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Goal and Description

The data is the measurements of electric power consumption in one household with a one-minute sampling rate over a period of almost 4 years.

The **raw data** can be downloaded from **here**

Different electrical quantities and some sub-metering values are available. The aim of this excersise to perform the **Timeseries forecasting and predictive analysis** on `Global_active_power variable`, which represent the total power consumption.

Importing the libraries

In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import pandas as pd
import seaborn as sns
import warnings
from time import time
import matplotlib.ticker as tkr
```

```
import matplotlib.ticker as tkr
from scipy import stats
from statsmodels.tsa.stattools import adfuller
from sklearn import preprocessing
from statsmodels.tsa.stattools import pacf
%matplotlib inline

import math
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM,GRU
from tensorflow.keras.layers import Dropout
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from tensorflow.keras.models import load_model
from tensorflow.keras.callbacks import EarlyStopping, CSVLogger, ModelCheckpoint,
ReduceLROnPlateau

warnings.filterwarnings('ignore')
```

Plot settings

In [2]:

```
plt.rcParams['axes.labelsize'] = 20
plt.rcParams['xtick.labelsize'] = 15
plt.rcParams['ytick.labelsize'] = 15
plt.rcParams['legend.fontsize'] = 23
plt.rcParams['figure.titlesize'] = 26
plt.rcParams['xtick.major.size'] = 10
plt.rcParams['xtick.major.width'] = 1
plt.rcParams['ytick.major.size'] = 10
plt.rcParams['ytick.major.width'] = 1
plt.rcParams['xtick.minor.width'] = 1
plt.rcParams['ytick.minor.size'] = 5
plt.rcParams['ytick.minor.width'] = 1
plt.rcParams['xtick.minor.size'] = 5
plt.rcParams['figure.figsize'] = 10,7
sns.set_style('ticks')
```

Reading and preprocessing the csv file

In [3]:

```
csv_file='household_power_consumption.txt'
df=pd.read_csv(csv_file, delimiter=';')
df.head()
```

Out[3]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_m
0	16/12/2006	17:24:00	4.216	0.418	234.840	18.400	0.000	1.000	
1	16/12/2006	17:25:00	5.360	0.436	233.630	23.000	0.000	1.000	
2	16/12/2006	17:26:00	5.374	0.498	233.290	23.000	0.000	2.000	
3	16/12/2006	17:27:00	5.388	0.502	233.740	23.000	0.000	1.000	
4	16/12/2006	17:28:00	3.666	0.528	235.680	15.800	0.000	1.000	

Combining datetime

In [4]:

```
df['Datetime'] =pd.to_datetime(df['Date'] + ' ' + df['Time'])
df.drop(['Date','Time'],axis=1,inplace=True)
```

Missing values

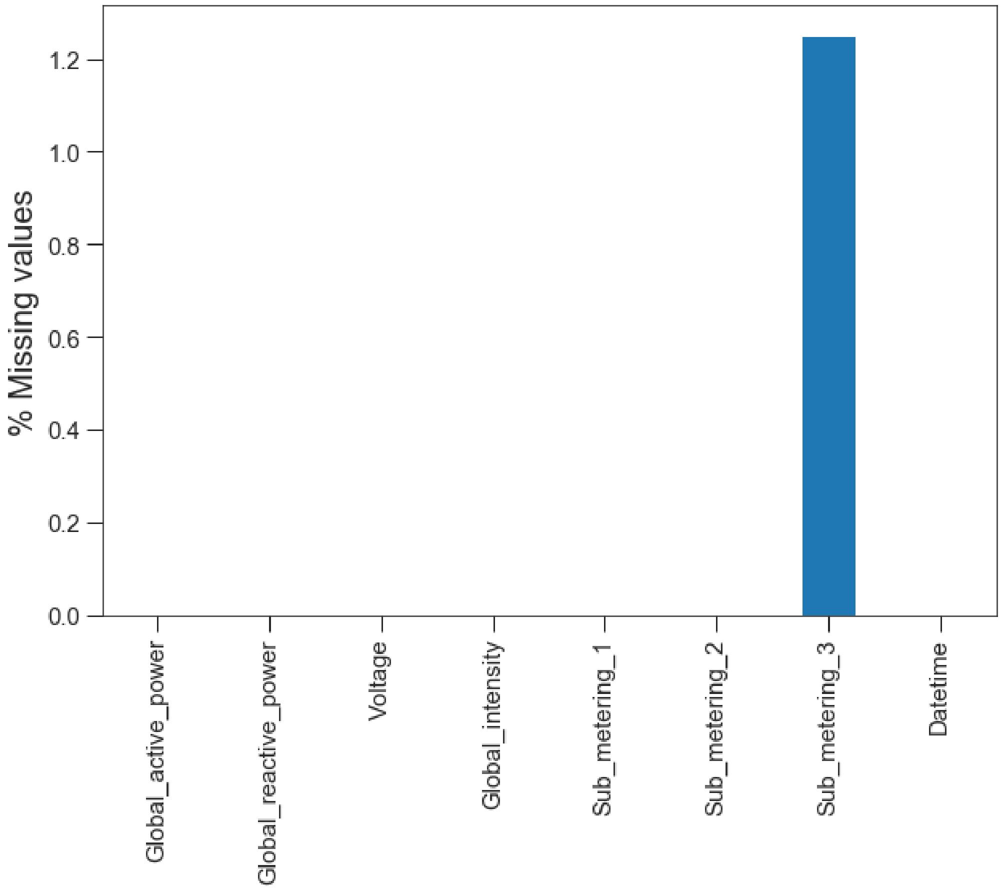
In [5]:

```
print(f'Total length : {len(df)}')
missing_values= df.isnull().sum()*100 / len(df)
missing_values.plot.bar()
plt.ylabel('% Missing values')
```

```
Total length : 2075259
```

Out[5]:

```
Text(0, 0.5, '% Missing values')
```



Approx **1.25%** of value in Sub_metering_3 column are missing. I can `ffill`, `bfill` them. However, I decided to drop them to avoid potential artifact.

Generating more time columns

In [6]:

```
df['Global_active_power'] = pd.to_numeric(df['Global_active_power'], errors='coerce') ## Removes in
valid entries with NaN
df.dropna(subset=['Global_active_power'],inplace=True)
df['year'] = df['Datetime'].apply(lambda x: x.year)
df['quarter'] = df['Datetime'].apply(lambda x: x.quarter)
df['month'] = df['Datetime'].apply(lambda x: x.month)
df['day'] = df['Datetime'].apply(lambda x: x.day)
```

In [7]:

```
df=df.loc[:,['Datetime','Global_active_power', 'year','quarter','month','day']]
df.index = df['Datetime']
df=df.sort_index(ascending=True)
df['weekday']=df['Datetime'].map(lambda x: x.weekday())
```

```
df['weekday'] = (df['weekday'] < 5).astype(int)
```

In [8]:

```
print('Number of rows and columns after removing missing values:', df.shape)
print('The time series starts from: ', df.Datetime.min())
print('The time series ends on: ', df.Datetime.max())
```

```
Number of rows and columns after removing missing values: (2049280, 7)
The time series starts from:  2006-12-16 17:24:00
The time series ends on:  2010-12-11 23:59:00
```

In [9]:

```
df.loc[:,'Global_active_power'].T.describe().round(3)
```

Out[9]:

```
count    2049280.000
mean           1.092
std            1.057
min            0.076
25%            0.308
50%            0.602
75%            1.528
max           11.122
Name: Global_active_power, dtype: float64
```

After removing the missing values, the final data contains **2049280** measurements gathered between **December 2006 and November 2010 (47 months)**.

The initial data contains several variables. We will here focus on a single value : a house's `Global_active_power` history, that is, household global minute-averaged active power in kilowatt.

Statistical Normality Test

There are several statistical tests that we can use to quantify whether our data looks as though it was drawn from a Gaussian distribution.

In the SciPy implementation of the test, the data can be interpretted using the p value as follows.

- p <= alpha: reject , not normal.
- p > alpha: fail to reject H0, normal.

Null Hypothesis (H_0) : The the sample was drawn from a Gaussian distribution.

In the SciPy implementation of these tests, you can interpret the p value as follows.

```
p <= alpha: reject H_0, not a normal distribution.
p > alpha: fail to reject H_0, normal distribution.
```

This means that, in general, a larger p-value to confirms that our sample was likely drawn from a Gaussian distribution.

A result above 5% does not mean that the null hypothesis is true. It means that it is very likely true given available evidence.

Hypothesis testing with Shiparo-Wilk test

In [10]:

```
stat, p = stats.shapiro(df.Global_active_power)
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05 ## threshold
if p > alpha:
    print('Data looks Gaussian (fail to reject H0)')
else:
    print('Data does not look Gaussian (reject H0)')
```

```
Statistics=0.806, p=0.000
Data does not look Gaussian (reject H0)
```

Hypothesis testing with D'Agostino's K^2 test

In [11]:

```
stat, p = stats.normaltest(df.Global_active_power)
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Data looks Gaussian (fail to reject H_0)')
else:
    print('Data does not look Gaussian (reject H_0)')
```

```
Statistics=724881.795, p=0.000
Data does not look Gaussian (reject H_0)
```

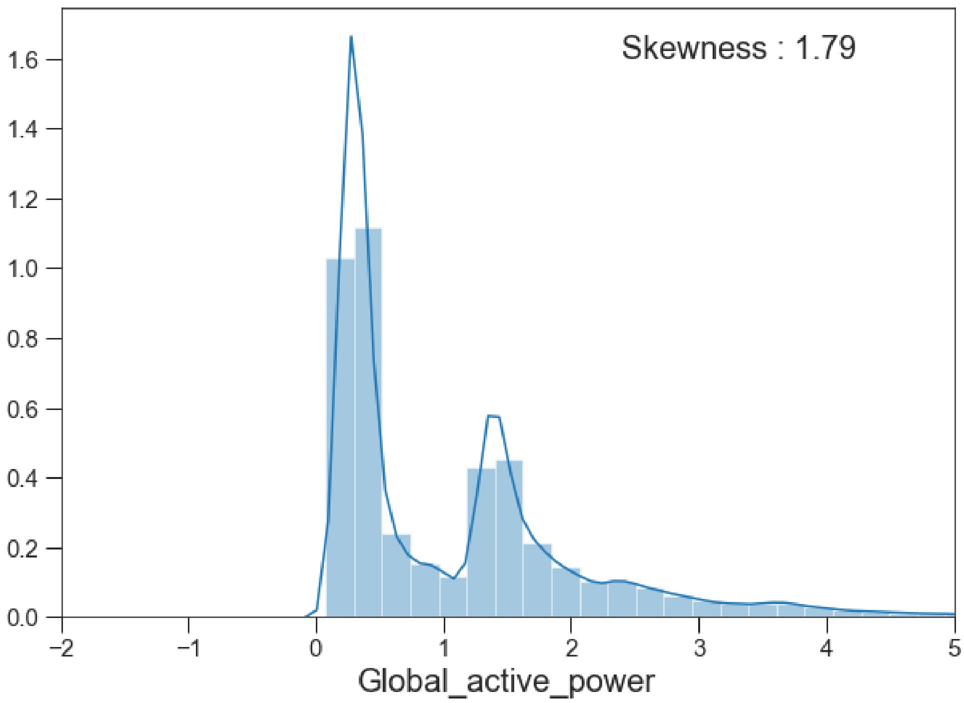
Skewness

In [12]:

```
ax=sns.distplot(df.Global_active_power)
skewness=stats.skew(df.Global_active_power)
ax.annotate(f'Skewness : {skewness:.2f}',xy=(2.4,1.6),size=20)
plt.xlim([-2,5])
```

Out[12]:

```
(-2, 5)
```

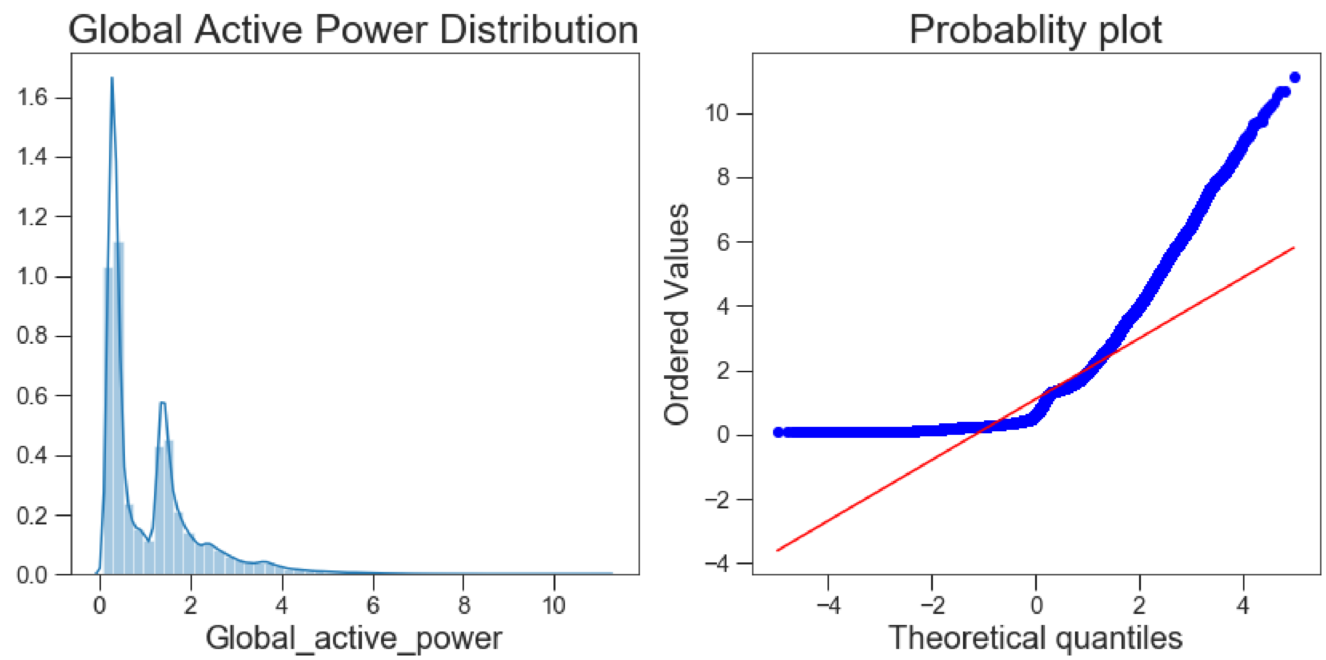


Global Active Power Distribution

In [13]:

```
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
sns.distplot(df['Global_active_power'])
plt.title('Global Active Power Distribution',size=25)

plt.subplot(1,2,2)
```

```
plt.subplot(1,2,2)
stats.probplot(df['Global_active_power'], plot=plt)
plt.title('Probablity plot',size=25);
```



Conclusion

- Shiparo-Wilk concludes that data is **not** sampled from a normal distribution.
- D'Agostino's K^2 test also concludes that data is **not** sampled from a normal distribution.
- `Global_active_power` data is highly skewed because the **skewness** is greater than 1, which can also be confirmed from the probability plot.

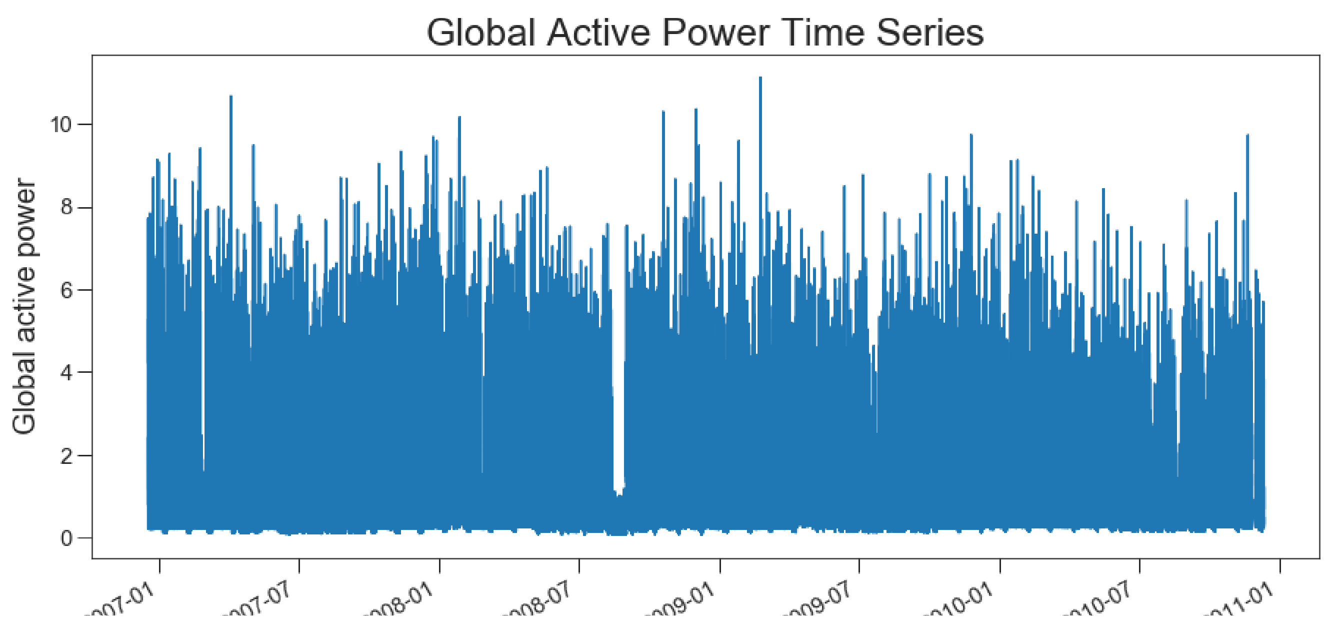
Timeseries analysis

In [14]:

```
df['Global_active_power'].plot(figsize=(15,7),legend=False)
plt.ylabel('Global active power')
plt.title('Global Active Power Time Series',size=26)
```

Out[14]:

```
Text(0.5, 1.0, 'Global Active Power Time Series')
```



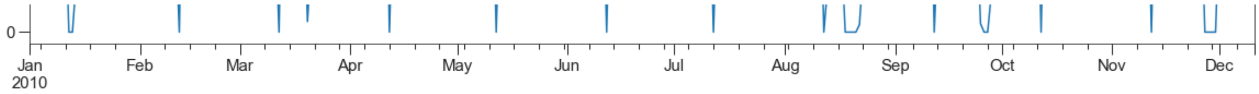
Global Active Power by Years

In [17]:

```
fig, axes = plt.subplots(ncols=1,nrows=5,figsize=(20,25))
years=df['year'].unique()
for i,ax in enumerate(axes.flat):
            df['Global_active_power'][str(years[i])].resample('D').sum().plot(ax=ax)
            ax.set_ylabel(years[i])
axes[0].set_title('Global active power in various years (Resample over day)',size=28);
plt.xlabel('Date')
```

Out[17]:

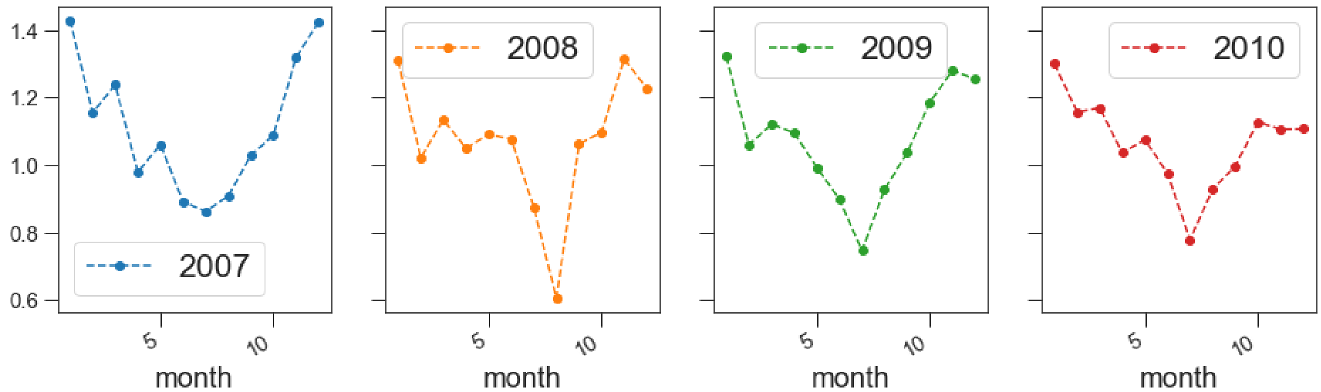
```
Text(0.5, 0, 'Date')
```



For 2006, we only have data for December, so **discarding 2006**.

In [18]:

```
pd.pivot_table(df.loc[df['year'] != 2006], values = "Global_active_power",
               columns = 'year', index = 'month').plot(
               subplots = True, figsize=(20, 15), layout=(3, 5), sharey=True, marker='o',ls='--');
```



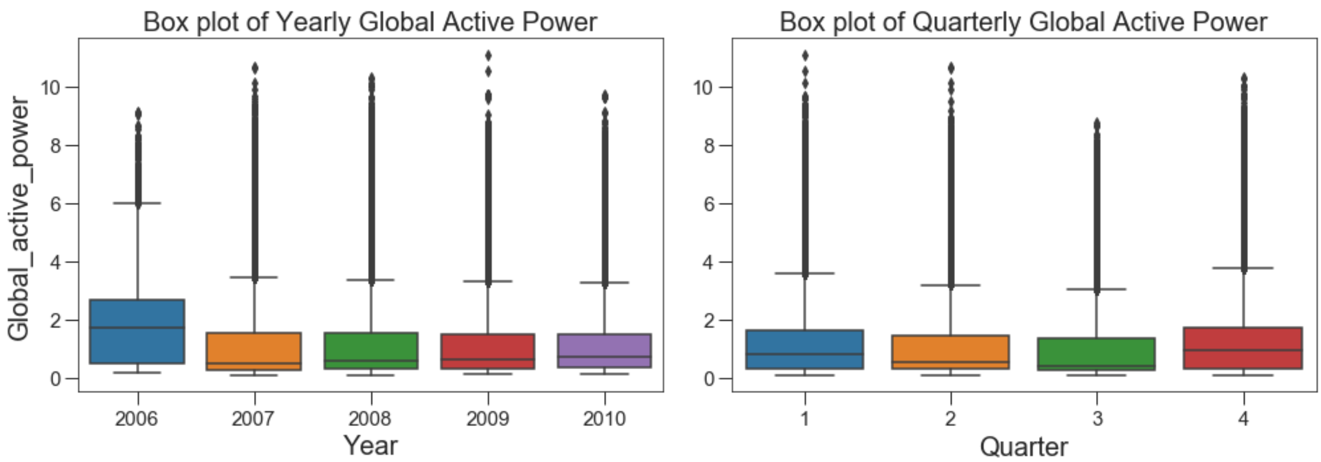
Box plot of yearly vs quarterly Global active power

In [19]:

```
fig,ax= plt.subplots(figsize=(14,5),sharey=True)
plt.subplot(1,2,1)
plt.subplots_adjust(wspace=1)
sns.boxplot(x='year', y='Global_active_power', data=df)
plt.xlabel('Year')
plt.title('Box plot of Yearly Global Active Power',size=20)
plt.tight_layout()

plt.subplot(1,2,2)
sns.boxplot(x='quarter', y='Global_active_power', data=df)
plt.xlabel('Quarter')
plt.ylabel('')
plt.title('Box plot of Quarterly Global Active Power',size=20)
```

Out[19]:

```
Text(0.5, 1.0, 'Box plot of Quarterly Global Active Power')
```



From the timeseries plots it is clear that we only have a month of data available for year **2006**. Therefore, interpretation of year **2006** should be excluded from the any yearwise analysis because it can be misleading. It can be noted in the boxplots above. The median of year 2006 in left lie above the median of other years. Also, consumption is increased in quarter 4, which can be noted in the quartely boxplot.

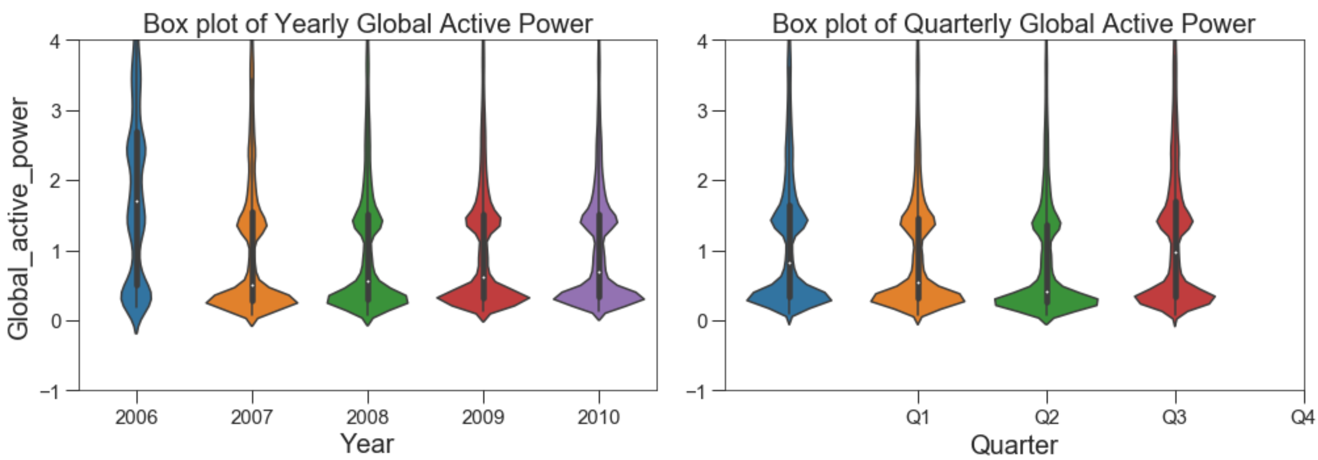
Violin plot of yearly vs quarterly Global active power

In [20]:

```
fig,ax= plt.subplots(figsize=(14,5),sharey=True)
plt.subplot(1,2,1)
plt.subplots_adjust(wspace=1)
sns.violinplot(x='year', y='Global_active_power', data=df)
plt.xlabel('Year')
plt.title('Box plot of Yearly Global Active Power',size=20)
plt.ylim([-1,4])
plt.tight_layout()

plt.subplot(1,2,2)
sns.violinplot(x='quarter', y='Global_active_power', data=df)
plt.xlabel('Quarter')
plt.ylabel('')
plt.ylim([-1,4])
plt.xticks(range(1,5),['Q1','Q2','Q3','Q4'])
plt.title('Box plot of Quarterly Global Active Power',size=20)
```

Out[20]:

```
Text(0.5, 1.0, 'Box plot of Quarterly Global Active Power')
```

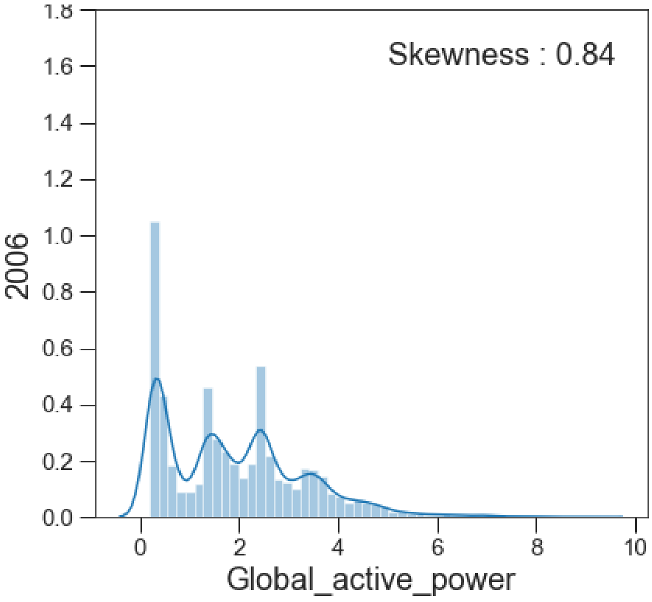


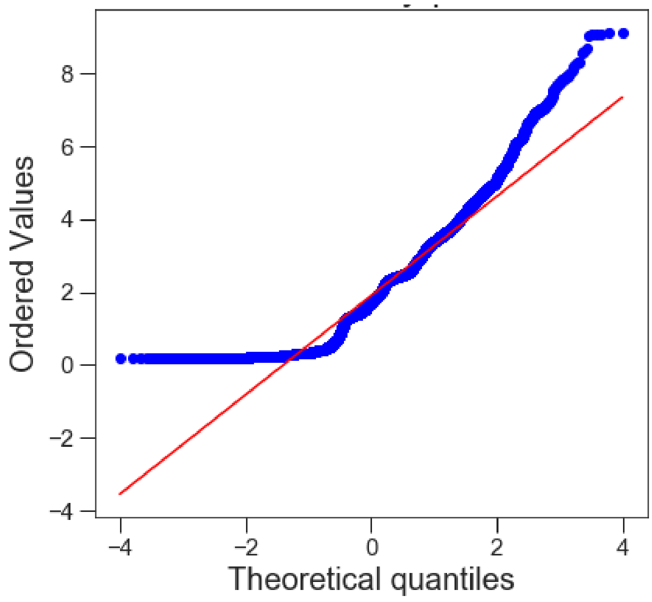
It can be noted that the distribution of yearly consumption looks very similar for every year excluding **2006**. Quaterly mean consumption is again **higher for Q1 and Q4**.

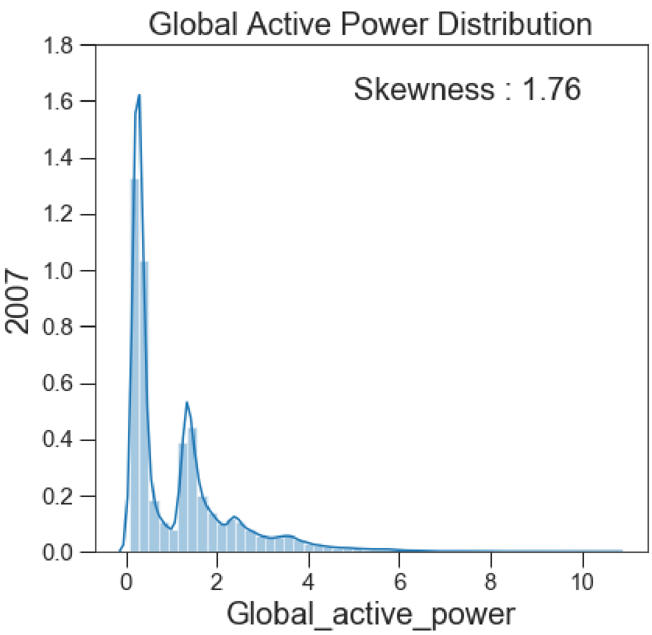
Yearly distribution and Skewness

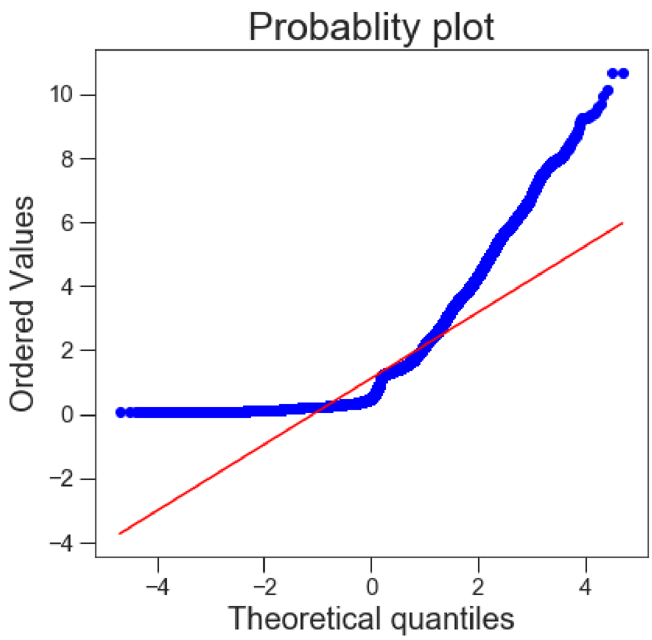
In [21]:

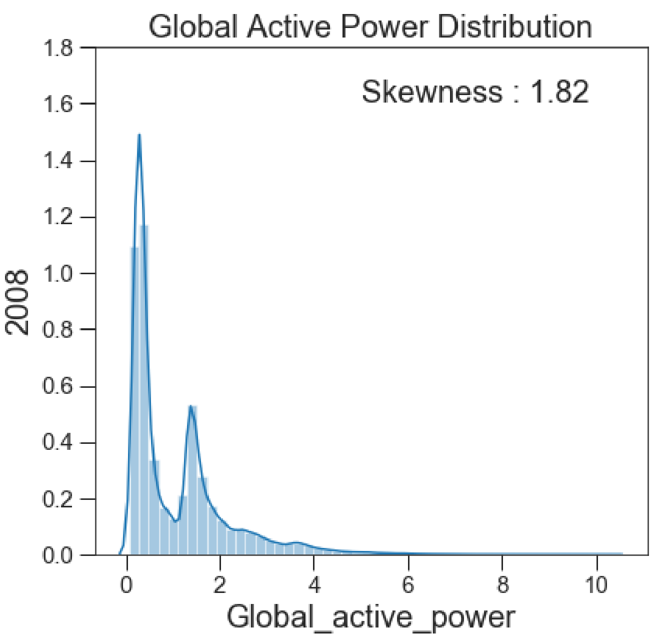
```
for year in years:
    plt.figure(figsize=(14,6))
    plt.subplot(1,2,1)
    ax=sns.distplot(df['Global_active_power'][str(year)])
    skewness=stats.skew(df.Global_active_power[str(year)])
    ax.annotate(f'Skewness : {skewness:.2f}',xy=(5,1.6),size=20)
    plt.title('Global Active Power Distribution',size=20)
    plt.ylim([0,1.8])
    plt.ylabel(year)

