importances_, index=feature_list, columns=['feature importance']).sort_values('feature importance', ascending=True)
# #df_feature_all = pd.DataFrame([tree.feature_importances_ for tree in reg.estimators_], columns=boston.feature_names)
# df_feature_importance_top10 = df_feature_importance.tail(10)
# df_feature_importance_top10.plot(kind='barh');
```

Statistical model

(Reference) in Japanese

- VAR(Intuitive): https://logics-of-blue.com/var%E3%83%A2%E3%83%87%E3%83%AB/ (https://logics-of-blue.com/var%E3%83%A2%E3%83%87%E3%83%AB/)
- VAR: https://analytics-note.xyz/time-series/statsmodels-var-fit/ (https://analytics-note.xyz/time-series/statsmodels-var-fit/)
- VAR(Theory and implementation): https://qiita.com/innovation1005/items/b5333a939c0341b46ba9 (https://qiita.com/innovation1005/items/b5333a939c0341b46ba9)
- ARIMAX(Equation): https://qiita.com/shu-yusa/items/1c6148e4e6e523d644ae (https://qiita.com/shu-yusa/items/1c6148e4e6e523d644ae)

In [58]:
```
# Top 5 coefficient from Linear model
coef_abs_list = list(coef_abs[:5].index)
# Pick up  Date, Time , Close and cols that have high importance on the linear model
arima_cols = ["Date", "Time", "Close"]
arima_cols = arima_cols + coef_abs_list
arima_cols
```

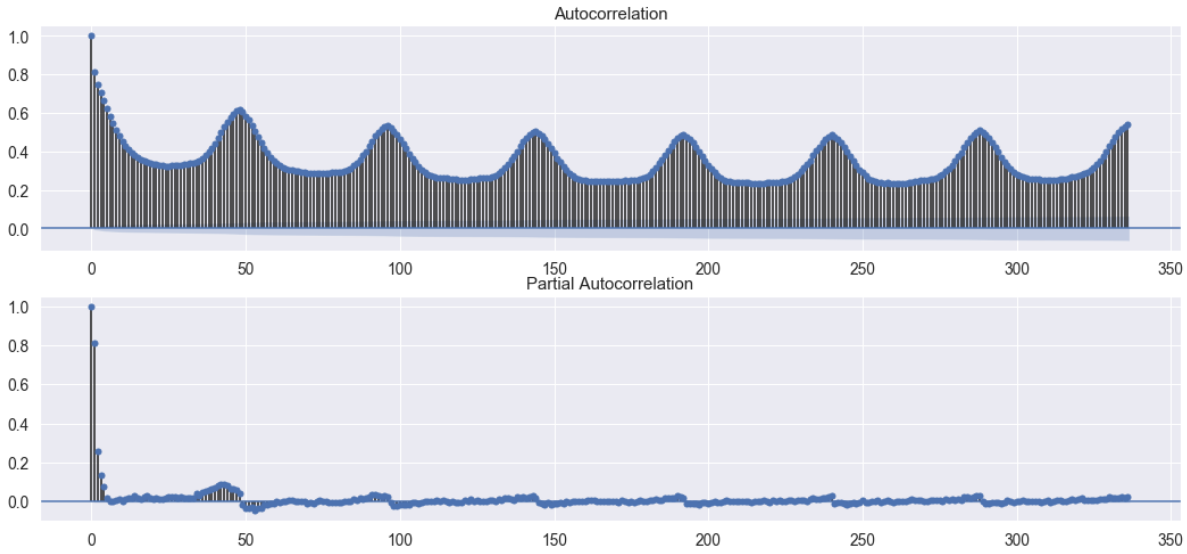
Out[58]:
```
['Date',
 'Time',
 'Close',
 'System_price(Yen/kWh)',
 'Price_Kansai(Yen/kWh)',
 'Price_Tokyo(Yen/kWh)',
 'Close_lag_2_Day',
 'Low_lag_2_Day']
```

In [59]:
```
# Data for statistical modeling
all_data_stats = all_data_log.copy()
all_data_stats = all_data_stats[arima_cols]
all_data_stats["DateTime"] = pd.to_datetime(all_data_stats["Date"].astype(str) + " "
+ all_data_stats["Time"].astype(str))
all_data_stats = all_data_stats.drop(["Date", "Time"], axis=1)
X_stats = all_data_stats.drop(['Close', "DateTime"], axis=1)
X_stats =  np.array(X_stats)
y_stats = all_data_stats[["Close"]]
y_stats =  np.array(y_stats)
```

In [60]:
```
# ADF test for logarithmic price
ctt = sm.tsa.adfuller(y_stats, regression="ctt")
round(ctt[1], 4)
```

Out[60]: 0.0

In [61]:
```
# Autocorrelation
fig = plt.figure(figsize=(18,8))
# Autocorrelation (1lag=30min --> 336 lags=1week)
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(y_stats, lags=336, ax=ax1)

