Source_Assignment_Manola

July 9, 2023

[1]:
```python
print ("The steps that I will follow will be the following:")
print ("1. Introduction")
print ("2. Exploration of Indoors temperature dataset")
print ("3. Stationarity Tests")
print ("4. Univariate Temperature forecasting using smoothing")
print ("5. Univariate Temperature forecasting using SARIMA Model")
print ("6. Multivariate Temperature forecasting using SARIMAX Model")
print ("7. Final Comparison of Models Using MSE")
```

```
The steps that I will follow will be the following:
1. Introduction
2. Exploration of Indoors temperature dataset
3. Stationarity Tests
4. Univariate Temperature forecasting using smoothing
5. Univariate Temperature forecasting using SARIMA Model
6. Multivariate Temperature forecasting using SARIMAX Model
7. Final Comparison of Models Using MSE
```

[2]:
```python
from IPython.display import Markdown

comment = "**1. Introduction**"
font_size = "20px"

Markdown(f"<span style='font-weight:bold; font-size:{font_size}'>{comment}</
 ↪span>")
```

[2]:

1. Introduction

[3]:
```python
print("Our goal for this assignment is to predict the indoors temperature of a␣
 ↪greenhouse for every hour for the \
next 24 hours. To start with this, let's have a look at our available data in␣
 ↪order to draw a good method for our \
forecasting methods. In the ReadMe.pdf several tables are given, but not all of␣
 ↪them are relevant for the indoors \
greenhouse temperature. For example the 'Production' and 'Crop parameters' are␣
 ↪relevant for the growth and yield \
of the plants, but not for the temperature of the greenhouse. We won't use␣
 ↪these tables. We are going to load the \
```

```
two relevant tables that are the 'Weather data', that gives information of the␣
↪weather conditions outside of the \
greenhouse, and the 'Greenhouse climate' that gives information about the␣
↪indoor climate, the status of actuators \
and irrigation.")
```

Our goal for this assignment is to predict the indoors temperature of a greenhouse for every hour for the next 24 hours. To start with this, let's have a look at our available data in order to draw a good method for our forecasting methods. In the ReadMe.pdf several tables are given, but not all of them are relevant for the indoors greenhouse temperature. For example the 'Production' and 'Crop parameters' are relevant for the growth and yield of the plants, but not for the temperature of the greenhouse. We won't use these tables. We are going to load the two relevant tables that are the 'Weather data', that gives information of the weather conditions outside of the greenhouse, and the 'Greenhouse climate' that gives information about the indoor climate, the status of actuators and irrigation.

[4]:
```
print("let's import some useful libraries first")

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from datetime import datetime
from datetime import timedelta
from dateutil.relativedelta import relativedelta
from IPython.display import display
import os
warnings.filterwarnings('ignore')
pd.options.display.float_format = '{:,.5f}'.format
%matplotlib inline
plotsize = (13, 5)
```

let's import some useful libraries first

[5]:
```
print("Let's have a first look at the table of the outdoors weather conditions.
↪")
df_outd = pd.read_csv("/Users/irismanola/Documents/ML/Source_Assignment/Weather.
↪csv")
df_outd.columns
df_outd.head()
```

Let's have a first look at the table of the outdoors weather conditions.

```
[5]:             time  AbsHumOut   Iglob  PARout     Pyrgeo     RadSum    Rain  \
     0 43,815.00000    6.22095 0.00000 0.00000 -72.00000 215.00000 0.00000
     1 43,815.00347    6.22095 0.00000 0.00000 -73.00000   0.00000 0.00000
     2 43,815.00694    6.20556 0.00000 0.00000 -76.00000   0.00000 0.00000
     3 43,815.01042    6.19017 0.00000 0.00000 -77.00000   0.00000 0.00000
     4 43,815.01389    6.16262 0.00000 0.00000 -75.00000   0.00000 0.00000

          Rhout     Tout  Winddir  Windsp
     0 80.60000 6.90000 32.00000 4.70000
     1 80.60000 6.90000 32.00000 4.70000
     2 80.40000 6.90000 32.00000 4.70000
     3 80.20000 6.90000 32.00000 4.70000
     4 80.90000 6.70000 32.00000 4.70000
```

```
[6]: print("And now let's have a look at the indoors conditions.")

     df_ind = pd.read_csv("/Users/irismanola/Documents/ML/Source_Assignment/
      ↪GreenhouseClimate.csv")
     df_ind.columns
     df_ind.head()
```

```
And now let's have a look at the indoors conditions.
```

```
[6]:             time  AssimLight  BlackScr    CO2air   Cum_irr  EC_drain_PC  \
     0 43,815.00000     0.00000  35.00000 472.00000  0.35480      3.98000
     1 43,815.00347     0.00000  85.00000 501.00000  0.53220      3.99000
     2 43,815.00694     0.00000  96.00000 489.00000  0.53220      3.99000
     3 43,815.01042     0.00000  96.00000 497.00000  0.53220      4.00000
     4 43,815.01389     0.00000  96.00000 477.00000  0.53220      4.00000

           EnScr  HumDef  PipeGrow  PipeLow  …  t_rail_min_sp  t_rail_min_vip  \
     0 100.00000 7.17000   0.00000 45.20000  …            NaN         0.00000
     1 100.00000 6.94000   0.00000 43.60000  …            NaN         0.00000
     2 100.00000 7.24000   0.00000 42.30000  …            NaN         0.00000
     3 100.00000 6.74000   0.00000 41.20000  …            NaN         0.00000
     4 100.00000 6.71000   0.00000 41.20000  …            NaN         0.00000

        t_vent_sp  t_ventlee_vip  t_ventwind_vip  water_sup  \
     0        NaN       25.00000        26.00000    4.00000
     1        NaN       25.00000        26.00000    6.00000
     2        NaN       25.00000        26.00000    6.00000
     3        NaN       25.00000        26.00000    6.00000
     4        NaN       25.00000        26.00000    6.00000

        water_sup_intervals_sp_min  water_sup_intervals_vip_min  window_pos_lee_sp  \
     0                         NaN                  1,000.00000                NaN
     1                         NaN                  1,000.00000                NaN
```

```
2                         NaN                 1,000.00000               NaN
3                         NaN                 1,000.00000               NaN
4                         NaN                 1,000.00000               NaN

   window_pos_lee_vip
0             1.20000
1             1.20000
2             1.20000
3             1.20000
4             1.20000

[5 rows x 50 columns]
```

