In [ ]:
```python
## Setup
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')
import statsmodels.tsa.stattools as ts
import statsmodels.api as sm
plt.rcParams['figure.figsize'] = [14, 4]
import pmdarima as pm
from pmdarima.arima import auto_arima
```

Exploratory Data Analysis

The dataset weather-data.csv is obtained from IOWA Environmental Mesonet - Iowa State University

Columns for this dataset:

- station: Acronym for the place of data capture.
- valid: Date and time of capture.
- tmpc: Temperature of the environment in celsius.
- dwpc: Temperature of the dew point in the environment in celsius.
- relh: Relative humidity of the environment in percentage.
- sknt: Wind Speed in knots.
- gust: Wind Gust in knots.
- peak_wind_drct: Peak Wind Gust Direction (from PK WND METAR remark). (deg).

In [ ]:
```python
data = pd.read_csv('weather-data.csv')
data.head()
```

Out[ ]:

	station	valid	tmpc	dwpc	relh	sknt	gust	peak_wind_drct
0	NZAA	2015-01-01 00:00	21.0	11.0	52.77	15.0	NaN	NaN
1	NZAA	2015-01-01 00:30	21.0	10.0	49.37	16.0	NaN	NaN
2	NZAA	2015-01-01 01:00	21.0	12.0	56.38	16.0	NaN	NaN
3	NZAA	2015-01-01 01:30	21.0	13.0	60.21	16.0	NaN	NaN
4	NZAA	2015-01-01 02:00	21.0	12.0	56.38	16.0	NaN	NaN

At a first glance, it's easy to spot that the data is sampled at a 30-min interval, so a time series modeling can be used at a later stage.

In [ ]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103713 entries, 0 to 103712
Data columns (total 8 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0    station        103713 non-null  object 
 1   valid           103713 non-null  object 
 2   tmpc            103678 non-null  float64
 3   dwpc            103678 non-null  float64
 4   relh            103593 non-null  float64
 5   sknt            103704 non-null  float64
 6   gust            1203 non-null    float64
 7   peak_wind_drct  0 non-null       float64
dtypes: float64(6), object(2)
memory usage: 6.3+ MB
```

In [ ]:

```
data['valid'] = data['valid'].astype("datetime64")
data.set_index('valid', inplace=True)
```

'valid' should be of datatime type and the index for the dataframe.

In [ ]:

```
len(data[' station'].unique())
```

Out[ ]: 1

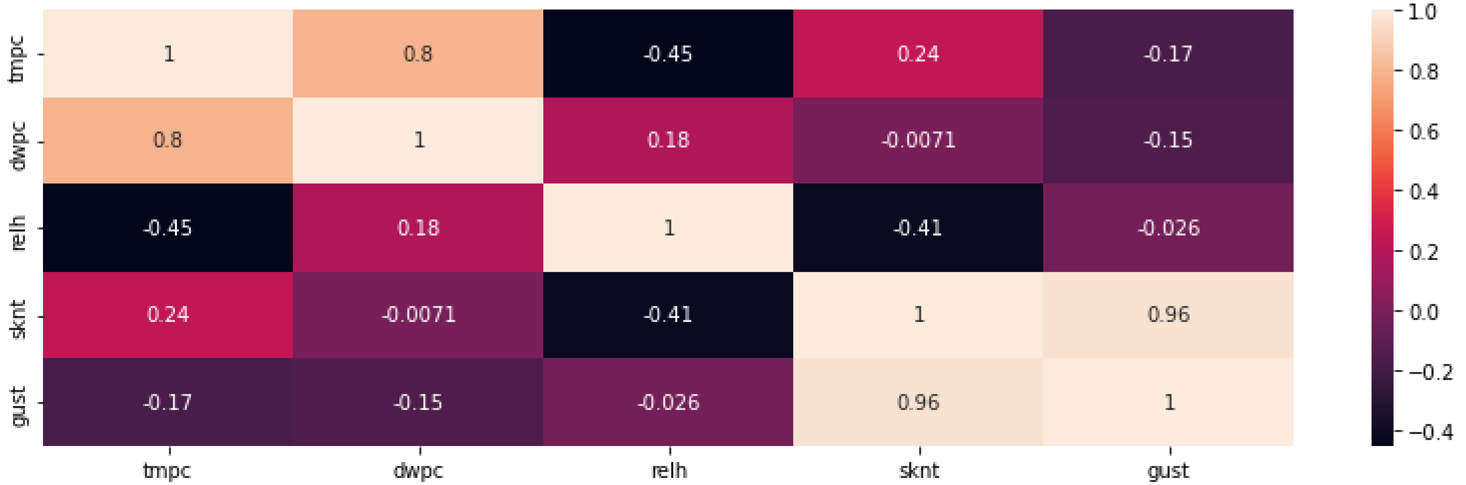
In [ ]:

```
data.drop('peak_wind_drct', 1, inplace=True)
data.drop(' station', 1, inplace=True)
```

peak_wind_drct' can be dropped as it has no non-null value, and 'station' can be dropped as it has a single value of 'NZAA'. Imputation should be considered at a later stage for other columns where there are some missing values (the number of non-null values is less than the record number), such as 'dwpc' (103678 < 103713).

In [ ]:
```
sns.heatmap(data.corr(), annot=True)
```

Out[ ]: <AxesSubplot:>



The dew point temperature is the temperature to which air must be cooled to become saturated with water vapor, assuming constant air pressure and water content. Therefore, it is understandably correlated with the temperature (the air needed to be cooled), relative humidity (water content) and the wind speed/gust (air pressure). Apart from that, the correlation between the wind speed and the wind gust is quite noticable.

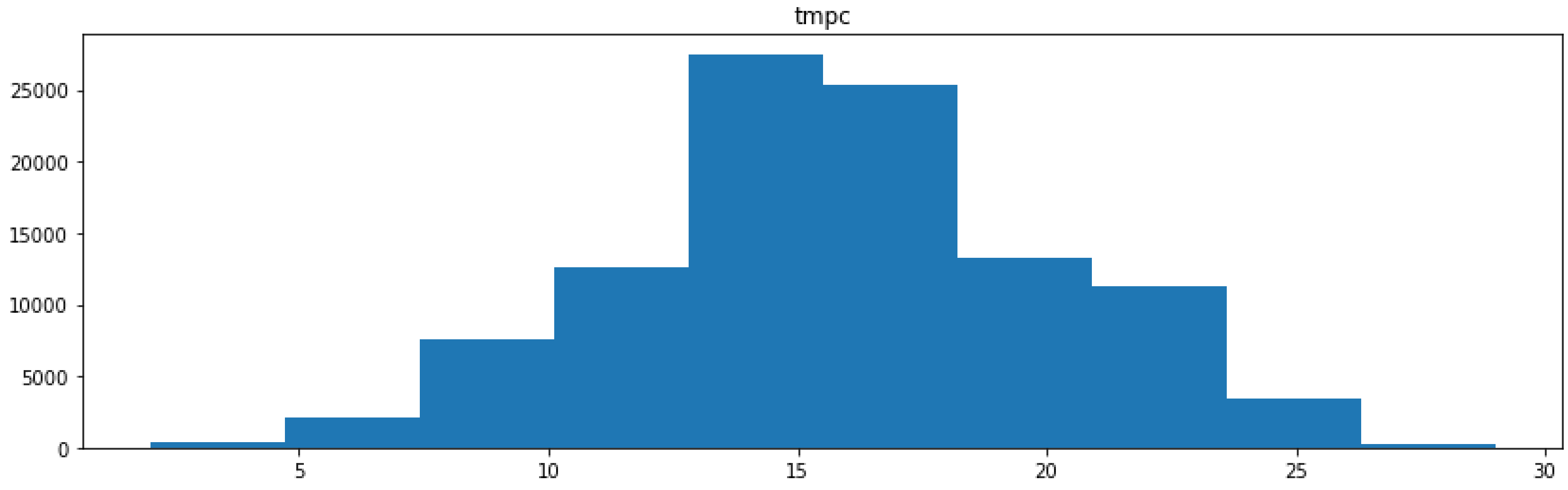
In [ ]:
```
data.describe()
```

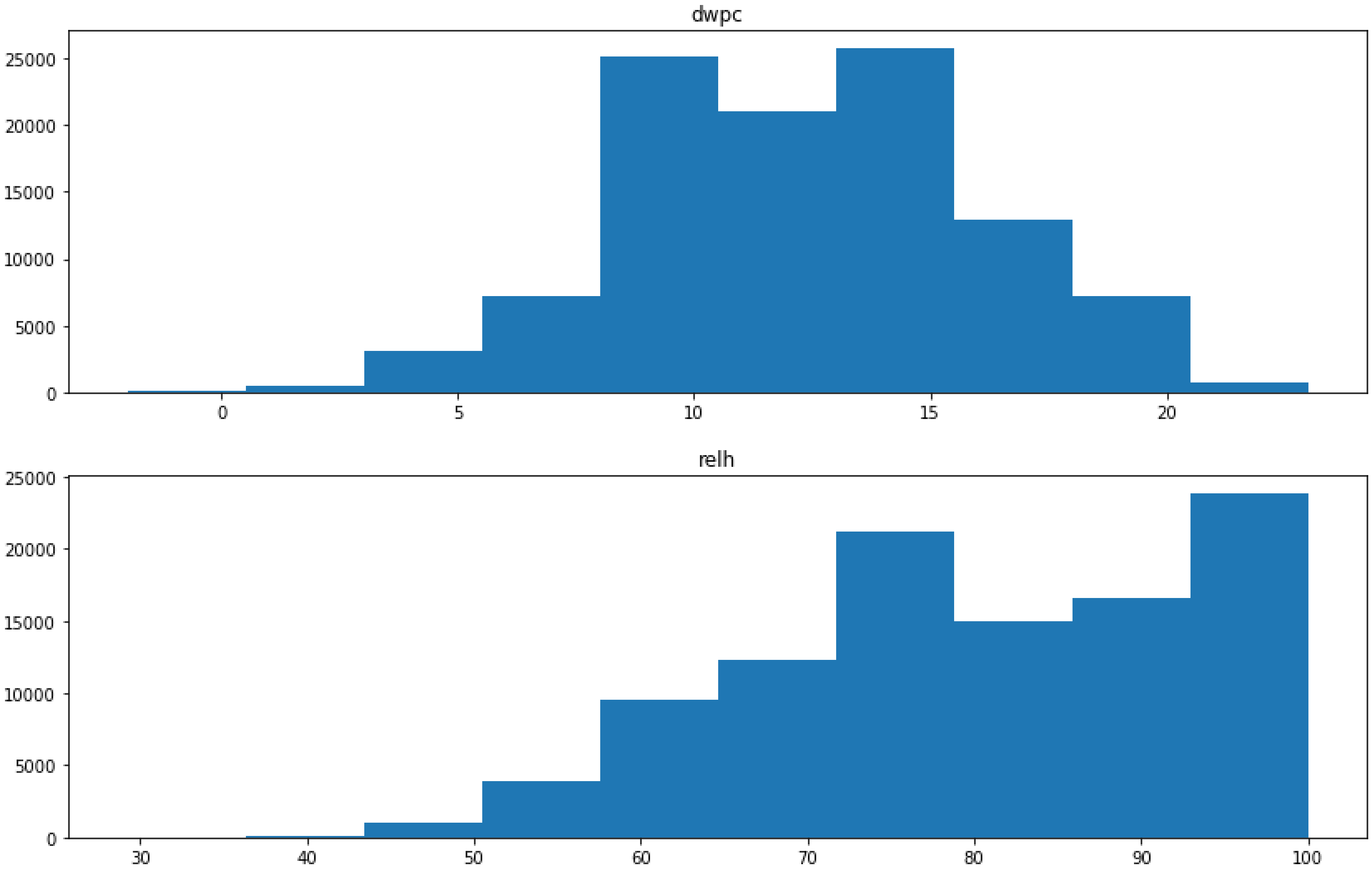
Out[ ]:

	tmpc	dwpc	relh	sknt	gust
count	103678.000000	103678.000000	103593.000000	103704.000000	1203.000000
mean	15.811503	12.115772	79.782307	8.919029	30.962594
std	4.235197	3.738005	12.562199	5.348379	6.319510
min	2.000000	-2.000000	29.230000	0.000000	13.000000
25%	13.000000	9.000000	71.450000	5.000000	27.000000
50%	16.000000	12.000000	81.990000	8.000000	31.000000