# Partial Autocorrelation
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(y_stats, lags=336, ax=ax2)
```

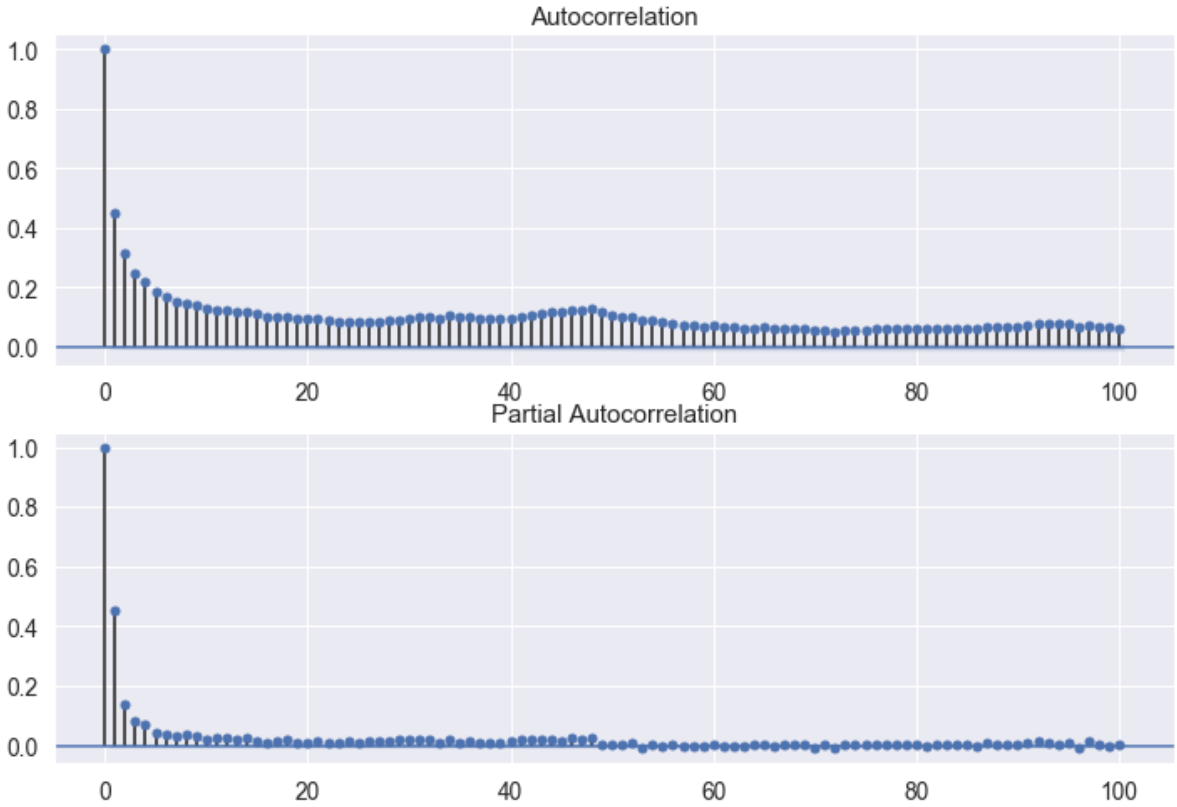


ARIMAX model

In [62]:
```
from statsmodels.tsa.arima.model import ARIMA

modelARIMA = ARIMA(y_stats, exog=X_stats).fit()

# Summary
print(modelARIMA.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                83237
Model:                          ARIMA   Log Likelihood              -71081.285
Date:                Wed, 31 Mar 2021   AIC                         142176.569
Time:                        00:47:10   BIC                         142241.875
Sample:                             0   HQIC                        142196.553
                                - 83237
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const      -4.68e-06      0.002     -0.002      0.998      -0.004       0.004
x1             0.3962      0.004     96.584      0.000       0.388       0.404
x2             0.2848      0.003     91.663      0.000       0.279       0.291
x3             0.1343      0.003     53.259      0.000       0.129       0.139
x4             0.0185      0.003      7.299      0.000       0.014       0.024
x5             0.0374      0.003     14.676      0.000       0.032       0.042
sigma2         0.3231      0.001    453.958      0.000       0.322       0.324
===================================================================================
Ljung-Box (L1) (Q):               17030.84   Jarque-Bera (JB):            228090.81
Prob(Q):                              0.00   Prob(JB):                         0.00
Heteroskedasticity (H):               1.69   Skew:                            -0.09
Prob(H) (two-sided):                  0.00   Kurtosis:                        11.11
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [63]:
```
# Check the residual
resid = modelARIMA.resid
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(resid.squeeze(), lags=100, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(resid, lags=100, ax=ax2)
```



If residual still has seasonality or any kind of patterns, ARIMA model is not appropriately trained.

-->It can be solved with incorporating explanatory variables into the model.