[7]:
```python
print("the columns are too many, so we do the following to see them all:")
pd.set_option('display.max_columns', None)
df_ind.head()
```

```
the columns are too many, so we do the following to see them all:
```

[7]:
```
           time  AssimLight  BlackScr    CO2air  Cum_irr  EC_drain_PC  \
0 43,815.00000     0.00000  35.00000 472.00000  0.35480      3.98000
1 43,815.00347     0.00000  85.00000 501.00000  0.53220      3.99000
2 43,815.00694     0.00000  96.00000 489.00000  0.53220      3.99000
3 43,815.01042     0.00000  96.00000 497.00000  0.53220      4.00000
4 43,815.01389     0.00000  96.00000 477.00000  0.53220      4.00000

      EnScr  HumDef  PipeGrow  PipeLow    Rhair     Tair  Tot_PAR  \
0 100.00000 7.17000   0.00000 45.20000 60.60000 20.90000  0.00000
1 100.00000 6.94000   0.00000 43.60000 61.40000 20.70000  0.00000
2 100.00000 7.24000   0.00000 42.30000 60.90000 21.20000  0.00000
3 100.00000 6.74000   0.00000 41.20000 62.50000 20.70000  0.00000
4 100.00000 6.71000   0.00000 41.20000 62.70000 20.70000  0.00000

   Tot_PAR_Lamps  VentLee  Ventwind  assim_sp  assim_vip  co2_dos  co2_sp  \
0        0.00000  0.80000   0.00000       NaN    0.00000      NaN     NaN
1        0.00000  0.80000   0.00000       NaN    0.00000  0.00034     NaN
2        0.00000  0.80000   0.00000       NaN    0.00000  0.00036     NaN
3        0.00000  0.80000   0.00000       NaN    0.00000  0.00201     NaN
4        0.00000  0.80000   0.00000       NaN    0.00000  0.00155     NaN

    co2_vip  dx_sp  dx_vip  int_blue_sp  int_blue_vip  int_farred_sp  \
0 400.00000    NaN 2.20000          NaN           NaN            NaN
1 400.00000    NaN 2.20000      0.00000           NaN        0.00000
2 400.00000    NaN 2.20000      0.00000           NaN        0.00000
3 400.00000    NaN 2.20000      0.00000           NaN        0.00000
4 400.00000    NaN 2.20000      0.00000           NaN        0.00000
```

```
   int_farred_vip  int_red_sp  int_red_vip  int_white_sp  int_white_vip  \
0             NaN         NaN          NaN           NaN            NaN
1             NaN     0.00000          NaN       0.00000            NaN
2             NaN     0.00000          NaN       0.00000            NaN
3             NaN     0.00000          NaN       0.00000            NaN
4             NaN     0.00000          NaN       0.00000            NaN

   pH_drain_PC  scr_blck_sp  scr_blck_vip  scr_enrg_sp  scr_enrg_vip  \
0      6.27000          NaN      96.00000          NaN     100.00000
1      6.28000          NaN      96.00000          NaN     100.00000
2      6.28000          NaN      96.00000          NaN     100.00000
3      6.27000          NaN      96.00000          NaN     100.00000
4      6.28000          NaN      96.00000          NaN     100.00000

   t_grow_min_sp  t_grow_min_vip  t_heat_sp  t_heat_vip  t_rail_min_sp  \
0            NaN        10.00000        NaN    21.00000            NaN
1            NaN        10.00000        NaN    21.00000            NaN
2            NaN        10.00000        NaN    21.00000            NaN
3            NaN        10.00000        NaN    21.00000            NaN
4            NaN        10.00000        NaN    21.00000            NaN

   t_rail_min_vip  t_vent_sp  t_ventlee_vip  t_ventwind_vip  water_sup  \
0         0.00000        NaN       25.00000        26.00000    4.00000
1         0.00000        NaN       25.00000        26.00000    6.00000
2         0.00000        NaN       25.00000        26.00000    6.00000
3         0.00000        NaN       25.00000        26.00000    6.00000
4         0.00000        NaN       25.00000        26.00000    6.00000

   water_sup_intervals_sp_min  water_sup_intervals_vip_min  window_pos_lee_sp  \
0                         NaN                  1,000.00000                NaN
1                         NaN                  1,000.00000                NaN
2                         NaN                  1,000.00000                NaN
3                         NaN                  1,000.00000                NaN
4                         NaN                  1,000.00000                NaN

   window_pos_lee_vip
0             1.20000
1             1.20000
2             1.20000
3             1.20000
4             1.20000
```

[8]:
```
print(df_outd.shape)
```

```
(47809, 11)
```

[9]:
```
print(df_ind.shape)
```

(47809, 50)

[10]:
```
print(f"Both tables have the same lengths. Every row is a measurement every 5␣
↪minutes. Then have have data for \
{47809*5/60:.1f} hours, which is {47809 * 5/60/24:.1f} days of data, or␣
↪approximately {47809 * 5/60/24/30:.1f} months.")
```

Both tables have the same lengths. Every row is a measurement every 5 minutes.
Then have have data for 3984.1 hours, which is 166.0 days of data, or
approximately 5.5 months.