75%	19.000000	15.000000	88.180000	12.000000	35.000000
max	29.000000	23.000000	100.000000	42.000000	56.000000

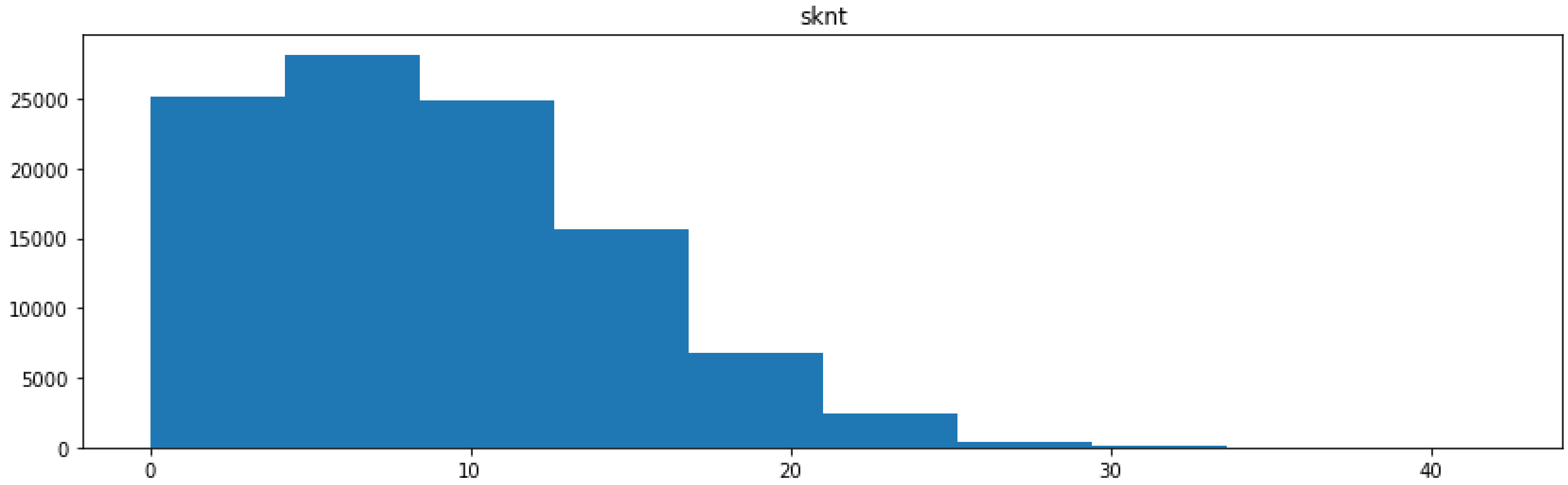
In [ ]:

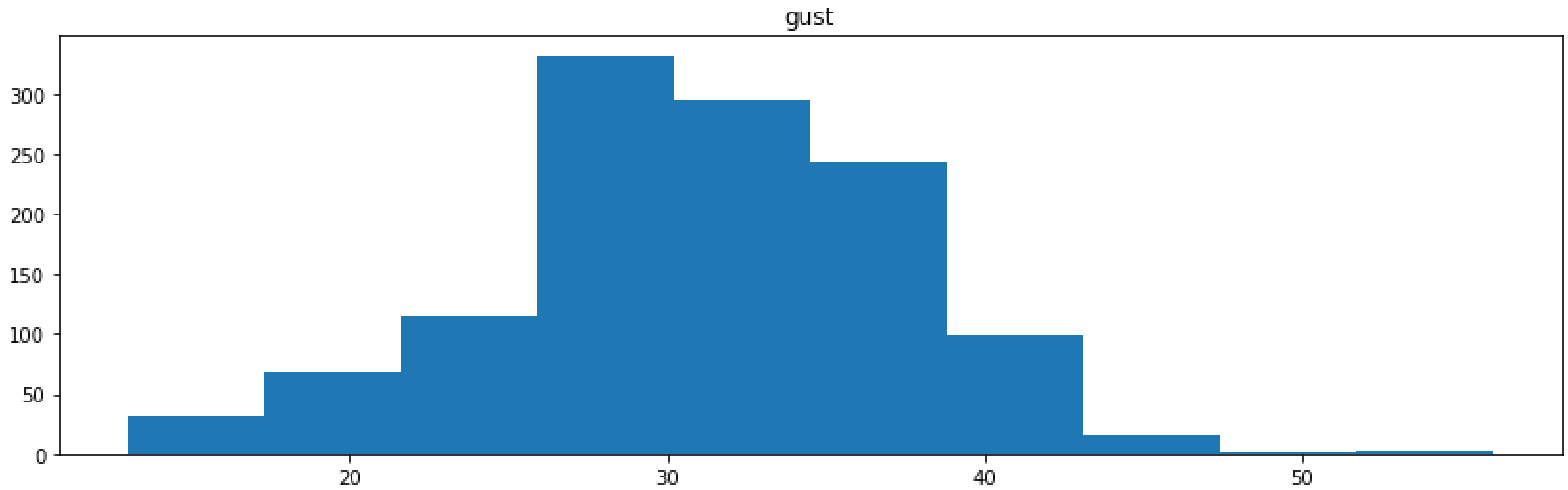
```
# distributions
for column_name in data.columns:
    plt.hist(data[column_name])
    plt.title(column_name)
    plt.show()
```





dwpc
0
5000
10000
15000
20000
25000
0
5
10
15
20
relh
0
5000
10000
15000
20000
25000
30
40
50
60
70
80
90
100





Since they're all numeric values, we care about distributions. Temperature and dew point temperature are approximately normally distributed, while others are skewed.

Data Preparation

Imputation

We impute missing values in the whole data set - it will yield similar results if we do it separately for the train and test sets as it's only to utilize the closest valid observations rather than other approaches such as extracting different means from the train and test sets for normalization.

In [ ]:
```
data['gust'].fillna(data['sknt'], inplace=True)
```

When 'gust' is nan, there's assumingly no significant change in the wind speed. -> it can be filled with the wind speed at the same time.

In [ ]:
```
data.fillna((data.fillna(method='bfill')+data.fillna(method='ffill'))/2, inplace=True)
```

When other columns are nan, we assume they don't significantly change over a short period. -> they can be filled with the average of the last and the next valid observations.