In [64]:
```
training_accuracy = []
valid_accuracy = []
rmse = []
mae = []
prediction_ARIMA = []

# Set the parameter for .predict() which is for in-sample prediciton
train_end =  prediction_point.to_pydatetime() - datetime.timedelta(minutes=30)

for train_index, valid_index in tscv.split(X):
  # Divide the train/valid set  into 10 folds and pick up it.
  all_train, all_valid = all_data_stats.iloc[train_index], all_data_stats.iloc[valid_index]
  all_train, all_valid = all_train.set_index("DateTime"), all_valid.set_index("DateTime")
  # Pandas --> ndarray
  X_train = all_train.drop(['Close'], axis=1)
  X_train =  np.array(X_train)
  y_train = all_train[["Close"]]
  y_train =  np.array(y_train)
  X_valid = all_valid.drop(['Close'], axis=1)
  X_valid =  np.array(X_valid)
  y_valid = all_valid[["Close"]]
  y_valid =  np.array(y_valid)

  #Fit train set to the model
  modelARIMA = ARIMA(y_train, exog=X_train
#                     order=(2, 0, 3),
                    ).fit() #上記セルのパラメータを参照
  # Generate prediction results
  y_pred = modelARIMA.forecast(steps=test_size, exog=X_valid) # test_size is set on
 "Preparation"
  true_values = y_valid
  # Save prediction results
  prediction_ARIMA.append(y_pred)
  # Save evaluation results for each 10 validation and get mean
  rmse.append(sqrt(mean_squared_error(true_values, y_pred)))
  mae.append(mean_absolute_error(true_values, y_pred))

# print("RMSE: {}".format(rmse))
print("RMSE: {}".format(np.mean(rmse)))
# print("MAE: {}".format(mae))
print("MAE: {}".format(np.mean(mae)))

# Convert prediction results with valid data from 2D list to 1D list
prediction_ARIMA = list(itertools.chain.from_iterable(prediction_ARIMA))
# Prediction with train data
y_pred_train = list(modelARIMA.predict())
y_pred_train = y_pred_train[:Min_valid_index]
# Store the prediction into the "graph data" table
graph_data_log = graph_data_log.reset_index()
graph_data_log["Close_pred_ARIMA"] = pd.Series(y_pred_train + prediction_ARIMA)
# Store the result of evaluation into the "Eval_table"
Eval_table_log["ARIMA"] = pd.Series([np.mean(rmse), np.mean(mae)])
```

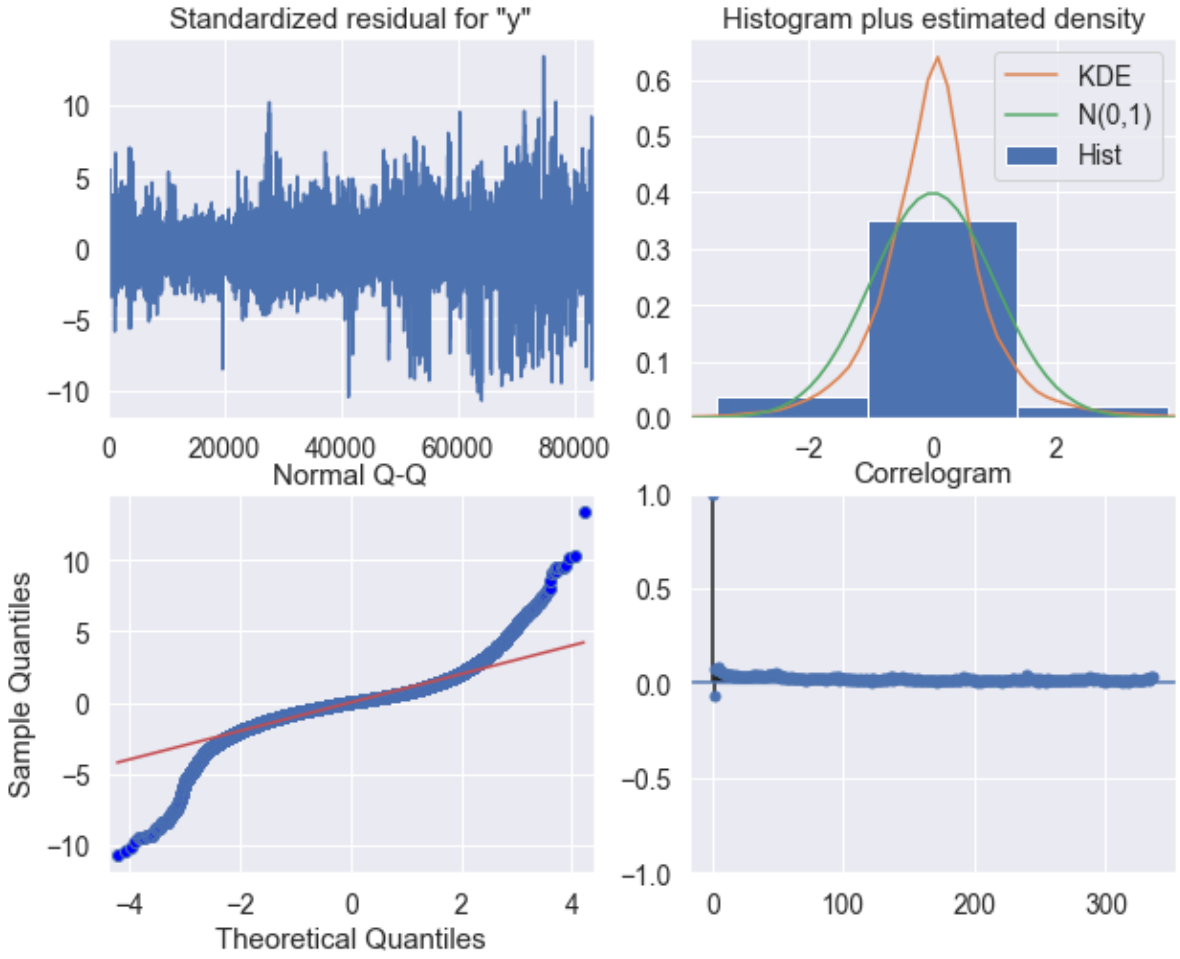
```
RMSE: 0.5962731747402621
MAE: 0.41552557822596087
```