[11]:
```
print ("In the ReadMe.pdf all the variable names are explained. The Tair␣
↪(Greenhouse Air temperature) is the \
variable that we have to forecast. To do so we can use either univariate␣
↪(involving only the Tair timeseries) \
or multivariate forecasting methods (involving other given variables that␣
↪influence the Tair). \
We will start with simple univariate methods and will move towards more complex␣
↪multivariate methods. For now let's \
focus only on the Tair and explore it.")
```

In the ReadMe.pdf all the variable names are explained. The Tair (Greenhouse Air
temperature) is the variable that we have to forecast. To do so we can use
either univariate (involving only the Tair timeseries) or multivariate
forecasting methods (involving other given variables that influence the Tair).
We will start with simple univariate methods and will move towards more complex
multivariate methods. For now let's focus only on the Tair and explore it.

[12]:
```
from IPython.display import Markdown

comment = "**2. Exploration of Indoors temperature dataset**"
font_size = "20px"

Markdown(f"<span style='font-weight:bold; font-size:{font_size}'>{comment}</
↪span>")
```

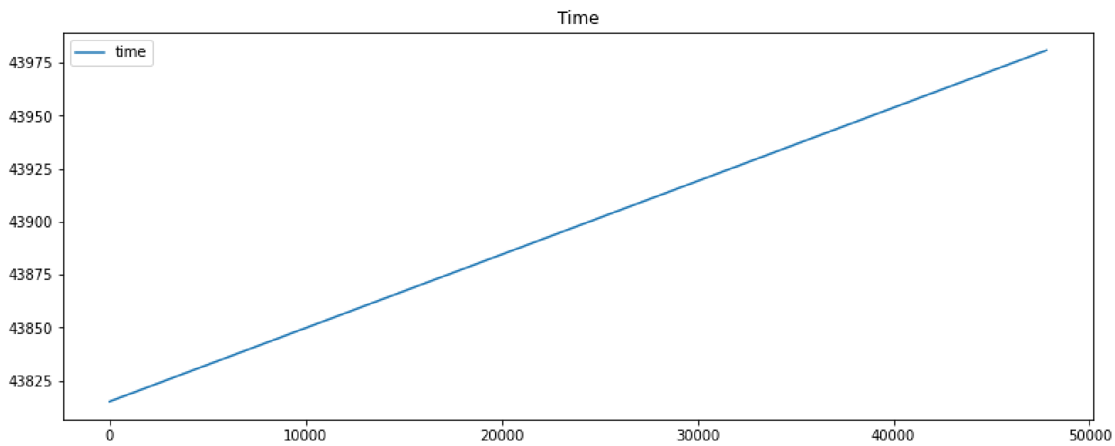
[12]:

2. Exploration of Indoors temperature dataset

[13]:
```
print ("Let's see if the time is well set every 5 minutes and without missing␣
↪variables.")
df_ind[['time']].plot(figsize=plotsize)

plt.title('Time')
```

Let's see if the time is well set every 5 minutes and without missing variables.

[13]: Text(0.5, 1.0, 'Time')



[14]:
```
print ("are there any missing values in the time ?")
time=df_ind[['time']]
time.isnull().sum()
```

```
are there any missing values in the time ?
```

[14]:
```
time    0
dtype: int64
```

[15]:
```
print ("the time variable looks nice and linear as it should and there are no␣
↪missing variables.")
```

```
the time variable looks nice and linear as it should and there are no missing
variables.
```

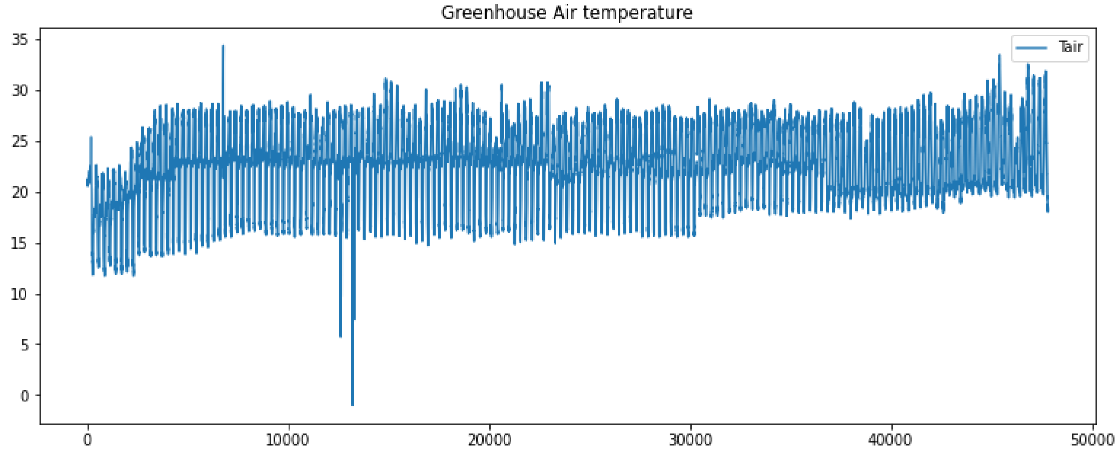
[16]:
```
Tair = df_ind[['Tair']]
Tair.head(10)
```

[16]:

	Tair
0	20.90000
1	20.70000
2	21.20000
3	20.70000
4	20.70000
5	20.60000
6	20.70000
7	20.60000
8	20.70000
9	21.00000

[17]:
```
Tair.plot(figsize=plotsize)
plt.title('Greenhouse Air temperature')
```

[17]: Text(0.5, 1.0, 'Greenhouse Air temperature')



[18]:
```python
statistics = Tair.describe()
print(statistics)
```

```
                Tair
count 47,738.00000
mean        22.71351
std          3.92040
min         -1.00000
25%         20.00000
50%         22.80000
75%         26.40000
max         34.32632
```