Preprocessing

Train and test sets

In [ ]:
```
pd.date_range(data.index.min(), data.index.max())
```

Out[ ]:
```
DatetimeIndex(['2015-01-01', '2015-01-02', '2015-01-03', '2015-01-04',
               '2015-01-05', '2015-01-06', '2015-01-07', '2015-01-08',
               '2015-01-09', '2015-01-10',
               ...
               '2020-12-21', '2020-12-22', '2020-12-23', '2020-12-24',
               '2020-12-25', '2020-12-26', '2020-12-27', '2020-12-28',
               '2020-12-29', '2020-12-30'],
              dtype='datetime64[ns]', length=2191, freq='D')
```

The data spanned 6 years from 2015 to 2020.

In [ ]:
```
train = data[:'2020-09'].resample("W").mean()
test = data['2020-10':].resample("W").mean()
```

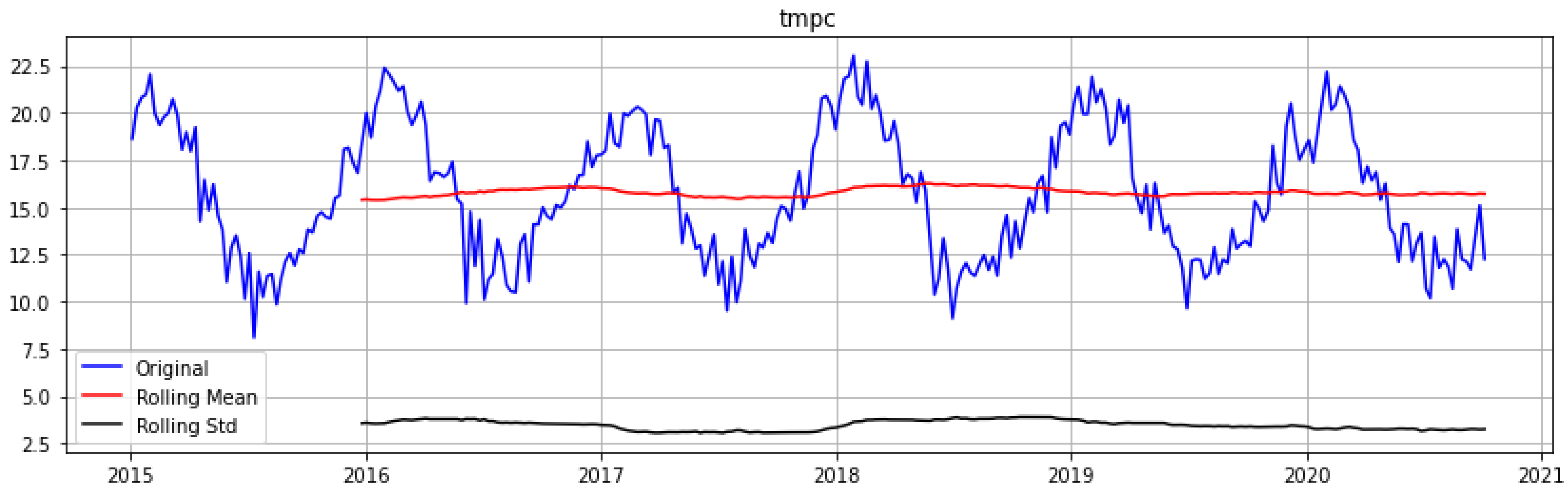
We use the last 3 months to evaluate our model. As we upsample it to weekly means, we assume the seasonality is of yearly 52-week windows.

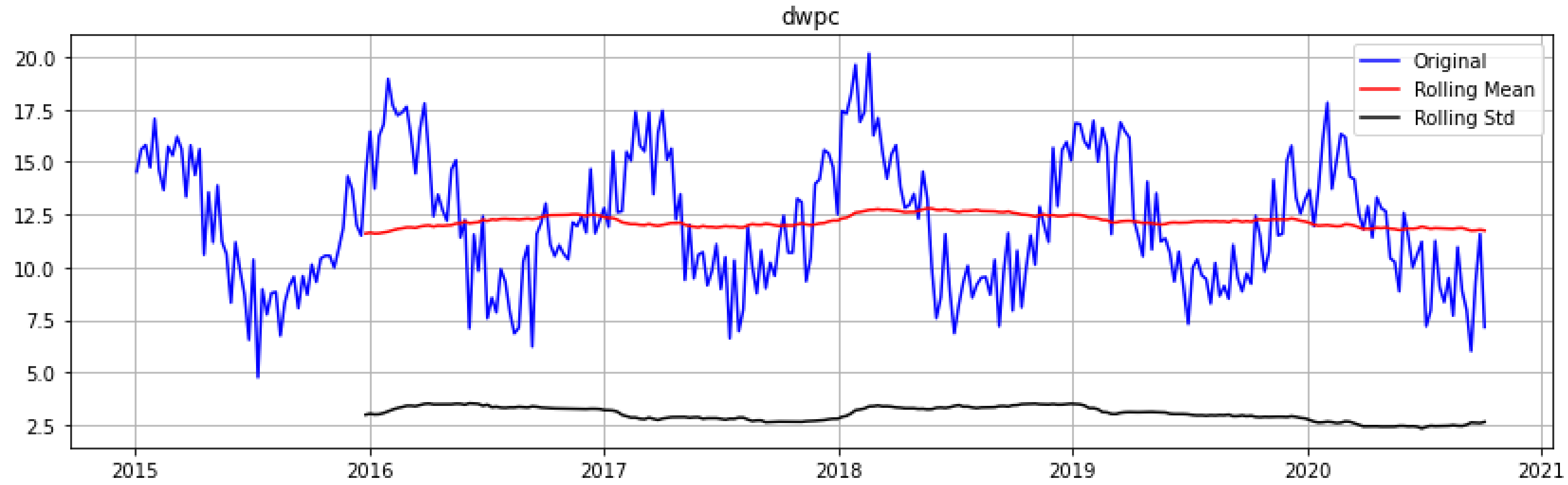
Data Modelling

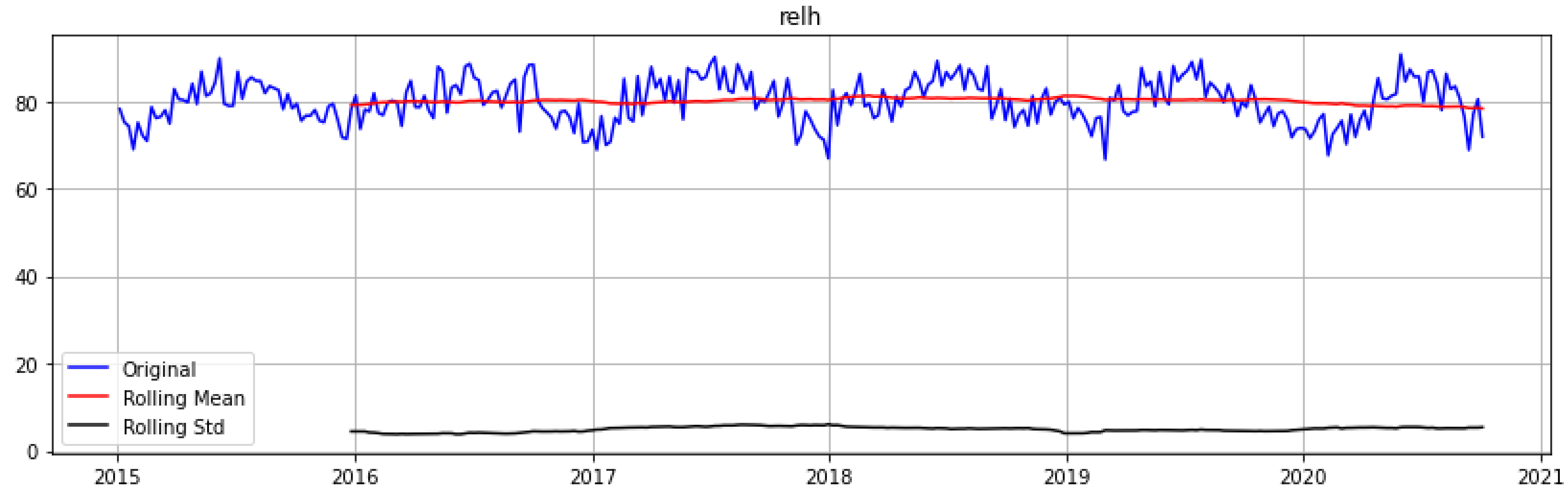
Visualize the Time Series

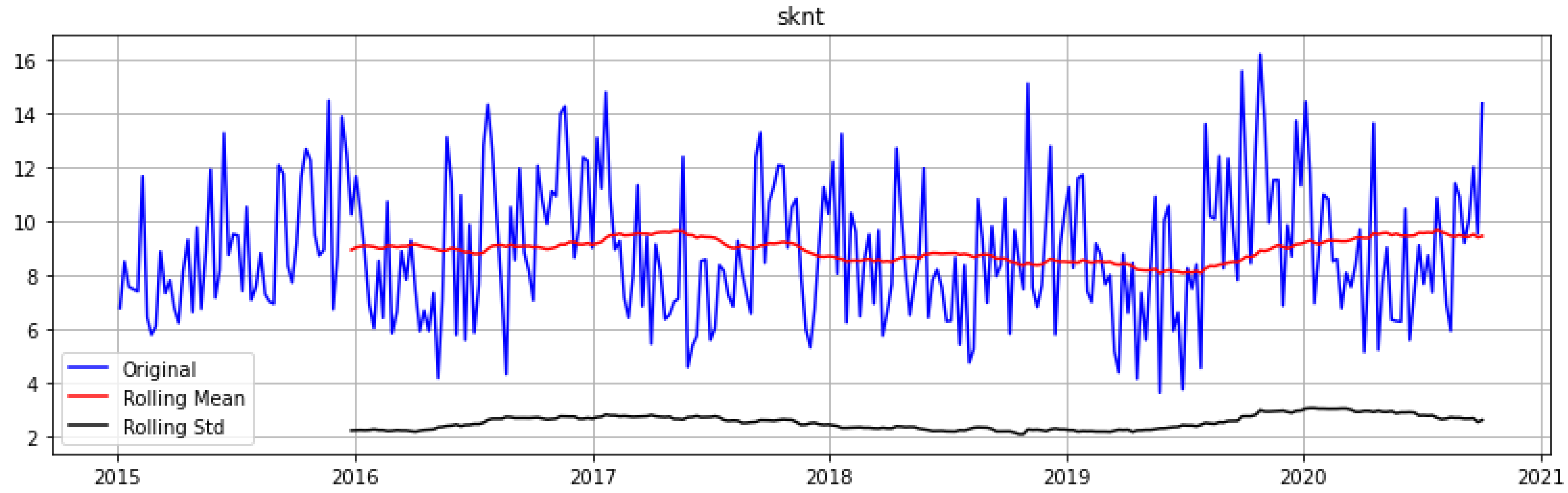
In [ ]:
```
## helper function to create run-sequence, rolling mean and rolling standard deviation
def tsplot(column_name):
    #Determing rolling statistics
    rolmean = train[column_name].rolling(window=52).mean()
    rolstd = train[column_name].rolling(window=52).std()