SARIMAX model

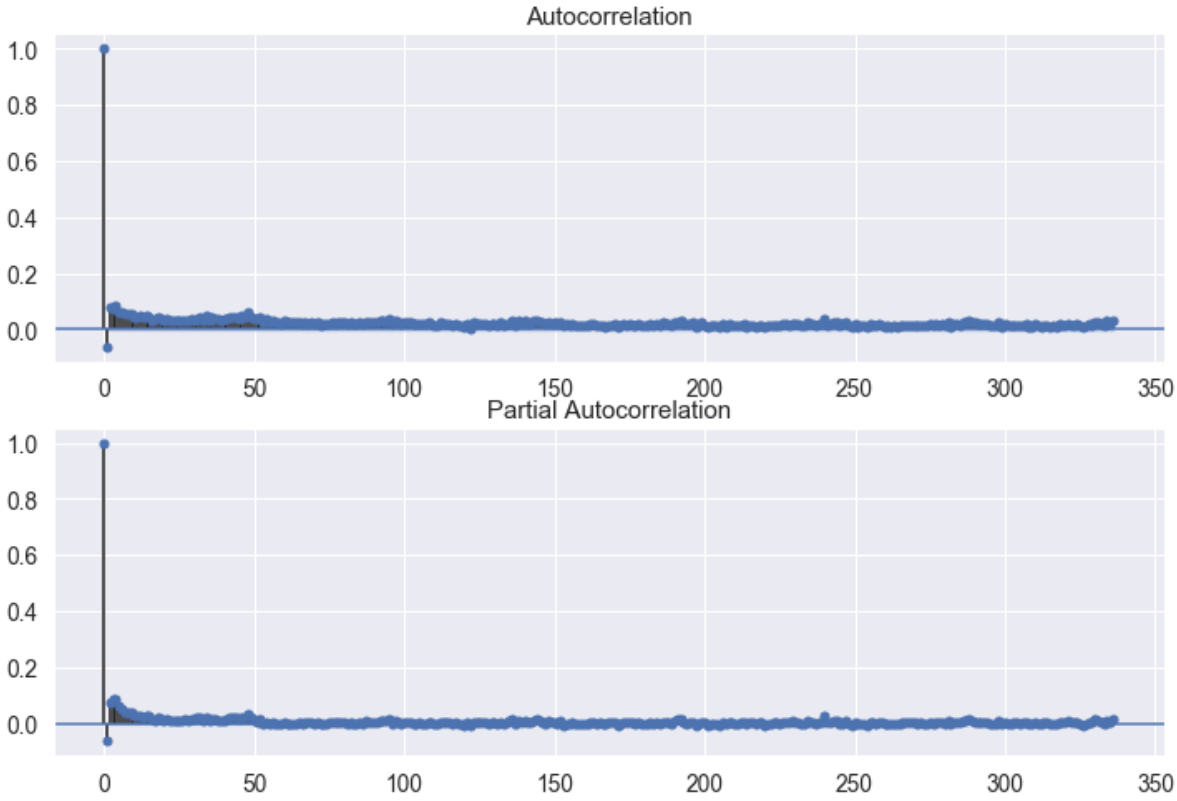
In [65]:
```
from statsmodels.tsa.statespace.sarimax import SARIMAX

modelSARIMA = SARIMAX(y_stats, exog=X_stats).fit()
print(modelSARIMA.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                83237
Model:               SARIMAX(1, 0, 0)   Log Likelihood              -61543.269
Date:                Wed, 31 Mar 2021   AIC                         123100.538
Time:                        00:57:39   BIC                         123165.844
Sample:                             0   HQIC                        123120.522
                                - 83237
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
x1             0.3965      0.005     80.617      0.000       0.387       0.406
x2             0.2691      0.004     68.877      0.000       0.261       0.277
x3             0.1397      0.003     40.523      0.000       0.133       0.146
x4             0.0133      0.002      5.424      0.000       0.008       0.018
x5             0.0397      0.003     13.123      0.000       0.034       0.046
ar.L1          0.4531      0.002    297.161      0.000       0.450       0.456
sigma2         0.2569      0.001    503.134      0.000       0.256       0.258
===================================================================================
Ljung-Box (L1) (Q):                 334.22   Jarque-Bera (JB):            422127.36
Prob(Q):                              0.00   Prob(JB):                         0.00
Heteroskedasticity (H):               2.01   Skew:                            -0.15
Prob(H) (two-sided):                  0.00   Kurtosis:                        14.03
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [66]:
```
# Check residual (If periodicity can be seen, SARIMA model would be better)
# Plot/confirm residual (White noise)
modelSARIMA.plot_diagnostics(lags=336, figsize=[10, 8]);
```



In [67]:
```
# Plot pertial Autocorrelation
resid = modelSARIMA.resid
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(resid.squeeze(), lags=336, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(resid, lags=336, ax=ax2)
```



It seems SARIMA would be better than ARIMA model.

In [68]:
```
training_accuracy = []
valid_accuracy = []
rmse = []
mae = []
prediction_SARIMA = []

# Set the parameter for .predict() which is for in-sample prediciton
train_end =  prediction_point.to_pydatetime() - datetime.timedelta(minutes=30)

for train_index, valid_index in tscv.split(X):
  # Divide the train/valid set  into 10 folds and pick up it.
  all_train, all_valid = all_data_stats.iloc[train_index], all_data_stats.iloc[valid_index]
  all_train, all_valid = all_train.set_index("DateTime"), all_valid.set_index("DateTime")
  # Pandas --> ndarray
  X_train = all_train.drop(['Close'], axis=1)
  X_train =  np.array(X_train)
  y_train = all_train[["Close"]]
  y_train =  np.array(y_train)
  X_valid = all_valid.drop(['Close'], axis=1)
  X_valid =  np.array(X_valid)
  y_valid = all_valid[["Close"]]
  y_valid =  np.array(y_valid)