[19]:
```python
print ("There are no crazy outliers to indicate a large mistake in the␣
↪measurements that need to be removed. \
There is a warm outlier at the beginning of the measurments and two cold ones.␣
↪The cold ones might be cold \
nights were the window of the greenhouse were left (forgotten?) open. \
There is no heretoscedasticity in the data and no obvious strong␣
↪autocorrelation. We can see some trend at the beginning \
of the data, probably indicating a seasonal change, like transition from spring␣
↪to summer. There is also a more \
abrupt temperature drop after the second half of the data, probably another␣
↪change in season from summer to autumn. \
We also see a large periodicity that looks like an intense daily cicle. Let's␣
↪zoom in to see if this is indeed \
a daily cicle.")
print (" ")
```

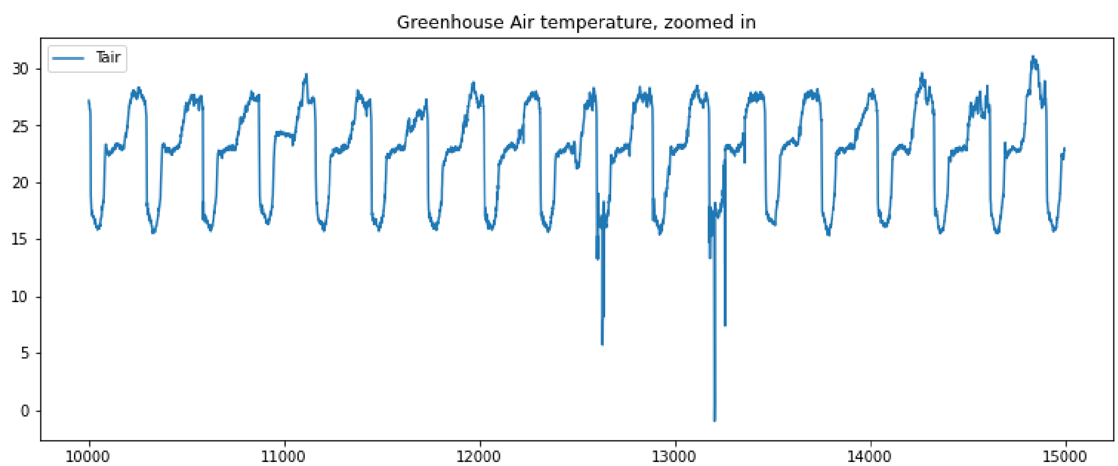
```
print ("Further below we will see why some of my preliminary assumptions are␣
 ↪not correct!")
```

There are no crazy outliers to indicate a large mistake in the measurements that need to be removed. There is a warm outlier at the beginning of the measurments and two cold ones. The cold ones might be cold nights were the window of the greenhouse were left (forgotten?) open. There is no heretoscedasticity in the data and no obvious strong autocorrelation. We can see some trend at the beginning of the data, probably indicating a seasonal change, like transition from spring to summer. There is also a more abrupt temperature drop after the second half of the data, probably another change in season from summer to autumn. We also see a large periodicity that looks like an intense daily cicle. Let's zoom in to see if this is indeed a daily cicle.

Further below we will see why some of my preliminary assumptions are not correct!

[20]:
```
start_index = 10000
end_index = 15000

Tair_slice = Tair[start_index:end_index]

Tair_slice.plot(figsize=plotsize)
plt.title('Greenhouse Air temperature, zoomed in')
```

[20]: Text(0.5, 1.0, 'Greenhouse Air temperature, zoomed in')



[21]:
```
print ("Yes, this looks indeed like a daily cicle (there are 288 - 5 minutes in␣
 ↪a dayt). The temperature change \
is not Gaussian though. We see an evening temperature drop, \
```

```
then in the morning a sharp temperature increase, a plateau and a second␣
↪temperature incease. This needs some \
thinking. Let's come back to this later again.")
```

```
Yes, this looks indeed like a daily cicle (there are 288 - 5 minutes in a dayt).
The temperature change is not Gaussian though. We see an evening temperature
drop, then in the morning a sharp temperature increase, a plateau and a second
temperature incease. This needs some thinking. Let's come back to this later
again.
```

[22]:
```
Tair.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 47809 entries, 0 to 47808
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Tair    47738 non-null  float64
dtypes: float64(1)
memory usage: 373.6 KB
```

[23]:
```
Tair.isnull().sum()
```

[23]:
```
Tair    71
dtype: int64
```

[24]:
```
print("We see that there are 71 missing values among the 47.809 numerical␣
↪entries.")
print ("Let's fill the missing values. They are not many and they are only␣
↪every 5 minutes, so the method we \
chose won't make a big difference. Let's do a simple foreward fill.")
```

```
We see that there are 71 missing values among the 47.809 numerical entries.
Let's fill the missing values. They are not many and they are only every 5
minutes, so the method we chose won't make a big difference. Let's do a simple
foreward fill.
```