    #Plot rolling statistics:
    orig = plt.plot(train[column_name], color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title(column_name)
    plt.grid()
    plt.show(block=False)
```

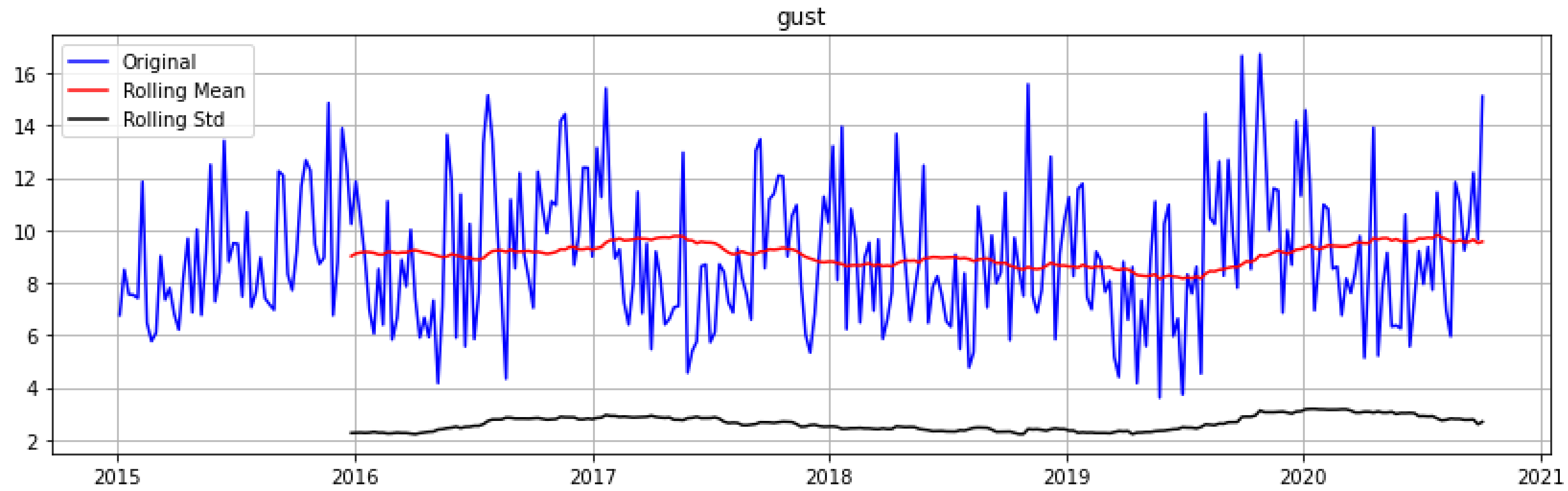
In [ ]:
```
## plot against each column
for column_name in train.columns:
    tsplot(column_name)
```




dwpc
Original
Rolling Mean
Rolling Std
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
2015
2016
2017
2018
2019
2020
2021


relh
Original
Rolling Mean
Rolling Std
80
60
40
20
0
2015
2016
2017
2018
2019
2020
2021





We can see from the plots that they are all additive models with strong seasonality for the first three columns and no obvious trend for all the columns.

Dickey-Fuller Test

In [ ]:
```
## helper function to perform a Dickey-Fuller Test where the null hypothesis is that the series is not stationary
def dftest(timeseries):
    dftest = ts.adfuller(timeseries,)
```