  #Fit train set to the model
  modelSARIMA = SARIMAX(y_train,
#                   order=(2, 0, 3),
                ).fit() #上記セルのパラメータを参照
  # Generate prediction results
  y_pred = modelSARIMA.forecast(steps=test_size, exog=X_valid) # test_size is set on
"Preparation"
  true_values = y_valid
  # Save prediction results
  prediction_SARIMA.append(y_pred)
  # Save evaluation results for each 10 validation and get mean
  rmse.append(sqrt(mean_squared_error(true_values, y_pred)))
  mae.append(mean_absolute_error(true_values, y_pred))

# print("RMSE: {}".format(rmse))
print("RMSE: {}".format(np.mean(rmse)))
# print("MAE: {}".format(mae))
print("MAE: {}".format(np.mean(mae)))

# Convert prediction results with valid data from 2D list to 1D list
prediction_SARIMA = list(itertools.chain.from_iterable(prediction_SARIMA))
# Prediction with train data
y_pred_train = list(modelSARIMA.predict())
y_pred_train = y_pred_train[:Min_valid_index]
# Store the prediction into the "graph data" table
graph_data_log = graph_data_log.reset_index()
graph_data_log["Close_pred_SARIMA"] = pd.Series(y_pred_train + prediction_SARIMA
)
# Store the result of evaluation into the "Eval_table"
Eval_table_log["SARIMA"] = pd.Series([np.mean(rmse), np.mean(mae)])
```

```
RMSE: 1.0435778265341165
MAE: 0.7790698929200144
```

Others --> Facebook Prophet

(Reference)

- Document of Prophet from Facebook: https://peerj.com/preprints/3190/ (https://peerj.com/preprints/3190/)
- Tutorial for incorporating external explanatory variable: https://nbviewer.jupyter.org/github/nicolasfauchereau/Auckland_Cycling/blob/master/notebooks/Auckland_cy (https://nbviewer.jupyter.org/github/nicolasfauchereau/Auckland_Cycling/blob/master/notebooks/Auckland_c
- Equation: https://devblog.thebase.in/entry/2019/12/20/110000_1 (https://devblog.thebase.in/entry/2019/12/20/110000_1)
- Information in Japanese (Very detailed): https://mikiokubo.github.io/analytics/15forecast.html (https://mikiokubo.github.io/analytics/15forecast.html)

In [69]:
```
## Pick up  Date, Time , Close and cols that have high importance on the linear model
X_cols =  coef_abs_list
```

In [70]:
```
X_cols
```

Out[70]:
```
['System_price(Yen/kWh)',
 'Price_Kansai(Yen/kWh)',
 'Price_Tokyo(Yen/kWh)',
 'Close_lag_2_Day',
 'Low_lag_2_Day']
```

In [71]:
```
all_data_prop = all_data_lagged[X_cols]
all_data_prop["Date"], all_data_prop["Time"], all_data_prop["Close"] = all_data_lagg
ed["Date"], all_data_lagged["Time"], all_data_lagged["Close"]
all_data_prop["DateTime"] = pd.to_datetime(all_data_prop["Date"].astype(str) + " "
+ all_data_prop["Time"].astype(str))
all_data_prop = all_data_prop.drop(["Date", "Time"], axis=1)
all_data_prop.tail()
```

Out[71]:

	System_price(Yen/kWh)	Price_Kansai(Yen/kWh)	Price_Tokyo(Yen/kWh)	Close_lag_2_Day	L
83232	35.0	50.0	35.0	14.90	
83233	45.0	50.0	40.0	9.90	
83234	40.0	40.0	40.0	29.82	
83235	35.0	35.0	35.0	4.05	
83236	25.0	25.0	25.0	4.18	

In [72]:
```
# Set ds and y for the model
all_data_prop = all_data_prop.rename(columns={'DateTime': 'ds', 'Close': 'y'})
```

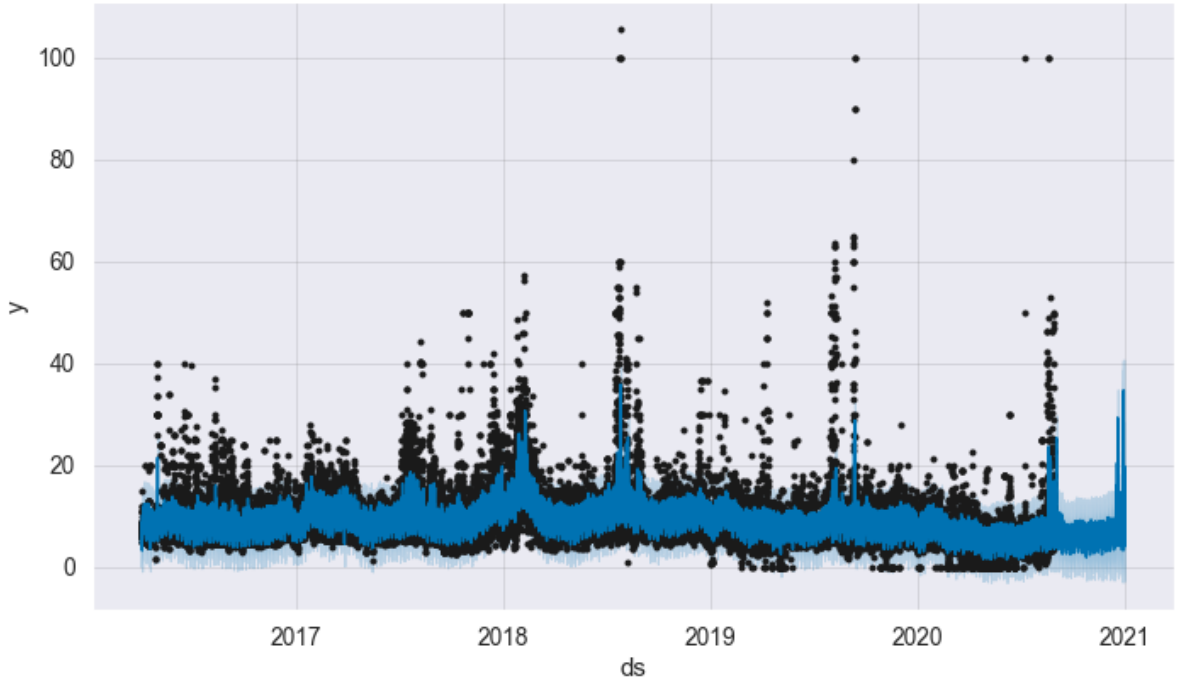
In [73]:
```
all_data_prop.head()
```

Out[73]:

	System_price(Yen/kWh)	Price_Kansai(Yen/kWh)	Price_Tokyo(Yen/kWh)	Close_lag_2_Day	Low_la
0	6.61	6.69	6.69	0.0	
1	6.34	6.34	6.34	0.0	
2	6.34	6.34	6.34	0.0	
3	6.25	6.03	6.03	0.0	
4	6.57	6.57	6.57	0.0	

In [74]:
```
# Divide dataset into train/valid set
all_data_prop_train = all_data_prop.iloc[all_data_prop.index[:len(X)-test_size]]
all_data_prop_valid = all_data_prop.iloc[all_data_prop.index[len(X)-test_size:]]
```

In [75]:
```
from fbprophet import Prophet
modelProp = Prophet()
# set exog for train data
for x in X_cols:
    modelProp = Prophet().add_regressor(x)