[25]:
```
Tair = Tair.fillna(method='ffill')
Tair.isnull().sum()
```

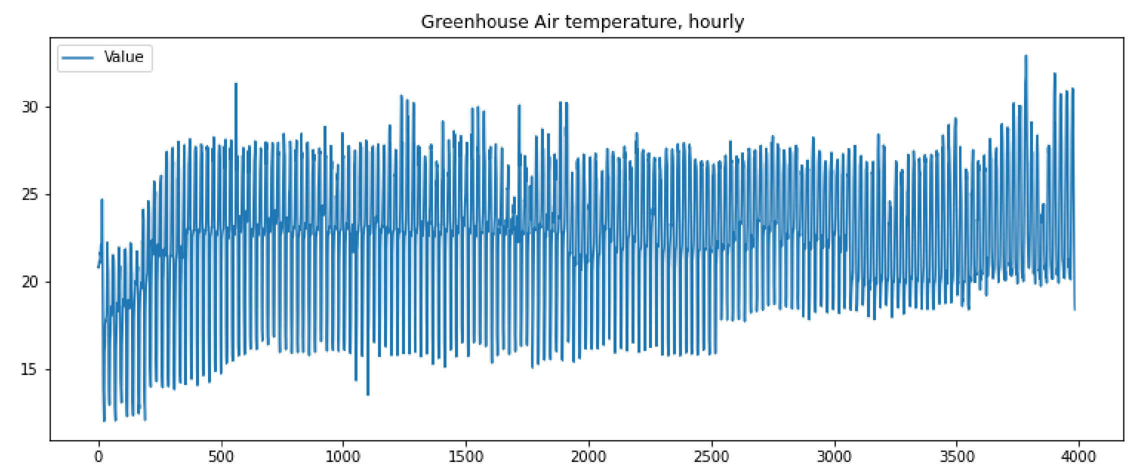
[25]:
```
Tair    0
dtype: int64
```

[26]:
```
print ("cool, there are no missing values any more.")
print ("Since we are interested in hourly observations let's smoothen the data␣
↪from 5-mins to hourly.")
```

```python
# Becausd the length of Tair (47809) is not devided exactly with 12 I make the␣
↪number of groups and a new length to fit them
num_groups = len(Tair) // 12
new_length = num_groups * 12

# Reshape the DataFrame with 12 rows
Tair_reshape = Tair.values[:new_length].reshape(num_groups, 12)

# Calculate the mean along the rows
Tair_mean = np.mean(Tair_reshape, axis=1)

# Create a new DataFrame with the averaged values
Tair_hr = pd.DataFrame(Tair_mean, columns=['Value'])

Tair_hr.plot(figsize=plotsize)
plt.title('Greenhouse Air temperature, hourly ')
```

cool, there are no missing values any more.
Since we are interested in hourly observations let's smoothen the data from 5-mins to hourly.

[26]: Text(0.5, 1.0, 'Greenhouse Air temperature, hourly ')




```
[27]: Tair_hr.head()
```

[27]:

	Value
0	20.77500
1	20.74167
2	20.92500
3	21.00833
4	21.11667

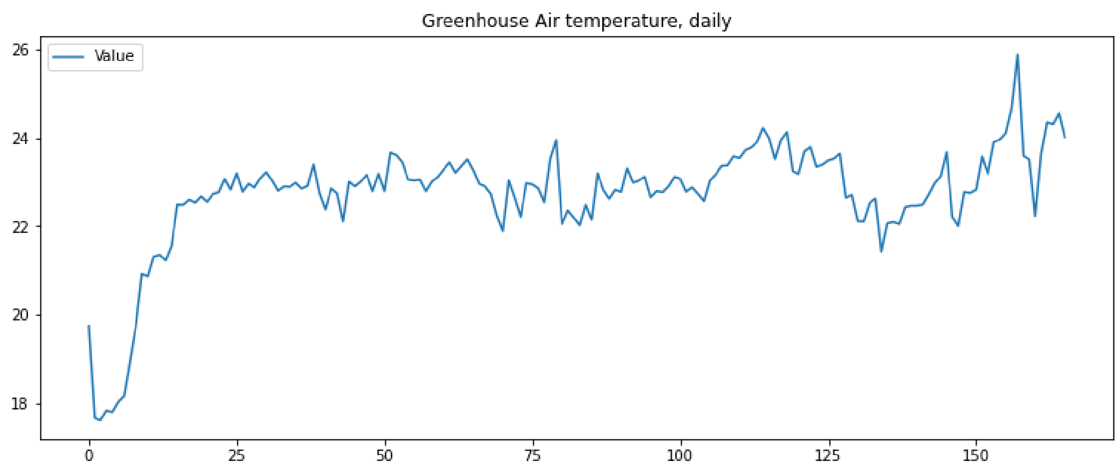
[28]:
```
len(Tair_hr)
```

[28]: 3984

[29]:
```
print ("The graph still looks quite noisy. Let's plot the daily values as well.
 ↪")

num_groups = len(Tair) // 288
new_length = num_groups * 288
Tair_reshape = Tair.values[:new_length].reshape(num_groups, 288)
Tair_mean = np.mean(Tair_reshape, axis=1)
Tair_day = pd.DataFrame(Tair_mean, columns=['Value'])

Tair_day.plot(figsize=plotsize)
plt.title('Greenhouse Air temperature, daily')
```

The graph still looks quite noisy. Let's plot the daily values as well.

[29]: Text(0.5, 1.0, 'Greenhouse Air temperature, daily')



[30]:
```
print ("This is interesting! We now clearly see the trend at the beginning (due␣
 ↪to change of season most likely). \
We also see some autocorrelation that was not visible in the 5-mins and hourly␣
 ↪data because of the noise.")
```

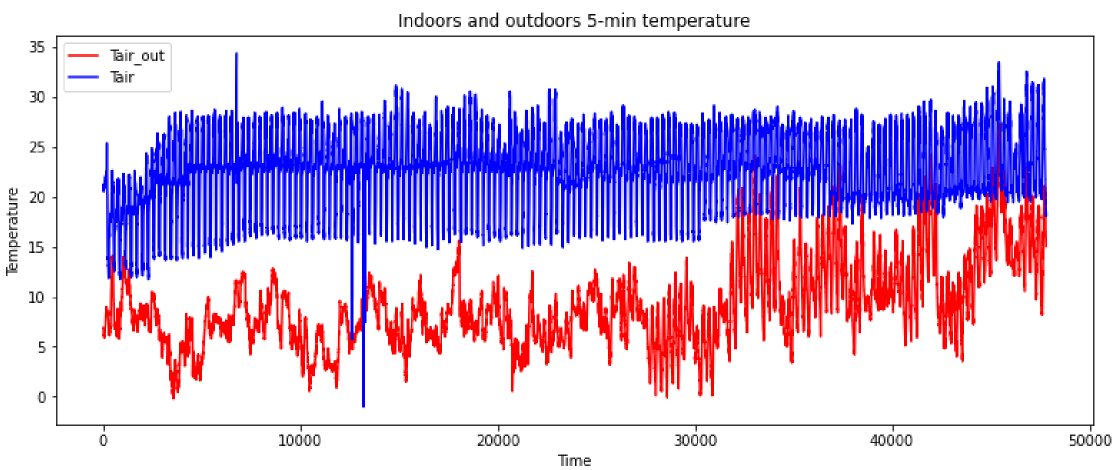
This is interesting! We now clearly see the trend at the beginning (due to change of season most likely). We also see some autocorrelation that was not visible in the 5-mins and hourly data because of the noise.