```python
    dfoutput = pd.Series(dftest[0:4],
                         index=['Test Statistic','p-value','Lags Used','Observations Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)
```

In [ ]:

```python
## test against each column
for colunm_name in train.columns:
    print("Please find the result below for %s: "%(colunm_name))
    dftest(train[[colunm_name]])
    print("\n")
```

```
Please find the result below for tmpc:
Test Statistic         -7.533179e+00
p-value                 3.534207e-11
Lags Used               1.500000e+01
Observations Used       2.850000e+02
Critical Value (1%)    -3.453505e+00
Critical Value (5%)    -2.871735e+00
Critical Value (10%)   -2.572202e+00
dtype: float64


Please find the result below for dwpc:
Test Statistic         -6.183423e+00
p-value                 6.373571e-08
Lags Used               1.300000e+01
Observations Used       2.870000e+02
Critical Value (1%)    -3.453342e+00
Critical Value (5%)    -2.871664e+00
Critical Value (10%)   -2.572164e+00
dtype: float64


Please find the result below for relh:
Test Statistic           -3.841106
p-value                   0.002514
Lags Used                 3.000000
Observations Used       297.000000
Critical Value (1%)      -3.452561
Critical Value (5%)      -2.871321
Critical Value (10%)     -2.571982
dtype: float64


Please find the result below for sknt:
Test Statistic           -4.662632
p-value                   0.000099
Lags Used                 4.000000
Observations Used       296.000000
Critical Value (1%)      -3.452637
Critical Value (5%)      -2.871354
Critical Value (10%)     -2.571999
dtype: float64
```

```
Please find the result below for gust:
Test Statistic             -4.797516
p-value                     0.000055
Lags Used                   4.000000
Observations Used         296.000000
Critical Value (1%)        -3.452637
Critical Value (5%)        -2.871354
Critical Value (10%)       -2.571999
dtype: float64
```

They all pass the test with the p-value small enough (< 0.05) to reject the null hypothesis, i.e., they are all stationary. However, bear in mind that both rolling mean/std plots and df tests can't capture seasonality, and we need to address that using SARIMA model.

Find Optimal Parameters

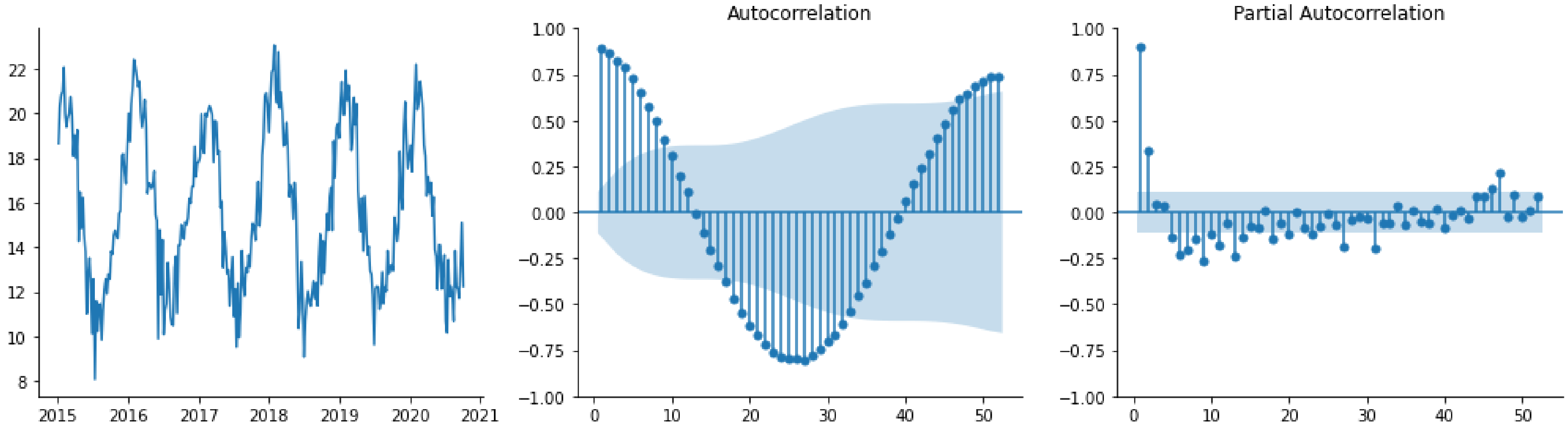
In [ ]:

```
# helper function to plot acf and pacf
def tsplot(data, lags=None):
    layout = (1, 3)
    raw  = plt.subplot2grid(layout, (0, 0))
    acf  = plt.subplot2grid(layout, (0, 1))
    pacf = plt.subplot2grid(layout, (0, 2))

    raw.plot(data)
    sm.tsa.graphics.plot_acf(data, lags=lags, ax=acf, zero=False)
    sm.tsa.graphics.plot_pacf(data, lags=lags, ax=pacf, zero=False)
    sns.despine()
    plt.tight_layout()
```

Moving forward, we will focus on tmpc as there could be some seasonality issues, and others could use a similar or simplified approach.

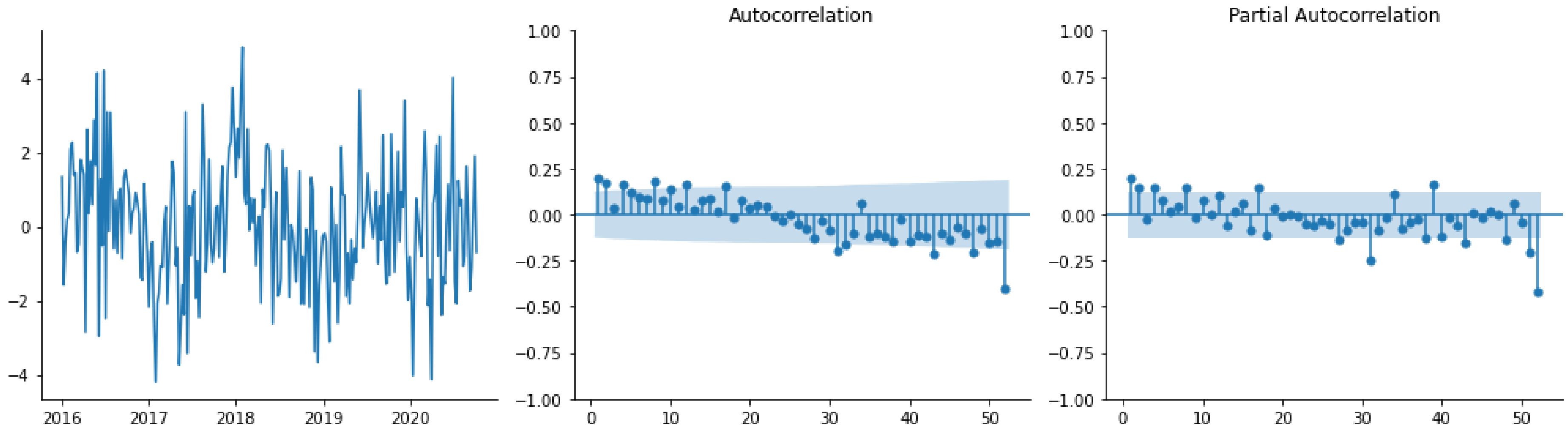
In [ ]:

```
tmpc_train = train[['tmpc']]
tmpc_test = test[['tmpc']]
tsplot(tmpc_train, 52)
```



We can see from pacf that the order of p caps at 2 and acf that the autocorrelation doesn't decay away, and recurs over time, indicating an MA model should not be used.

In [ ]:
```
tsplot(tmpc_train.diff(52).dropna(), 52)
```



We can see from pacf that the order of seasonal P caps 2 and acf that the order of seasonal Q caps at 2.

In [ ]:
```
stepwise_model = pm.auto_arima(tmpc_train, start_p=1, start_q=0,
                               max_p=2, max_q=0, m=52,
```

```
                           start_P=1, start_Q=1, seasonal=True,
                           max_P=2, max_Q=2,
                           d=0, D=0, trace=True,
                           error_action='ignore',
                           suppress_warnings=True,
                           stepwise=True)
print(stepwise_model.aic())
```

```
Performing stepwise search to minimize aic
 ARIMA(1,0,0)(1,0,1)[52] intercept   : AIC=inf, Time=4.44 sec
 ARIMA(0,0,0)(0,0,0)[52] intercept   : AIC=1607.948, Time=0.01 sec
 ARIMA(1,0,0)(1,0,0)[52] intercept   : AIC=1114.813, Time=4.66 sec
 ARIMA(0,0,0)(0,0,1)[52] intercept   : AIC=inf, Time=0.45 sec
 ARIMA(0,0,0)(0,0,0)[52]             : AIC=2530.036, Time=0.01 sec
 ARIMA(1,0,0)(0,0,0)[52] intercept   : AIC=1116.219, Time=0.03 sec
 ARIMA(1,0,0)(2,0,0)[52] intercept   : AIC=1116.724, Time=37.27 sec
 ARIMA(1,0,0)(0,0,1)[52] intercept   : AIC=inf, Time=1.53 sec
 ARIMA(1,0,0)(2,0,1)[52] intercept   : AIC=inf, Time=40.96 sec
 ARIMA(0,0,0)(1,0,0)[52] intercept   : AIC=inf, Time=2.81 sec
 ARIMA(2,0,0)(1,0,0)[52] intercept   : AIC=1076.349, Time=4.86 sec
 ARIMA(2,0,0)(0,0,0)[52] intercept   : AIC=1082.717, Time=0.02 sec
 ARIMA(2,0,0)(2,0,0)[52] intercept   : AIC=1075.985, Time=63.45 sec
 ARIMA(2,0,0)(2,0,1)[52] intercept   : AIC=inf, Time=57.96 sec
 ARIMA(2,0,0)(1,0,1)[52] intercept   : AIC=inf, Time=3.66 sec
 ARIMA(2,0,0)(2,0,0)[52]             : AIC=inf, Time=16.36 sec