    plt.subplot(1,2,2)
    stats.probplot(df['Global_active_power'][str(year)], plot=plt)
    plt.title('Probablity plot',size=25)
    plt.show()
```

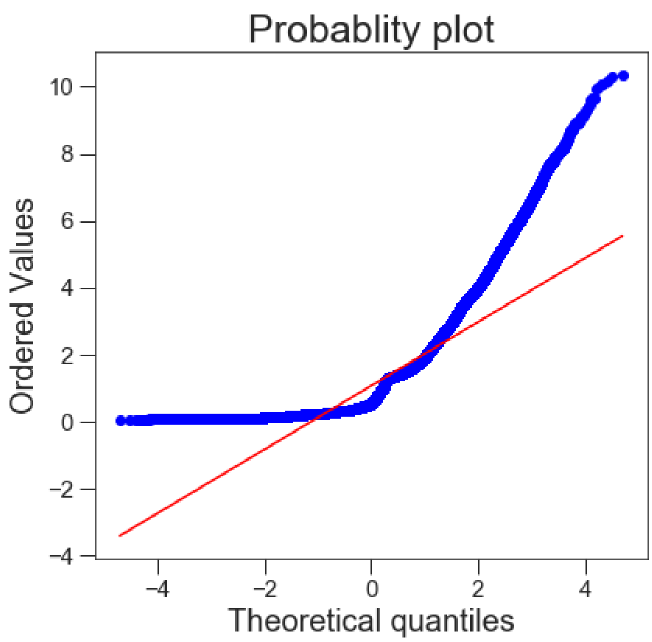

Skewness : 0.84
2006
Global_active_power


Ordered Values
Theoretical quantiles


Global Active Power Distribution
Skewness : 1.76
2007
Global_active_power

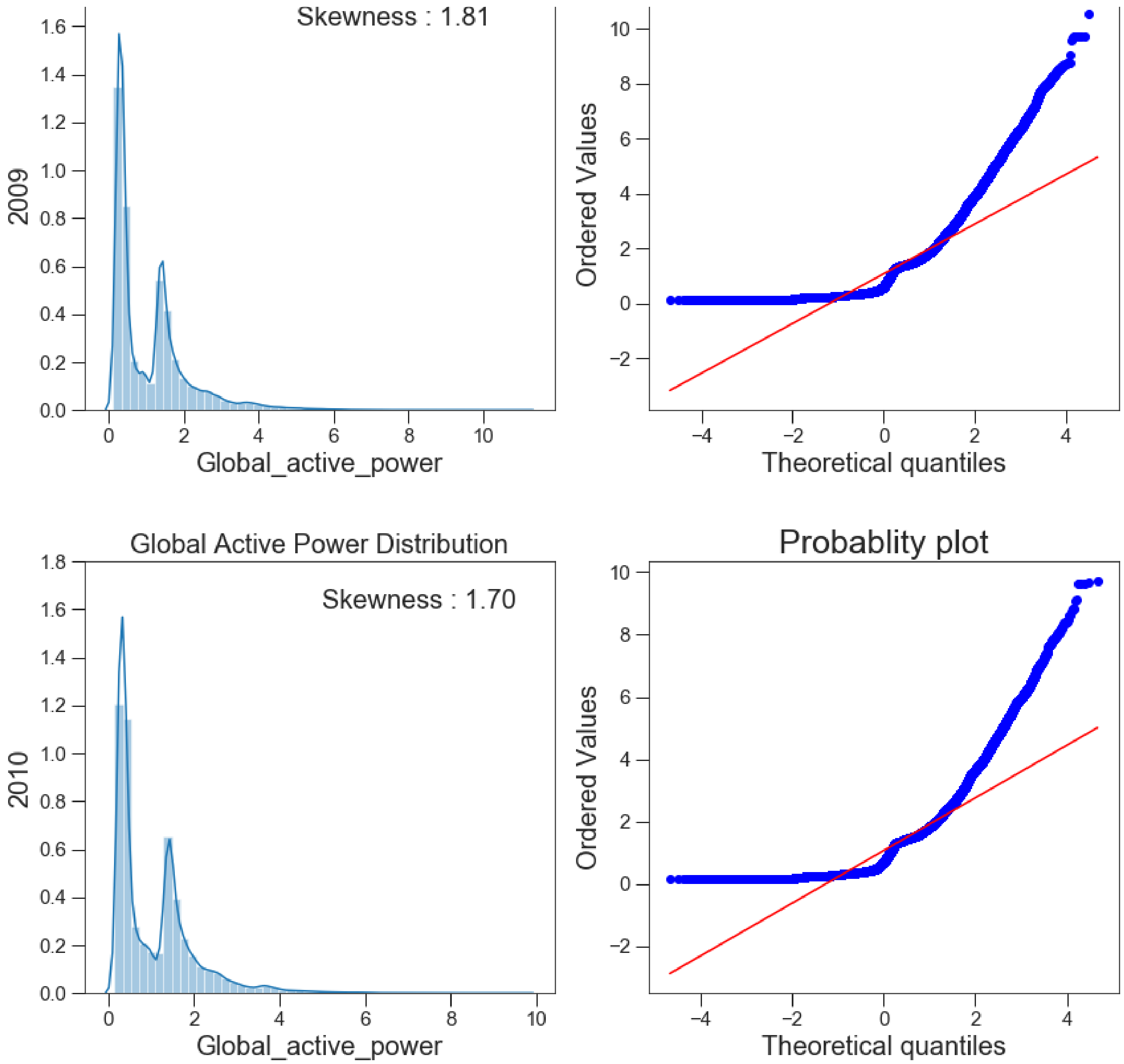

Probablity plot
Ordered Values
Theoretical quantiles


Global Active Power Distribution
Skewness : 1.82
2008
Global_active_power


Probablity plot
Ordered Values
Theoretical quantiles


Global Active Power Distribution


Probablity plot

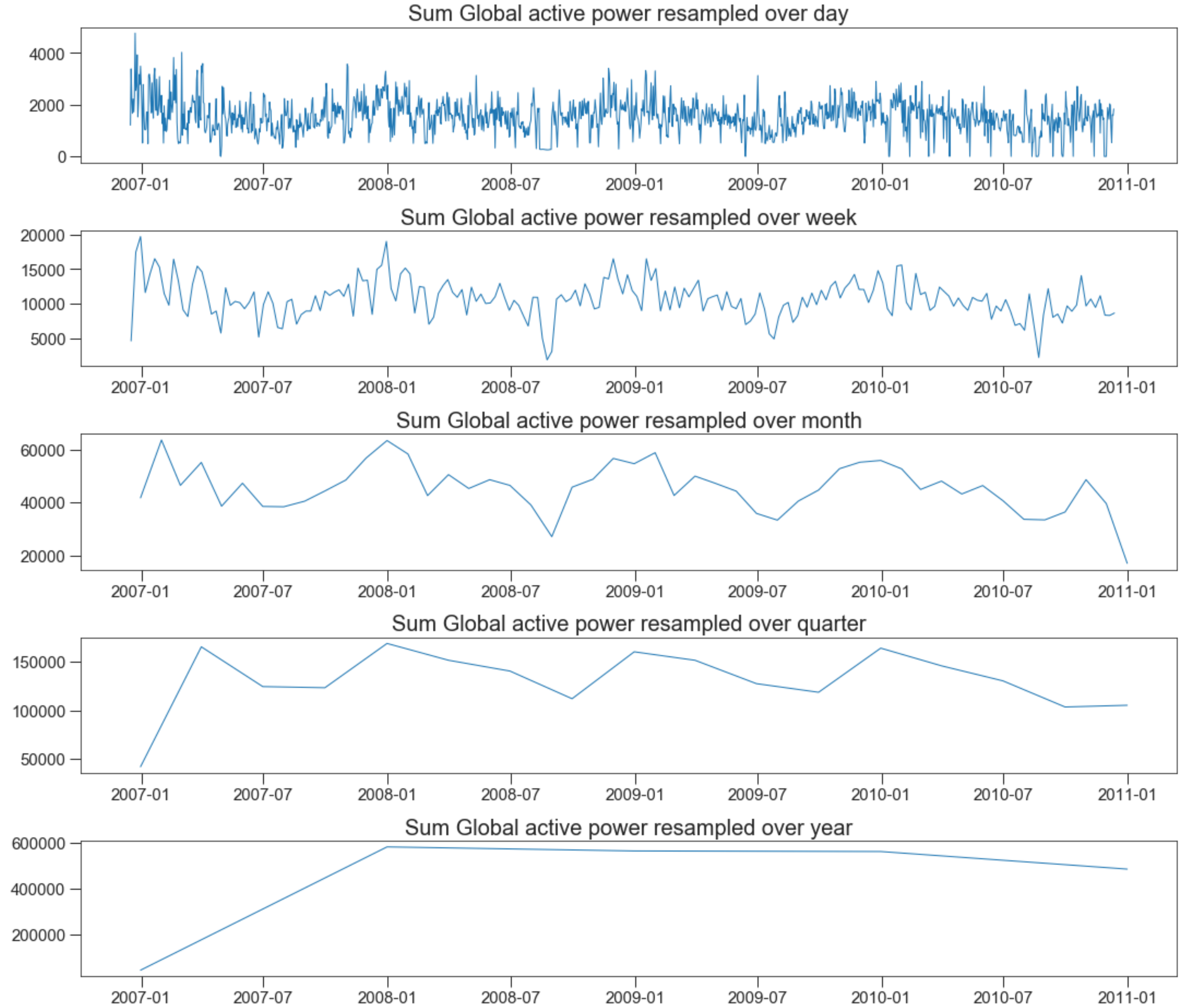


Average Global Active Power resampled over day, week, month, quarter and year.

In [22]:

```
fig= plt.figure(figsize=(18,16))
fig.subplots_adjust(hspace=0.5)
ax1 = fig.add_subplot(5,1,1)
ax1.plot(df['Global_active_power'].resample('D').sum(),linewidth=1)
ax1.set_title('Sum Global active power resampled over day',size=20)
ax1.tick_params(axis='both', which='major')

ax2 = fig.add_subplot(5,1,2, sharex=ax1)
ax2.plot(df['Global_active_power'].resample('W').sum(),linewidth=1)
ax2.set_title('Sum Global active power resampled over week',size=20)
ax2.tick_params(axis='both', which='major')

ax3 = fig.add_subplot(5,1,3, sharex=ax1)
ax3.plot(df['Global_active_power'].resample('M').sum(),linewidth=1)
ax3.set_title('Sum Global active power resampled over month',size=20)
ax3.tick_params(axis='both', which='major')

ax4  = fig.add_subplot(5,1,4, sharex=ax1)
ax4.plot(df['Global_active_power'].resample('Q').sum(),linewidth=1)
ax4.set_title('Sum Global active power resampled over quarter',size=20)
ax4.tick_params(axis='both', which='major')

ax5  = fig.add_subplot(5,1,5, sharex=ax1)
ax5.plot(df['Global_active_power'].resample('A').sum(),linewidth=1)
```

```
ax5.set_title('Sum Global active power resampled over year',size=20)
ax5.tick_params(axis='both', which='major');
```



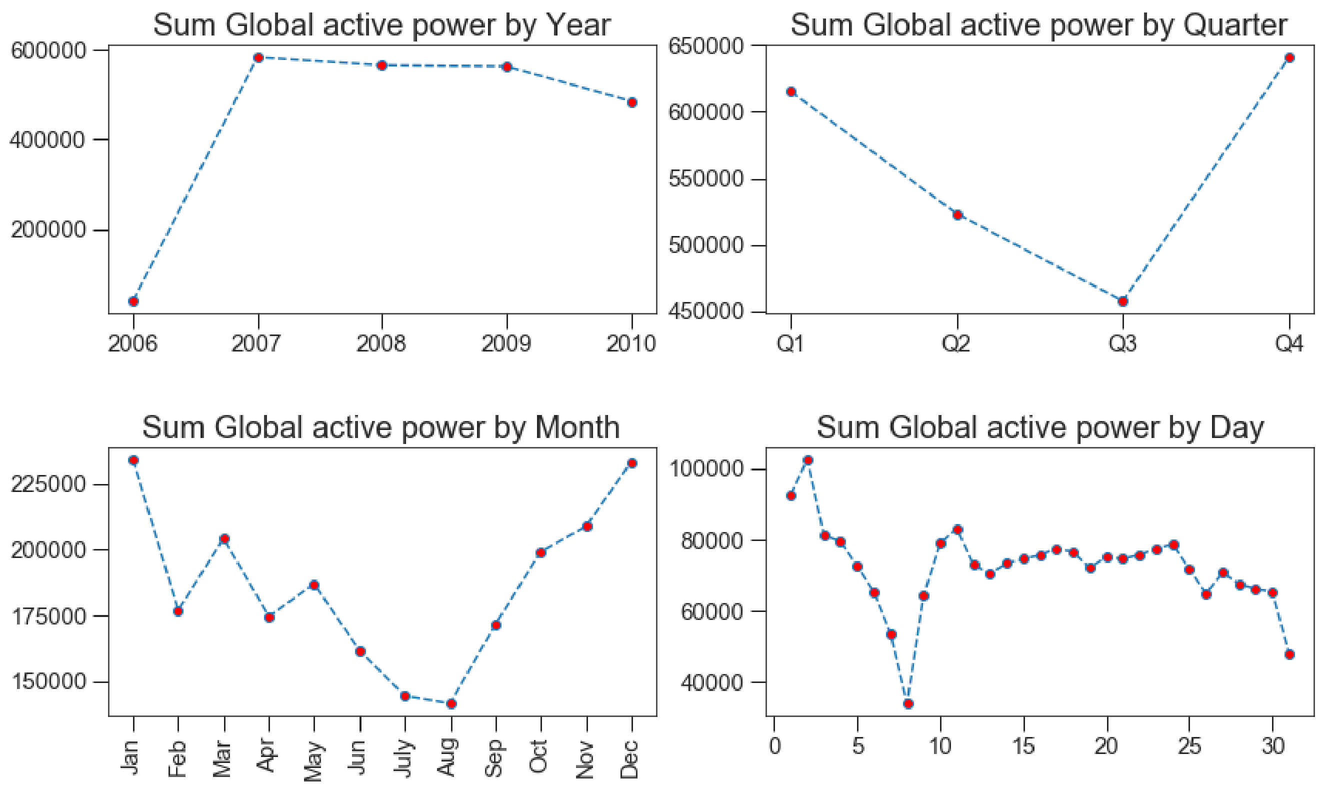
In general, time series does not show any trend have a general upward or downward trend. The year power consumption looks almost constant, which have noted previously. There is some periodicity/seasonality that can be seen in the plots, which suggests that `Global active power` is **highest at the end and early part of the year**.

Plot mean global active power grouped by year, quarter, month and day.

In [23]:

```
fig,ax=plt.subplots(figsize=(14,8))
plt.subplot(2,2,1)
fig.subplots_adjust(hspace=0.5)
df.groupby('year').Global_active_power.agg('sum').plot(marker='o',markerfacecolor='r',ls='--')
plt.xlabel('')
plt.title('Sum Global active power by Year',size=20)

plt.subplot(2,2,2)
df.groupby('quarter').Global_active_power.agg('sum').plot(marker='o', markerfacecolor='r',ls='--')
plt.xlabel('')
plt.title('Sum Global active power by Quarter',size=20)
plt.xticks(range(1,5),['Q1','Q2','Q3','Q4'])

plt.subplot(2,2,3)
df.groupby('month').Global_active_power.agg('sum').plot(marker='o',markerfacecolor='r',ls='--')
plt.xlabel('')
plt.title('Sum Global active power by Month',size=20)
plt.xticks(range(1,13),['Jan','Feb','Mar','Apr','May','Jun','July','Aug','Sep','Oct','Nov','Dec'],r
otation=90)
```

```
plt.subplot(2,2,4)
df.groupby('day').Global_active_power.agg('sum').plot(marker='o',markerfacecolor='r',ls='--')
plt.xlabel('')
plt.title('Sum Global active power by Day',size=20);
```

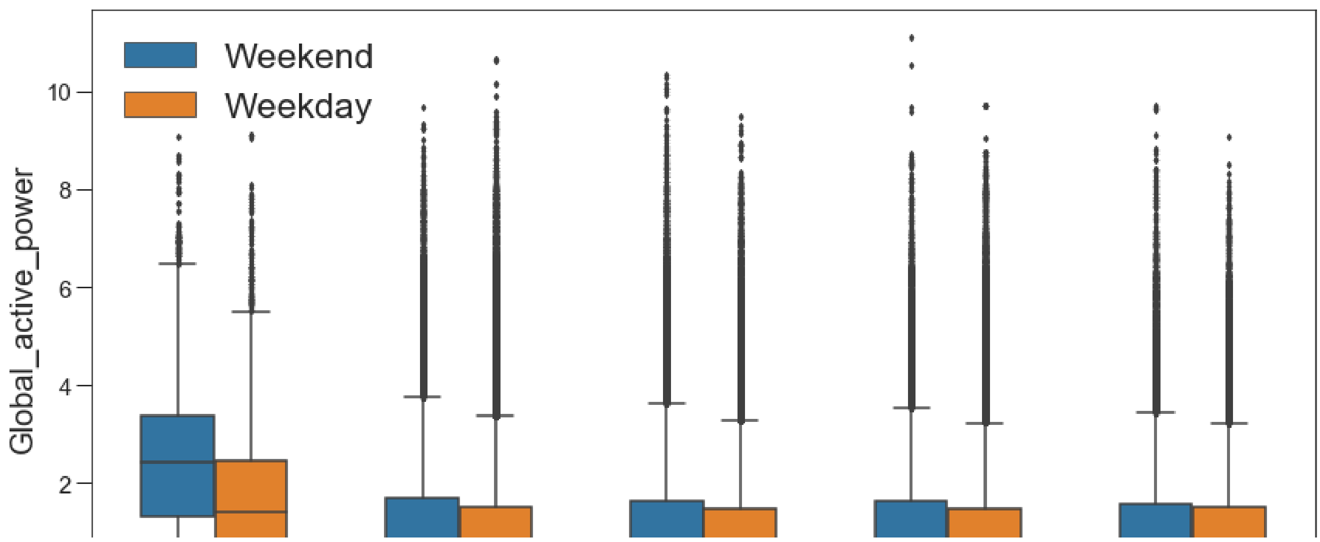


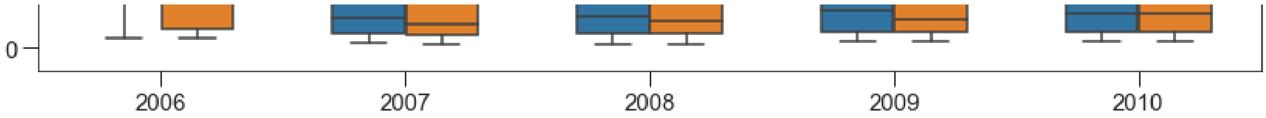
The plot above confirms the previous observations. **Q4 and Q1** have the highest power consumption possibly due to winter, when heating is on.

Global active power consumption in Weekdays vs. Weekends

In [24]:

```
dic={0:'Weekend',1:'Weekday'}
df['Day'] = df.weekday.map(dic)
plt.figure(figsize=(12,6))
sns.boxplot('year','Global_active_power',hue='Day',width=0.6,fliersize=3,data=df)

plt.xlabel('')
plt.tight_layout()

plt.legend(frameon=False);
```



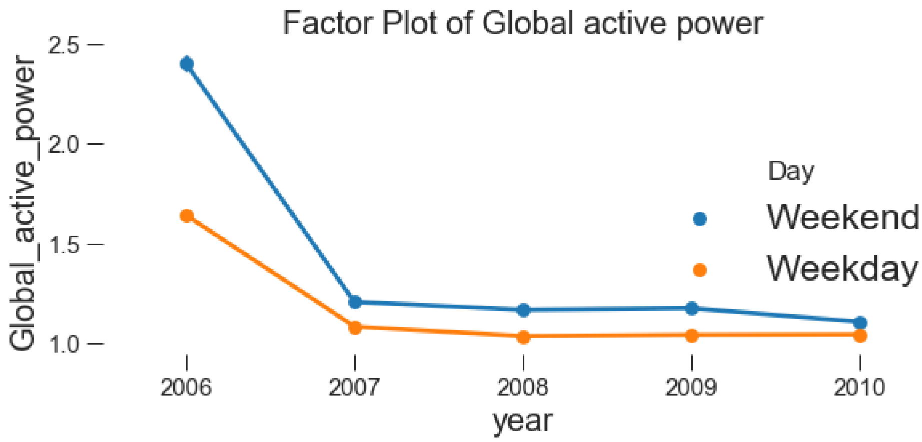


The median global active power in appears to be **lower than the weekends prior to 2010**, possibly due to subject being at work during the weekdays.

In [25]:

```
plt.figure(figsize=(10,7))
sns.factorplot('year','Global_active_power',hue='Day',
                    data=df, size=4, aspect=1.5,)

plt.title('Factor Plot of Global active power',size=20)

plt.tight_layout()

sns.despine(left=True, bottom=True)
```

```
<Figure size 720x504 with 0 Axes>
```



Both weekdays and weekends have the similar trends over year.

Checking Stationarity in Timeseries data

In principle we do not need to check for stationarity nor correct for it when we are using an LSTM. However, if the data is stationary, it will help with better performance and make it easier for the neural network to learn.

Dickey-Fuller test

Null Hypothesis (H_0): It suggests the time series has a unit root, meaning it is non-stationary. It has some time dependent structure.

Alternate Hypothesis (H_1): It suggests the time series does not have a unit root, meaning it is stationary. It does not have time-dependent structure.

```
p-value > 0.05: Accept the null hypothesis (H0), the data has a unit root and is non-stationary.
p-value <= 0.05: Reject the null hypothesis (H0), the data does not have a unit root and is stationary.
```

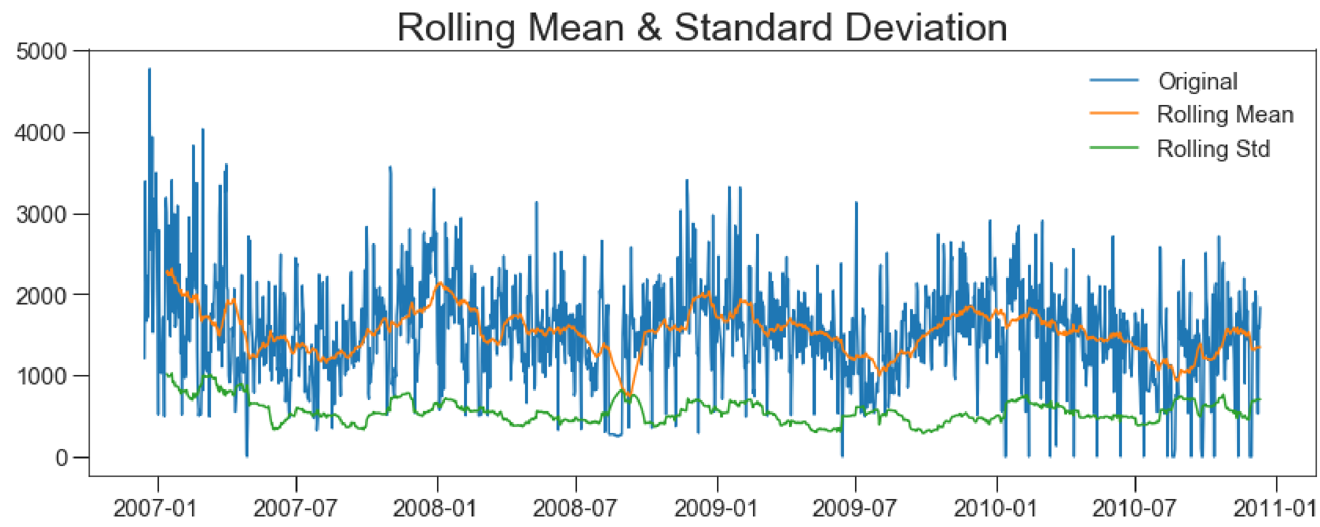
In [26]:

```
def test_stationarity(timeseries):
    rolmean = timeseries.rolling(window=30).mean()
    rolstd = timeseries.rolling(window=30).std()

    plt.figure(figsize=(14,5))
    sns.despine(left=True)
```

```
    orig = plt.plot(timeseries,label='Original')
    mean = plt.plot(rolmean,label='Rolling Mean')
    std = plt.plot(rolstd,label = 'Rolling Std')

    plt.legend(frameon=False,prop={'size':15})
    plt.title('Rolling Mean & Standard Deviation',size=25)
    plt.show()

    print ('<Results of Dickey-Fuller Test>')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4],
                         index=['Test Statistic','p-value','#Lags Used','Number of Observations Use
'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput.round(2))
```

In [27]:

```
test_stationarity(df.resample('D').sum()['Global_active_power'].dropna())
```




```
<Results of Dickey-Fuller Test>
Test Statistic                  -9.42
p-value                          0.00
#Lags Used                       7.00
Number of Observations Used   1449.00
Critical Value (1%)             -3.43
Critical Value (5%)             -2.86
Critical Value (10%)            -2.57
dtype: float64
```

From the above results, `p-value` is really suggesting that given the evidence the null hypothesis H_0 can be rejected, the data does not have a unit root and is stationary.

Recurrent Neural Networks : LSTM

Preprocessing for the model

In [127]:

```
data = df.Global_active_power.resample('10T').sum().values.reshape(-1, 1)
scaler = MinMaxScaler(feature_range=(0, 1))
data = scaler.fit_transform(data)
```

In [128]:

```
train = data[0:int(len(data) * 0.80)]
test = data[int(len(data) * 0.80) : int(len(data) * 0.90)]
valid = data[int(len(data) * 0.90) :]
```

```
valid = data[int(len(data) * 0.90) :]
print(f'train : {len(train)}\ntrain : {len(test)}\nvalidation : {len(valid)}' )
```

```
train : 167763
train : 20970
validation : 20971
```

Formulating into a supervised learning problem

In [129]:

```
def create_dataset(dataset, look_back=1):
    X, Y = [], []
    for i in range(len(dataset)-look_back-1):
        a = dataset[i:(i+look_back), 0]
        X.append(a)
        Y.append(dataset[i + look_back, 0])
    return np.array(X), np.array(Y)
```

In [130]:

```
look_back = 30
X_train, Y_train = create_dataset(train, look_back)
X_test, Y_test = create_dataset(test, look_back)
X_val, Y_val = create_dataset(valid, look_back)
```

In [131]:

```
print(f'Feature Shape{X_train.shape}\nTarget Shape{Y_train.shape}')
```

```
Feature Shape(167732, 30)
Target Shape(167732,)
```

In [132]:

```
X_train = np.reshape(X_train, (X_train.shape[0], 1, X_train.shape[1]))
X_test = np.reshape(X_test, (X_test.shape[0], 1, X_test.shape[1]))
X_val = np.reshape(X_val, (X_val.shape[0], 1, X_val.shape[1]))
```

Model Creation

In [44]:

```
n_units=128
batch_size=64
n_epochs=20
patience=10

model = Sequential()
model.add(LSTM(n_units, return_sequences=True, input_shape=(X_train.shape[1:])))
model.add(Dropout(0.5))
model.add(LSTM(n_units))
model.add(Dropout(0.5))
model.add(Dense(1))
model.compile(loss='mean_squared_error',
              metrics=['mse','mape'],
              optimizer='adam')
model.summary()


model.fit(X_train, Y_train,
                    epochs=n_epochs, batch_size=batch_size,
                    validation_data=(X_test, Y_test),
                    callbacks=[ReduceLROnPlateau(),
                    ModelCheckpoint('LSTM-N{}-D0.5-B{}.h5'.format(n_units,batch_size)),
                    EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=10),
                    CSVLogger(f"LSTM-log-Nodes-{n_units}-dropout-0.5-batchsize-{batch_size}.csv")],