[31]:
```
print ("Out of curiocity, let's see how the temperature inside the greenhouse␣
 ↪relates to the observed temperature \
```

```
outside of it.")
```

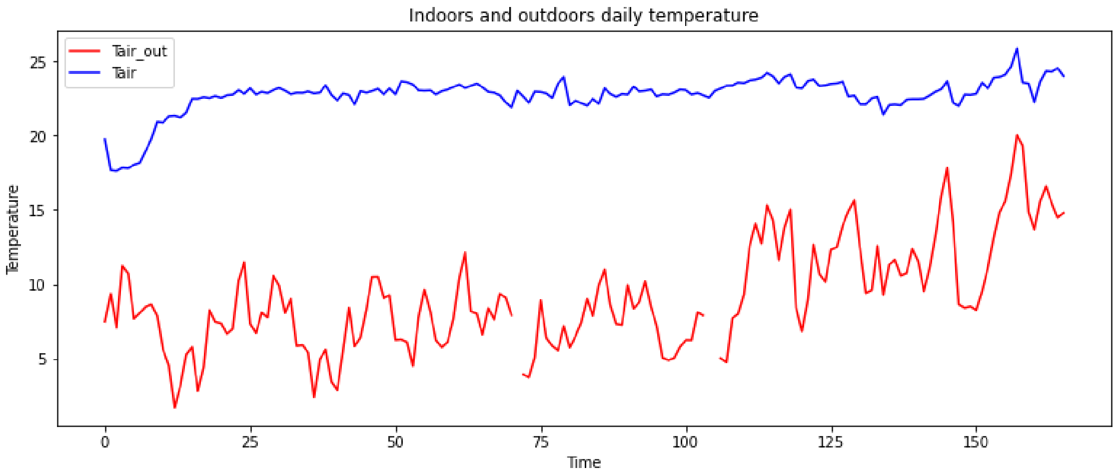
Out of curiocity, let's see how the temperature inside the greenhouse relates to the observed temperature outside of it.

[32]:
```
Tair_out = df_outd[['Tout']]



fig, ax = plt.subplots(figsize=plotsize)
ax.plot(Tair_out.index, Tair_out, color='red', label='Tair_out')
ax.plot(Tair.index, Tair, color='blue', label='Tair')

ax.set_xlabel('Time')
ax.set_ylabel('Temperature')
ax.legend()
ax.set_title('Indoors and outdoors 5-min temperature')

plt.show()
```



[33]:
```
Tair_out = df_outd[['Tout']]
num_groups = len(Tair_out) // 288
new_length = num_groups * 288
Tair_reshape = Tair_out.values[:new_length].reshape(num_groups, 288)
Tair_mean = np.mean(Tair_reshape, axis=1)
Tairout_day = pd.DataFrame(Tair_mean, columns=['Value'])



fig, ax = plt.subplots(figsize=plotsize)
ax.plot(Tairout_day.index, Tairout_day, color='red', label='Tair_out')
ax.plot(Tair_day.index, Tair_day, color='blue', label='Tair')
```

```python
ax.set_xlabel('Time')
ax.set_ylabel('Temperature')
ax.legend()
ax.set_title('Indoors and outdoors daily temperature')

plt.show()
```



[34]:
```python
print ("We can see that the outdoors temperature timeseries is non-stationary,␣
 ↪as there is heteroscedasticity and \
autocorrelation and seasonality.")
print ("")
print ("By comparing the in- with the out-door temperature we can see how more␣
 ↪smooth the indoor temperature is. \
We see that the average difference in T in and out is more than 10 degrees. We␣
 ↪can also see that my initial assumption \
that there is a transition from spring to summer to autumn was not correct! We␣
 ↪rather see a transition from a \
(cold) spring to more summer-like temperatures (assuming this is data from the␣
 ↪Netherlands of course!). My assumption \
now is that the increase that we see in the T in at the beginning of the␣
 ↪measurments and the abrupt drop after the \
second half is that this is intentionaly done to help the plant growth.")
```

```
We can see that the outdoors temperature timeseries is non-stationary, as there
is heteroscedasticity and autocorrelation and seasonality.

By comparing the in- with the out-door temperature we can see how more smooth
the indoor temperature is. We see that the average difference in T in and out is
more than 10 degrees. We can also see that my initial assumption that there is a
transition from spring to summer to autumn was not correct! We rather see a
```

transition from a (cold) spring to more summer-like temperatures (assuming this is data from the Netherlands of course!). My assumption now is that the increase that we see in the T in at the beginning of the measurments and the abrupt drop after the second half is that this is intentionaly done to help the plant growth.