# fit train data
modelProp = modelProp.fit(all_data_prop_train)
# Make prediction datatable
future = modelProp.make_future_dataframe(periods=len(all_data_prop_valid), freq='30min')

# set exog for valid data
for x in X_cols:
    future[x] = all_data_prop[x]

# Plot
forecast = modelProp.predict(future)
modelProp.plot(forecast);
```

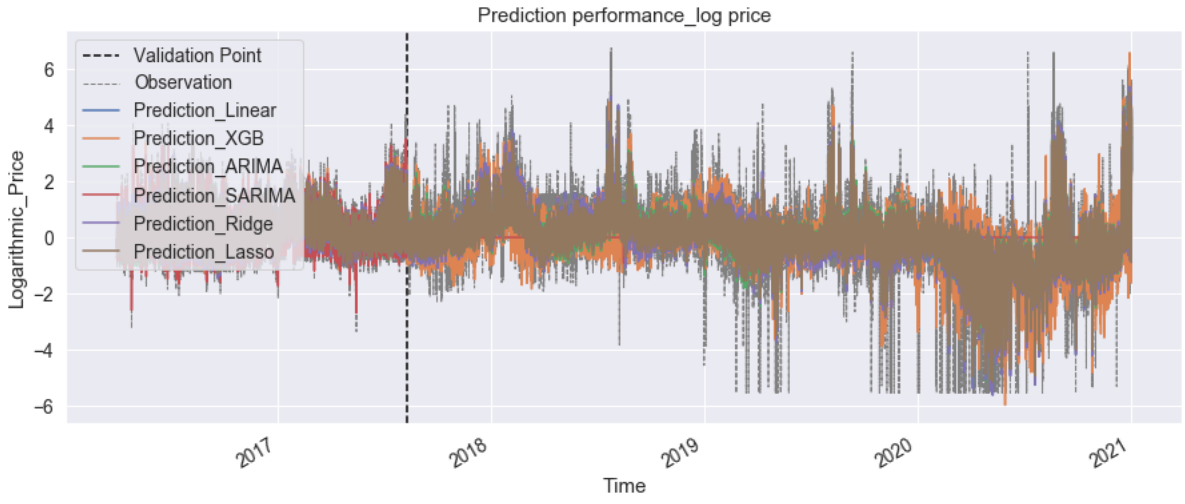


In [76]:
```
training_accuracy = []
valid_accuracy = []
rmse = []
mae = []
prediction_Prophet = []

# Set the parameter for .predict() which is for in-sample prediciton
train_end =  prediction_point.to_pydatetime() - datetime.timedelta(minutes=30)

for train_index, valid_index in tscv.split(X):
    # Divide the train/valid set  into 10 folds and pick up it.
    train_prop, valid_prop = all_data_prop.iloc[train_index], all_data_prop.iloc[valid_ind
ex]
#     y_train, y_valid = train_prop.set_index("ds"), valid_prop.set_index("ds")

    # Add exog for train data
    for x in X_cols:
        modelProphet = Prophet(yearly_seasonality=True).add_regressor(x)

    # fit train data
    modelProphet = modelProphet.fit(train_prop)
    # Make prediction datatable (Need to adjust the parameter of period to match the nu
mber of rows)
    future = modelProphet.make_future_dataframe(periods=len(valid_prop), freq='30mi
n')
    # Add exog for valid data
    for x in X_cols:
        # Add exog for valid data
        future[x] = all_data_prop[x]