Best model:  ARIMA(2,0,0)(2,0,0)[52] intercept
Total fit time: 238.503 seconds
1075.9850239055843
```

We narrow down the search to find the best model ARIMA(2,0,0)(2,0,0)[52] with the lowest AIC.

In [ ]:

```
sar = sm.tsa.statespace.SARIMAX(tmpc_train,
                                order=(2,0,0),
                                seasonal_order=(2,0,0,52),
                                trend='c').fit()
sar.summary()
```

```
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            6     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  2.41614D+01    |proj g|=  4.17484D+01
 This problem is unconstrained.
```

```
At iterate    5    f=  2.25412D+00    |proj g|=  2.28661D-01

At iterate   10    f=  2.16539D+00    |proj g|=  8.20872D-02

At iterate   15    f=  2.14779D+00    |proj g|=  1.74718D-01

At iterate   20    f=  1.98182D+00    |proj g|=  6.74428D-01

At iterate   25    f=  1.91213D+00    |proj g|=  1.86063D-01

At iterate   30    f=  1.84291D+00    |proj g|=  1.92881D-01

At iterate   35    f=  1.76986D+00    |proj g|=  6.91306D-02

At iterate   40    f=  1.76742D+00    |proj g|=  4.69389D-04

At iterate   45    f=  1.76742D+00    |proj g|=  1.18809D-03

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    6     49     60      1     0     0   1.092D-05   1.767D+00
  F =   1.7674169832318676

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
```

Out[ ]:

SARIMAX Results

Dep. Variable:	tmpc	**No. Observations:**	301
Model:	SARIMAX(2, 0, 0)x(2, 0, 0, 52)	**Log Likelihood**	-531.993
Date:	Mon, 17 Oct 2022	**AIC**	1075.985
Time:	22:29:15	**BIC**	1098.228
Sample:	01-04-2015	**HQIC**	1084.886
	- 10-04-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	1.1381	0.373	3.054	0.002	0.408	1.869
ar.L1	0.5233	0.057	9.102	0.000	0.411	0.636
ar.L2	0.3733	0.056	6.666	0.000	0.264	0.483
ar.S.L52	0.1834	0.070	2.629	0.009	0.047	0.320
ar.S.L104	0.1181	0.064	1.857	0.063	-0.007	0.243
sigma2	1.9728	0.153	12.861	0.000	1.672	2.273

Ljung-Box (L1) (Q):	0.42	**Jarque-Bera (JB):**	11.29
Prob(Q):	0.52	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.05	**Skew:**	-0.42
Prob(H) (two-sided):	0.81	**Kurtosis:**	3.46

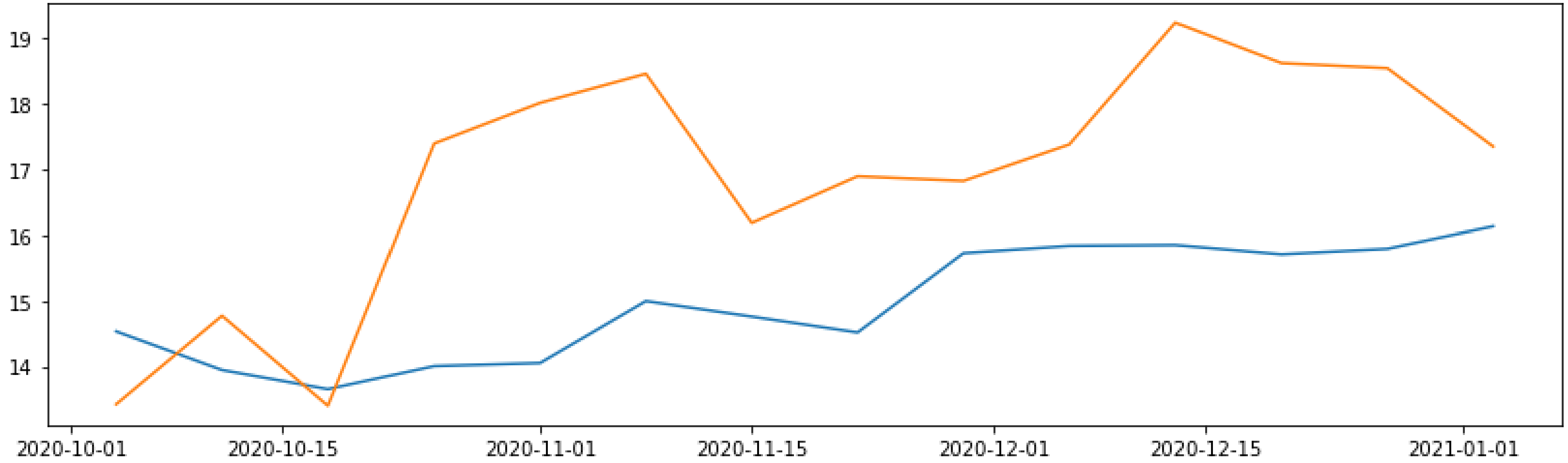
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Now we've got a fitted model for prediction!

Prediction

In [ ]:
```
forcast = sar.predict(start = len(tmpc_train)-1, end= len(tmpc_train)+len(tmpc_test)-2)
plt.plot(forcast)
plt.plot(tmpc_test)
```

Out[ ]:
```
[<matplotlib.lines.Line2D at 0x15ab1bb50>]
```



Cross-validation isn't working for time series for we have to test against the forest horizon instead of randomized observations. Therefore, we plot the hold-out test set and prediction together to see if it's a good fit. The conclusion is that, hmm, I tried.