                    verbose=1, shuffle=False)
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_2 (LSTM)                (None, 1, 128)            81408     
_________________________________________________________________
dropout_2 (Dropout)          (None, 1, 128)            0         
_________________________________________________________________
lstm_3 (LSTM)                (None, 128)               131584    
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129       
=================================================================
Total params: 213,121
Trainable params: 213,121
Non-trainable params: 0
_________________________________________________________________
Train on 167732 samples, validate on 20939 samples
Epoch 1/20
167732/167732 [==============================] - 20s 121us/sample - loss: 0.0040 - mse: 0.0040 - m
ape: 144396.2344 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 472863.9375
Epoch 2/20
167732/167732 [==============================] - 18s 107us/sample - loss: 0.0033 - mse: 0.0033 - m
ape: 121330.4219 - val_loss: 0.0026 - val_mse: 0.0026 - val_mape: 275201.3750
Epoch 3/20
167732/167732 [==============================] - 18s 105us/sample - loss: 0.0033 - mse: 0.0033 - m
ape: 121219.9609 - val_loss: 0.0025 - val_mse: 0.0025 - val_mape: 241980.9219
Epoch 4/20
167732/167732 [==============================] - 17s 104us/sample - loss: 0.0033 - mse: 0.0033 - m
ape: 115183.6484 - val_loss: 0.0025 - val_mse: 0.0025 - val_mape: 281137.2812
Epoch 5/20
167732/167732 [==============================] - 18s 104us/sample - loss: 0.0033 - mse: 0.0033 - m
ape: 108462.9375 - val_loss: 0.0026 - val_mse: 0.0026 - val_mape: 68561.7891
Epoch 6/20
167732/167732 [==============================] - 19s 110us/sample - loss: 0.0033 - mse: 0.0033 - m
ape: 106913.2891 - val_loss: 0.0025 - val_mse: 0.0025 - val_mape: 124852.7734
Epoch 7/20
167732/167732 [==============================] - 18s 105us/sample - loss: 0.0033 - mse: 0.0033 - m
ape: 106945.6094 - val_loss: 0.0025 - val_mse: 0.0025 - val_mape: 100389.7578
Epoch 8/20
167732/167732 [==============================] - 17s 104us/sample - loss: 0.0032 - mse: 0.0032 - m
ape: 102682.5781 - val_loss: 0.0025 - val_mse: 0.0025 - val_mape: 142619.6250
Epoch 9/20
167732/167732 [==============================] - 18s 108us/sample - loss: 0.0032 - mse: 0.0032 - m
ape: 100858.8750 - val_loss: 0.0025 - val_mse: 0.0025 - val_mape: 83940.9141
Epoch 10/20
167732/167732 [==============================] - 17s 101us/sample - loss: 0.0032 - mse: 0.0032 - m
ape: 97814.0859 - val_loss: 0.0025 - val_mse: 0.0025 - val_mape: 88959.0703
Epoch 11/20
167732/167732 [==============================] - 17s 104us/sample - loss: 0.0032 - mse: 0.0032 - m
ape: 104790.7734 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 84765.2578
Epoch 12/20
167732/167732 [==============================] - 18s 110us/sample - loss: 0.0031 - mse: 0.0031 - m
ape: 97104.8281 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 143229.0469
Epoch 13/20
167732/167732 [==============================] - 18s 106us/sample - loss: 0.0031 - mse: 0.0031 - m
ape: 96157.9219 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 142006.5156
Epoch 14/20
167732/167732 [==============================] - 18s 109us/sample - loss: 0.0031 - mse: 0.0031 - m
ape: 93189.9531 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 164490.3906
Epoch 15/20
167732/167732 [==============================] - 17s 102us/sample - loss: 0.0031 - mse: 0.0031 - m
ape: 91524.1094 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 163063.2969
Epoch 16/20
167732/167732 [==============================] - 18s 106us/sample - loss: 0.0031 - mse: 0.0031 - m
ape: 93321.5781 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 158300.1562
Epoch 17/20
167732/167732 [==============================] - 18s 106us/sample - loss: 0.0031 - mse: 0.0031 - m
ape: 91597.2578 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 190239.4531
Epoch 18/20
167732/167732 [==============================] - 18s 105us/sample - loss: 0.0031 - mse: 0.0031 - m
ape: 93481.0156 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 165880.8594
Epoch 19/20
167732/167732 [==============================] - 19s 112us/sample - loss: 0.0031 - mse: 0.0031 - m
```

```
ape: 90828.2188 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 167334.9688
Epoch 20/20
167732/167732 [==============================] - 18s 108us/sample - loss: 0.0031 - mse: 0.0031 - m
ape: 95067.6328 - val_loss: 0.0024 - val_mse: 0.0024 - val_mape: 138964.7500
```

Out[44]:

```
<tensorflow.python.keras.callbacks.History at 0x7f403056f510>
```

Forecasting with LSTM

In [21]:

```
model=load_model('LSTM-N128-D0.5-B64.h5')
```

In [22]:

```
val_predict = model.predict(X_val)
val_predict = scaler.inverse_transform(val_predict)
Y_val = scaler.inverse_transform(Y_val.reshape(-1,1))


print('Validation Mean Absolute Error:', mean_absolute_error(Y_val.flatten(), val_predict.flatten(
)))
print('Validation Root Mean Squared Error:',math.sqrt(mean_squared_error(Y_val.flatten(),
val_predict.flatten())))
```

```
Validation Mean Absolute Error: 2.3376886336106986
Validation Root Mean Squared Error: 4.151285605046135
```

Convergence LSTM

In [23]:

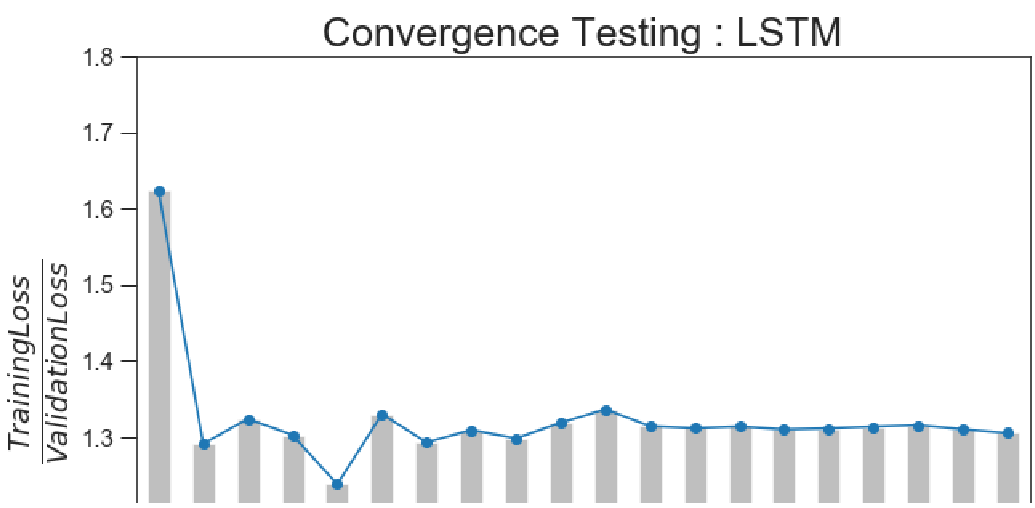
```
LSTM=pd.read_csv('LSTM-log-Nodes-128-dropout-0.5-batchsize-64.csv')
```

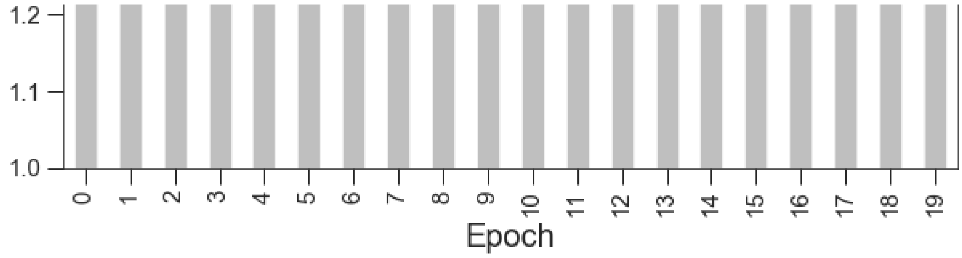
In [24]:

```
plt.figure(figsize=(10,7))
LSTM['Training_Loss/Validation_Loss'] = LSTM['loss']/LSTM['val_loss']
ax=LSTM['Training_Loss/Validation_Loss'].plot(x='epoch',marker='o')
LSTM['Training_Loss/Validation_Loss'].plot.bar(x='epoch',ax=ax,alpha=0.5,color='gray')
plt.ylabel(r'${\frac{Training Loss}{Validation Loss}}$',size=25)
plt.xlabel('Epoch')
plt.title('Convergence Testing : LSTM',size=25)
plt.ylim([1,1.8])
```

Out[24]:

```
(1, 1.8)
```





The above plot suggests that model quickly converges in less in 10 epochs and there is not improvement in the performance. Also, training loss and validation Loss are not very far from each other suggesting that there is no over/underfitting.

Target vs Prediction on Valdiation (LSTM)

In [25]:

```
comparision=df.resample('10T').sum()[-len(valid)+look_back+1:] #removing the lookback to match the index
comparision['Predicted-LSTM'] = val_predict
comparision.drop(['year','quarter','month','day','weekday'],axis=1,inplace=True)
comparision.to_csv('LSTM-predicted.csv',index=True)
```

Recurrent Neural Networks : GRU

In [119]:

```
n_units=128
batch_size=64
n_epochs=20
patience=10

model = Sequential()
model.add(GRU(n_units, return_sequences=True, input_shape=(X_train.shape[1:])))
model.add(Dropout(0.5))
model.add(GRU(n_units))
model.add(Dropout(0.5))
model.add(Dense(1))
model.compile(loss='mean_squared_error',
              metrics=['mse','mape'],
              optimizer='adam')
model.summary()

model.fit(X_train, Y_train,
                    epochs=n_epochs, batch_size=batch_size,
                    validation_data=(X_test, Y_test),
                    callbacks=[ReduceLROnPlateau(),
                    ModelCheckpoint('GRU-N{}-D0.5-B{}.h5'.format(n_units,batch_size)),
                    EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=10),
                    CSVLogger(f"GRU-log-Nodes-{n_units}-dropout-0.5-batchsize-{batch_size}.csv")],
                    verbose=1, shuffle=False)
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
gru (GRU)                    (None, 1, 128)            61440
_________________________________________________________________
dropout (Dropout)            (None, 1, 128)            0
_________________________________________________________________
gru_1 (GRU)                  (None, 128)               99072
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense (Dense)                (None, 1)                 129
=================================================================
Total params: 160,641
Trainable params: 160,641
Non-trainable params: 0
_________________________________________________________________
```

Forecasting with GRU

In [133]:

```
model=load_model('GRU-N128-D0.5-B64.h5')
```

In [134]:

```
val_predict = model.predict(X_val)
val_predict = scaler.inverse_transform(val_predict)
Y_val = scaler.inverse_transform(Y_val.reshape(-1,1))


print('Validation Mean Absolute Error:', mean_absolute_error(Y_val.flatten(), val_predict.flatten(
)))
print('Validation Root Mean Squared Error:',math.sqrt(mean_squared_error(Y_val.flatten(),
val_predict.flatten())))
```