[35]:
```
comment = "**3. Stationarity Tests**"
font_size = "20px"

Markdown(f"<span style='font-weight:bold; font-size:{font_size}'>{comment}</
↪span>")
```

[35]: **3. Stationarity Tests**

[36]:
```
print ("It is important to determine whether the Tair is stationary. This will␣
↪determine which methods we will \
use to forecast it, and will tell whether we have to transform the data to get␣
↪a cleaner signal (in non-stationary).")
print ("In order for  a timeseries data to be stationary, the data must exhibit␣
↪four properties over time: 1) \
constant mean (no trend), 2) constant variance (no heteroscedasticity), 3)␣
↪constant autocorrelation structure, \
4) no periodic component (no seasonality).")
print ("Above we discussed visually that the data seem to have to some extend a␣
↪constant mean, a constant variance \
a daily periodicity and some autocorrelation when the daily values are averaged.
↪")


print("Now let's use some summary statistics and statistical tests to determine␣
↪the stationarity.")
```

```
It is important to determine whether the Tair is stationary. This will determine
which methods we will use to forecast it, and will tell whether we have to
transform the data to get a cleaner signal (in non-stationary).
In order for  a timeseries data to be stationary, the data must exhibit four
properties over time: 1) constant mean (no trend), 2) constant variance (no
heteroscedasticity), 3) constant autocorrelation structure, 4) no periodic
component (no seasonality).
Above we discussed visually that the data seem to have to some extend a constant
mean, a constant variance a daily periodicity and some autocorrelation when the
daily values are averaged.
Now let's use some summary statistics and statistical tests to determine the
stationarity.
```

[37]:
```
Tair_hr_values = Tair_hr.values
chunks = np.array_split(Tair_hr_values[:, 0], 50)
```

```
chunks[0]
```

[37]:
```
array([20.775     , 20.74166667, 20.925     , 21.00833333, 21.11666667,
       20.98333333, 21.09166667, 21.15      , 21.65      , 21.49166667,
       22.01666666, 22.05833333, 21.82500001, 21.68333333, 22.91666666,
       24.65833333, 23.35      , 20.81666667, 17.65833334, 14.53333334,
       13.80833333, 13.175     , 12.55833333, 11.95833333, 14.46666666,
       15.93333333, 16.175     , 16.41666666, 17.49166666, 17.725     ,
       17.675     , 17.85833333, 17.88333333, 18.13333333, 19.36666666,
       20.31666666, 20.95     , 22.19999999, 22.03333333, 21.24166667,
       20.85      , 20.50833333, 18.75000001, 15.56666667, 13.69166667,
       13.1       , 12.925     , 12.90833333, 14.85833332, 16.29166666,
       16.85833333, 16.91666666, 17.79166666, 18.51666666, 18.29166667,
       18.01666667, 18.10833333, 18.225     , 20.        , 21.3       ,
       21.48333333, 21.48333334, 21.05833333, 21.33333334, 21.15      ,
       20.58333333, 17.45000002, 13.70833333, 12.88333334, 12.39166667,
       12.18333333, 11.99166666, 14.48333332, 16.14166667, 16.83333333,
       17.15833333, 17.61666666, 18.73333333, 18.69166667, 18.51666667])
```

[38]:
```
print("{} | {:7} | {}".format("Chunk", "Mean", "Variance"))
print("-" * 26)
for i, chunk in enumerate(chunks, 1):
    print("{:5} | {:.6} | {:.6}".format(i, np.mean(chunk), np.var(chunk)))
```

```
Chunk | Mean    | Variance
--------------------------
    1 | 18.2396 | 10.4118
    2 | 18.3018 | 9.2496
    3 | 19.4288 | 15.9035
    4 | 21.0478 | 17.9846
    5 | 22.5196 | 20.286
    6 | 22.1696 | 22.8943
    7 | 22.6919 | 17.2257
    8 | 23.3164 | 15.1268
    9 | 22.6403 | 15.5943
   10 | 23.0004 | 13.8433
   11 | 23.2543 | 15.0368
   12 | 22.6644 | 15.9071
   13 | 22.6557 | 12.6901
   14 | 23.0409 | 16.0373
   15 | 22.746 | 16.9179
   16 | 23.2919 | 16.5727
   17 | 23.5159 | 15.0981
   18 | 22.6602 | 15.4158
   19 | 23.2593 | 13.5949
   20 | 23.7118 | 16.1951
```

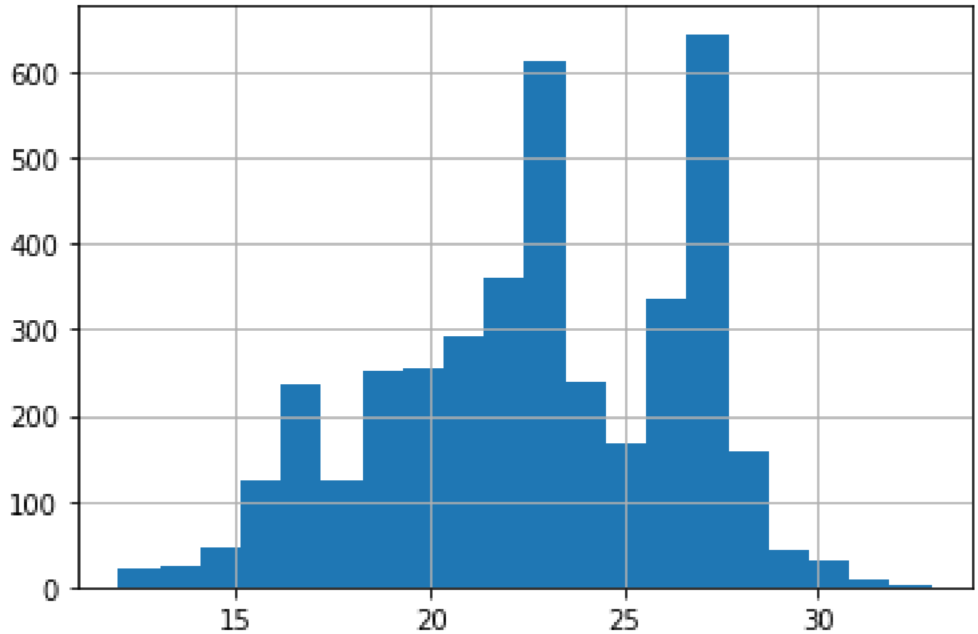
```
21 | 22.2999 | 13.6625
22 | 22.5501 | 10.5809
23 | 23.0509 | 13.9558
24 | 22.9685 | 19.048
25 | 22.1141 | 11.8366
26 | 22.8354 | 12.3359
27 | 22.467  | 14.4393
28 | 22.9278 | 13.1766
29 | 23.2932 | 13.7182
30 | 22.6157 | 17.0552
31 | 22.8194 | 13.3028
32 | 23.1356 | 12.6402
33 | 23.2129 | 10.8642
34 | 23.6071 | 8.64246
35 | 24.1937 | 9.29517
36 | 23.7237 | 9.49956
37 | 23.3552 | 9.74342
38 | 23.5098 | 8.22818
39 | 23.2488 | 11.2616
40 | 22.0418 | 10.9013
41 | 21.8893 | 8.7423
42 | 22.5912 | 10.6787
43 | 22.4973 | 11.6862
44 | 22.9328 | 13.7114
45 | 22.5078 | 9.08623
46 | 23.3632 | 9.26753
47 | 23.6667 | 12.643
48 | 24.4284 | 15.9175
49 | 23.7815 | 11.3102
50 | 24.1479 | 16.2739
```