    # Generate prediction results
#     future = future.fillna(0, inplace=True)
    forecast = modelProphet.predict(future)
    y_pred = forecast["yhat"][valid_index]
    true_values = valid_prop["y"]
    # Save prediction results
    prediction_Prophet.append(y_pred)
    # Save evaluation results for each 10 validation and get mean
    rmse.append(sqrt(mean_squared_error(true_values, y_pred)))
    mae.append(mean_absolute_error(true_values, y_pred))

# print("RMSE: {}".format(rmse))
print("RMSE: {}".format(np.mean(rmse)))
# print("MAE: {}".format(mae))
print("MAE: {}".format(np.mean(mae)))

# Convert prediction results with valid data from 2D list to 1D list
prediction_Prophet = list(itertools.chain.from_iterable(prediction_Prophet))
# Prediction with train data
y_pred_train = list(forecast["yhat"][:Min_valid_index])
# Store the prediction into the "graph data" table
graph_data_original["Close_pred_Prophet"] = pd.Series(y_pred_train + prediction_Pro
phet)
# Store the result of evaluation into the "Eval_table"
Eval_table_original["Prophet"] = pd.Series([np.mean(rmse), np.mean(mae)])
```

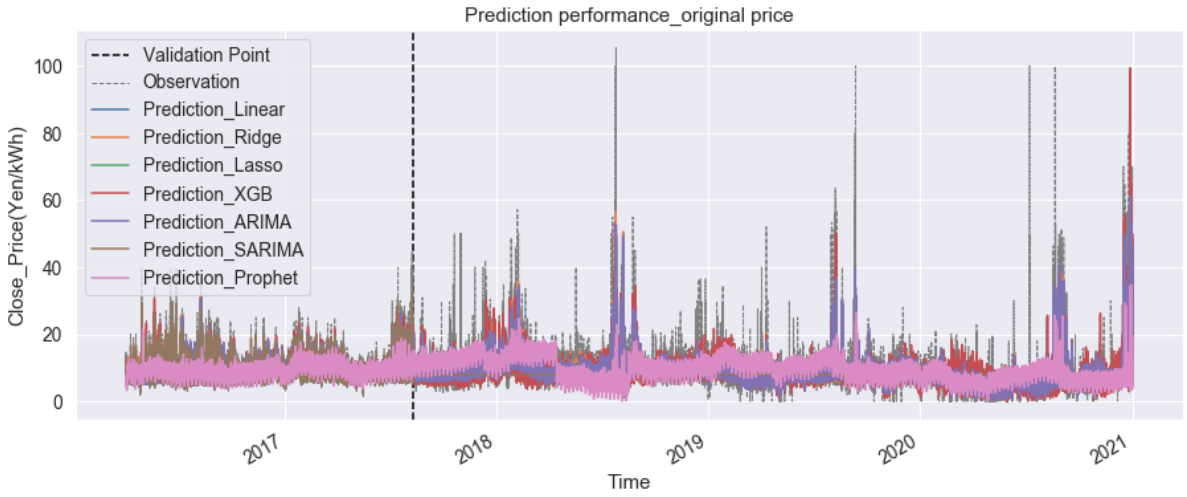
RMSE: 4.769914222748598
MAE: 3.151088811930336

Visualisation of the model performance

In [77]:
```
#対数化されたターゲットと予測値の比較

Models = [
   "Linear",
#    ,"PolyLinear",
       "XGB", "ARIMA", "SARIMA", "Ridge", "Lasso"
        ]

fig, ax = plt.subplots(1, figsize=(15, 6))
plt.title('Prediction performance_log price')

# Set index
graph_data_log = graph_data_log.set_index("DateTime")
start = "2016-04-01 00:00:00"
end = "2020-12-31 23:30:00"

# Vertical line (need to convert the date type from timestamp to datetime.datetime as x
-axis)
plt.axvline(prediction_point.to_pydatetime(), label="Validation Point", linestyle="dashe
d", color="black")
# Add text for the vertical line
# plt.text(prediction_point.to_pydatetime(), -2, 'Prediction Point',rotation=0)

# Plot Close
graph_data_log.Close[graph_data_log.index > start].plot(ax=ax, label="Observation", li
nestyle="dashed", color="gray", linewidth=1)

for model in Models:
   graph_data_log["Close_pred_" + model][graph_data_log.index > start].plot(ax=ax, l
abel="Prediction_" + model)

# x-axis
plt.gcf().autofmt_xdate()
ax.set(xlabel="Time", ylabel="Logarithmic_Price")
plt.legend(loc="upper left");
```



In [91]:
```
graph_data_original = graph_data_original.reset_index()

Models = [
        "Linear", "Ridge", "Lasso", "XGB"
#         , "PolyLinear",
   ,"ARIMA"
   ,"SARIMA"
]

for model in Models:
   # inverse for Prediction
   y_pred_original = inverse_trans_yeo_johnson(all_data_lagged["Close"].values.resha
pe(-1,1), graph_data_log["Close_pred_" + model].values.reshape(-1, 1))
   y_pred_original =  pd.DataFrame(y_pred_original)
   # Add the data on "graph_data"
   graph_data_original["Close_pred_" + model] = y_pred_original