```
Validation Mean Absolute Error: 2.343087949382133
Validation Root Mean Squared Error: 4.140600573147707
```

Convergence GRU

In [136]:

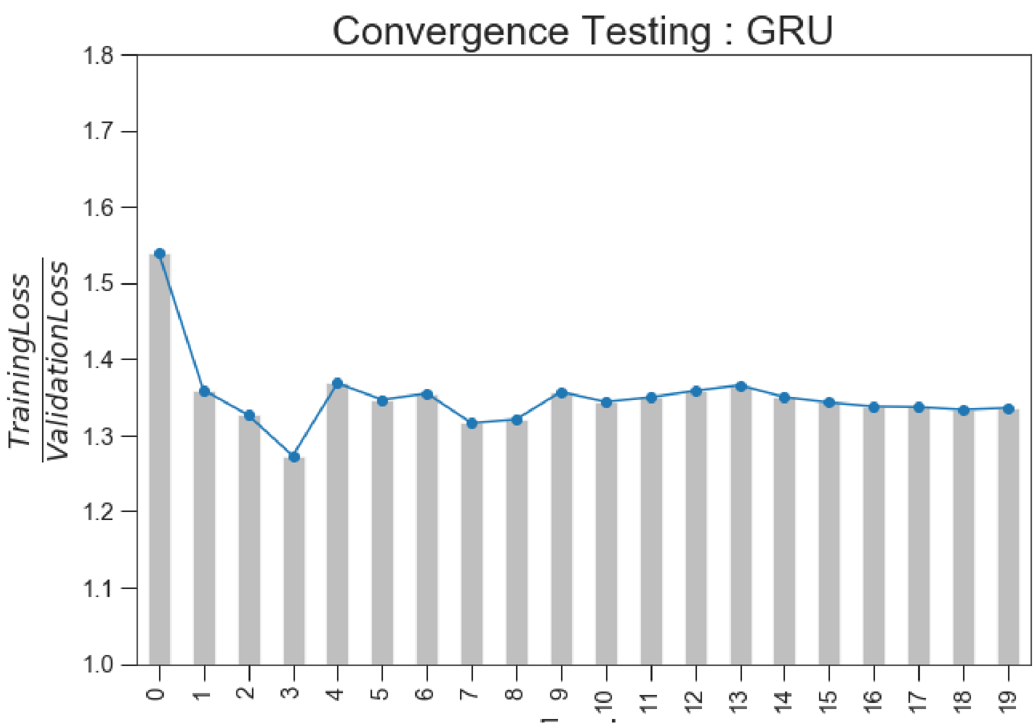
```
GRU=pd.read_csv('GRU-log-Nodes-128-dropout-0.5-batchsize-64.csv')
```

In [137]:

```
plt.figure(figsize=(10,7))
GRU['Training_Loss/Validation_Loss'] = GRU['loss']/GRU['val_loss']
ax=GRU['Training_Loss/Validation_Loss'].plot(x='epoch',marker='o')
GRU['Training_Loss/Validation_Loss'].plot.bar(x='epoch',ax=ax,alpha=0.5,color='gray')
plt.ylabel(r'${\frac{Training Loss}{Validation Loss}}$',size=25)
plt.xlabel('Epoch')
plt.title('Convergence Testing : GRU',size=25)
plt.ylim([1,1.8])
```

Out[137]:

```
(1, 1.8)
```



Epoch

The above plot suggests that GRU also converges quickly. There is not improvement in the performance after 6 epochs. Also, training loss and validation Loss are not very far from each other suggesting that there is no over/underfitting.

Target vs Prediction on Valdiation (GRU)

In [138]:

```
comparision=df.resample('10T').sum()[-len(valid)+look_back+1:] #removing the lookback to match the index
comparision['Predicted-GRU'] = val_predict
comparision.drop(['year','quarter','month','day','weekday'],axis=1,inplace=True)
comparision.to_csv('GRU-predicted.csv',index=True)
```

Comparision : LSTM vs GRU

In [20]:

```
LSTM_pred = pd.read_csv('LSTM-predicted.csv',index_col=0,parse_dates=['Datetime'])
GRU_pred = pd.read_csv('GRU-predicted.csv',index_col=0,parse_dates=['Datetime'])
```

In [21]:

```
models=pd.concat([LSTM_pred['Global_active_power'], LSTM_pred['Predicted-LSTM'],
GRU_pred['Predicted-GRU']],axis=1)
```

In [22]:

```
models.head(10).style.bar(axis=0)
```

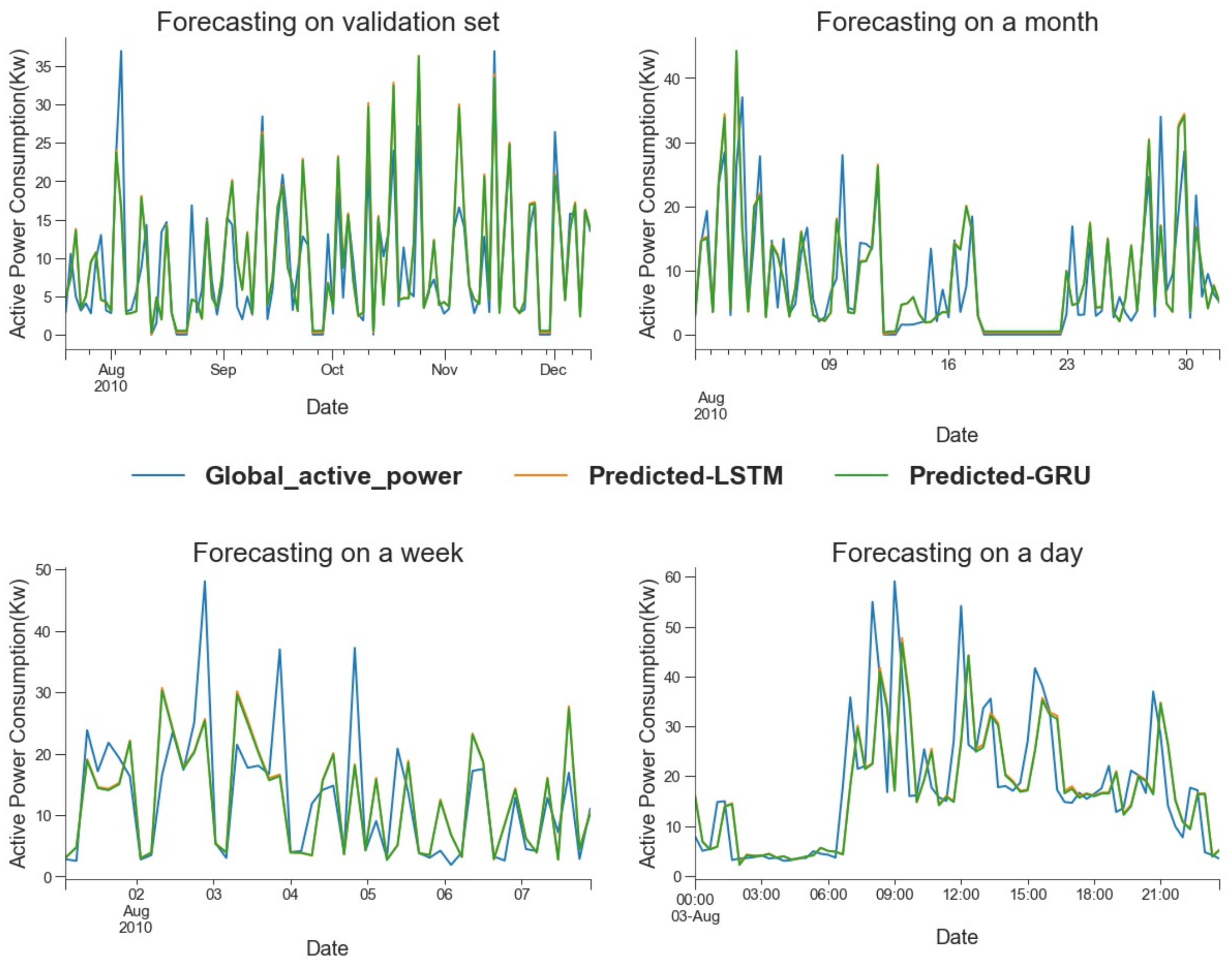
Out[22]:

Datetime	Global_active_power	Predicted-LSTM	Predicted-GRU
2010-07-19 14:00:00	2.928000	4.812406	4.833897
2010-07-19 14:10:00	6.298000	4.956984	4.989286
2010-07-19 14:20:00	2.866000	3.565779	3.604172
2010-07-19 14:30:00	4.178000	7.699077	7.678381
2010-07-19 14:40:00	2.932000	3.180972	3.255842
2010-07-19 14:50:00	1.580000	5.149462	5.133724
2010-07-19 15:00:00	3.766000	3.557820	3.609186
2010-07-19 15:10:00	6.882000	2.160094	2.203777
2010-07-19 15:20:00	8.860000	4.783637	4.817093
2010-07-19 15:30:00	4.200000	8.221926	8.184235

In [23]:

```
fig = plt.figure(figsize=(20,15))
fig.subplots_adjust(hspace=0.7)

ax=fig.add_subplot(221)
models[::200].plot(lw=2,ax=ax,legend=False)
sns.despine(top=True)
plt.ylabel('Active Power Consumption(Kw)')
plt.xlabel('Date')
plt.title('Forecasting on validation set',size=26)

ax=fig.add_subplot(222)
models[::50]['2010-08'].plot(lw=2,ax=ax)
```

```
plt.legend(frameon=False,loc='best',bbox_to_anchor=(0.8,-0.3), ncol=3,prop={'size':25, 'weight':'bo
ld'})
sns.despine(top=True)
plt.ylabel('Active Power Consumption(Kw)')
plt.xlabel('Date')
plt.title('Forecasting on a month',size=26)


ax=fig.add_subplot(223)
models[::20]['2010-08-01':'2010-08-07'].plot(lw=2,ax=ax,legend=False)
sns.despine(top=True)
plt.ylabel('Active Power Consumption(Kw)')
plt.xlabel('Date')
plt.title('Forecasting on a week',size=26)


ax=fig.add_subplot(224)
models[::2]['2010-08-03'].plot(lw=2,ax=ax,legend=False)
sns.despine(top=True)
plt.ylabel('Active Power Consumption(Kw)')
plt.xlabel('Date')
plt.title('Forecasting on a day',size=26);
```



Interestingly both models are good at forecasting the time series with very minor deviation. Hyperparameter tuning is required to improve upon current prediction.

Future direction

- hyperparameter tuning of existing models and introduction of newer apporches such as facebook prophet, which can account for seasonality in the data.
- more statistical analysis to understand autocorrelation within the `Global_active_power` variable.