   # Validation setに対してYen/kWhでの評価
   rmse = sqrt(mean_squared_error(graph_data_original.Close[Min_valid_index:], graph
_data_original["Close_pred_" + model][Min_valid_index:]))
   mae = mean_absolute_error(graph_data_original.Close[Min_valid_index:], graph_dat
a_original["Close_pred_" + model][Min_valid_index:])
   # Store the result of evaluation into the "Eval_table"
   Eval_table_original[model] = pd.Series([np.mean(rmse), np.mean(mae)])

graph_data_original = graph_data_original.set_index("DateTime")

# Plot the original close price and  predicted price
fig, ax = plt.subplots(1, figsize=(15, 6))
# Vertical line (need to convert the date type from timestamp to datetime.datetime as x
-axis)
plt.axvline(prediction_point.to_pydatetime(), label="Validation Point", linestyle="dashe
d", color="black")
# Plot Close
graph_data_original.Close[graph_data_original.index > start].plot(ax=ax, label="Observ
ation", linestyle="dashed", color="gray", linewidth=1)

# Plot the predicted price with each model
for model in Models:
   graph_data_original["Close_pred_" + model][graph_data_original.index > start].plot
(ax=ax, label="Prediction_" + model)

# Plot Prophet
graph_data_original["Close_pred_Prophet"][graph_data_original.index > start].plot(ax
=ax, label="Prediction_Prophet")

# x-axis
plt.title('Prediction performance_original price')
plt.gcf().autofmt_xdate()
ax.set(xlabel="Time", ylabel="Close_Price(Yen/kWh)")
plt.legend(loc="upper left");
```



In [80]:
```
# Evalation for the prediction of validation data based on log
Eval_table_log
```

Out[80]:

	EvalFunc	Linear	Ridge	Lasso	XGB	ARIMA	SARIMA
0	RMSE_log	0.608042	0.607720	0.598954	0.732057	0.596273	1.043578
1	MAE_log	0.430938	0.430592	0.420225	0.537617	0.415526	0.779070

In [92]:
```
# Evalation for the prediction of validation data based on original
Eval_table_original
```

Out[92]:

	EvalFunc	Prophet	ARIMA	Linear	Ridge	Lasso	XGB	SARIMA
0	RMSE_Yen/kWh	4.769914	2.898006	2.907833	2.907096	2.938542	3.482836	5.075197
1	MAE_Yen/kWh	3.151089	1.535714	1.585864	1.584548	1.558018	1.949493	2.855057

The folloing information could be the benchmark for the prediction performance.

In [84]:
```
spot = all_data["System_price(Yen/kWh)"][Min_valid_index:]
close = all_data["Close"][Min_valid_index:]

print("RMSE_Spot/Close: {}".format(round(sqrt(mean_squared_error(close, spot)), 4
)))
print("MAE_Spot/Close: {}".format(round(mean_absolute_error(close, spot), 4)))
```

```
RMSE_Spot/Close: 2.8517
MAE_Spot/Close: 1.4936
```

In [82]:
```
all_data["Close"][Min_valid_index:].describe()
```

Out[82]:
```
count    59460.000000
mean         8.569872
std          5.037051
min          0.010000
25%          5.960000
50%          7.760000
75%          9.990000
max        105.500000
Name: Close, dtype: float64
```

Target

- Mean: 6.693
- Std; 5.888

Making combined price data for the Phase 2

In [101]:
```
# Finalise dataset and make the csv data for trading phase

# Decide one model for trading
model = "ARIMA"

df_prediction = all_data[['Date', 'HH', 'Open', 'High', 'Low', 'Close', 'System_price(Yen/kWh)']]
df_prediction["DateTime"] = graph_data_original.reset_index()["DateTime"]
df_prediction = df_prediction.rename(columns={'System_price(Yen/kWh)': 'Spot'})

graph_data_original = graph_data_original.reset_index()
df_prediction['Close_pred'] = graph_data_original["Close_pred_" + model].round(2)
df_prediction = df_prediction[df_prediction.index >= Min_valid_index]

# CSV file
df_prediction.to_csv('/Users/kenotsu/Documents/master_thesis/Datasets/Master_thesis/df_prediction.csv', index=False)
```

In [102]:
```
df_prediction
```

Out[102]:

	Date	HH	Open	High	Low	Close	Spot	DateTime	Close_pred
23777	2017-08-09	18	19.5	20.00	5.39	9.55	10.68	2017-08-09 08:30:00	10.19
23778	2017-08-09	19	20.0	20.00	9.32	9.32	14.75	2017-08-09 09:00:00	14.02
23779	2017-08-09	20	25.0	25.50	10.78	13.01	16.00	2017-08-09 09:30:00	16.05
23780	2017-08-09	21	28.5	29.00	13.00	20.34	19.90	2017-08-09 10:00:00	17.08
23781	2017-08-09	22	30.0	31.99	13.00	13.50	20.00	2017-08-09 10:30:00	19.19
...	...	...	...	...	...	...	...	...	...
83232	2020-12-31	44	35.0	70.00	33.00	70.00	35.00	2020-12-31 21:30:00	32.30
83233	2020-12-31	45	42.0	70.00	41.01	45.48	45.00	2020-12-31 22:00:00	35.72
83234	2020-12-31	46	42.0	70.00	35.00	41.33	40.00	2020-12-31 22:30:00	33.04
83235	2020-12-31	47	37.0	70.00	33.93	36.66	35.00	2020-12-31 23:00:00	27.00
83236	2020-12-31	48	27.0	37.50	23.93	26.46	25.00	2020-12-31 23:30:00	20.35

59460 rows × 9 columns

In [ ]:
```

```