[39]:
```
print ("There is some small deviation from the mean, where the initial values␣
↪are a little smaller and the last ones \
a little higher, but not too much. There is some change in the variance, but it␣
↪is not too big. Let's do more tests \
before we drive conclusions.")
```

```
There is some small deviation from the mean, where the initial values are a
little smaller and the last ones a little higher, but not too much. There is
some change in the variance, but it is not too big. Let's do more tests before
we drive conclusions.
```

[40]:
```
Tair_hr_values = Tair_hr.values
Tair_hr_series = pd.Series(Tair_hr_values[:, 0])

Tair_hr_series.hist(bins=20)
```

[40]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9b3c0d7b50>



[41]:
```
print ("This is not a Gaussian distribution. This indicates that the dataset is␣
 ↪non stationary. \
In the histogram we can see the daily cicle of the data.")
```

This is not a Gaussian distribution. This indicates that the dataset is non stationary. In the histogram we can see the daily cicle of the data.

[42]:
```
print("Let's run the augmented Dikey-Fuller statistical test to test the \
stationarity of our dataset. The null hypothesis is that the series is␣
 ↪nonstationary. We set a significance \
level to accept or reject the null to 0.05.")
# lets transform the pandas dataframe to a numpy array
Tair_hr_values = Tair_hr.values
from statsmodels.tsa.stattools import adfuller

adf, pvalue, usedlag, nobs, critical_values, icbest = adfuller(Tair_hr_values[:
 ↪, 0])

print("The adf value is ",adf)
print ("The more negative the value, the more confident we can be that the␣
 ↪series is stationary. But let's \
print the p-value:",pvalue)
print ("The p-value is too small, so we reject the null that our data is␣
 ↪nonstationary")
```

```
print ("The Dickey-Fuller test indicates that the dataset is stationary, but we␣
↪do see a daily pattern in the data. \
This can happen because the test primarily focuses on detecting trends rather␣
↪than periodic patterns.")
```

Let's run the augmented Dikey-Fuller statistical test to test the stationarity of our dataset. The null hypothesis is that the series is nonstationary. We set a significance level to accept or reject the null to 0.05.
The adf value is -3.933187900689058
The more negative the value, the more confident we can be that the series is stationary. But let's print the p-value: 0.0018037339247767325
The p-value is too small, so we reject the null that our data is nonstationary
The Dickey-Fuller test indicates that the dataset is stationary, but we do see a daily pattern in the data. This can happen because the test primarily focuses on detecting trends rather than periodic patterns.

[43]:
```
print ("Presence of seasonality: The ADF test is primarily designed to assess␣
↪the presence of a unit root and \
does not directly account for seasonality. If the data exhibits significant␣
↪seasonal patterns, the ADF test may \
fail to identify non-stationarity caused by seasonal components. Let's run an␣
↪ADF test that has a focus on seasonality")
```

Presence of seasonality: The ADF test is primarily designed to assess the presence of a unit root and does not directly account for seasonality. If the data exhibits significant seasonal patterns, the ADF test may fail to identify non-stationarity caused by seasonal components. Let's run an ADF test that has a focus on seasonality

[44]:
```
from statsmodels.tsa.stattools import adfuller

# Assuming Tair_hr_values is your hourly dataset
Tair_hr_series = pd.Series(Tair_hr_values[:, 0])

# Perform the ADF test on the seasonal component
adf_result = adfuller(Tair_hr_series.diff(24).dropna())

# Extract the p-value
p_value = adf_result[1]

# Print the test result and explanation
print("ADF Test Result:")
if p_value < 0.05:
    print("The dataset is not stationary, indicating the presence of a daily␣
↪cycle.")
else:
```

```
    print("The dataset is stationary.")
```

```
ADF Test Result:
The dataset is not stationary, indicating the presence of a daily cycle.
```

[45]:
```
from statsmodels.tsa.stattools import kpss

# Perform KPSS test
result = kpss(Tair_hr_values[:, 0])

# Extract the p-value from the test result
p_value = result[1]

# Compare the p-value with a significance level (e.g., 0.05) to determine␣
↪stationarity
if p_value < 0.05:
    print("The time series is not stationary.")
else:
    print("The time series is stationary.")
print (p_value)
```

```
The time series is not stationary.
0.01
```

[46]:
```
comment = "**4. Univariate Temperature forecasting using smoothing**"
font_size = "20px"

Markdown(f"<span style='font-weight:bold; font-size:{font_size}'>{comment}</
↪span>")
```

[46]:

4. Univariate Temperature forecasting using smoothing

[47]:
```
print ("We will forecast the last 24 hours of the indoors temperature using:")
print ("1. Simple Average Smoothing")
print ("2. Triple Exponential Smoothing")

print ("We won't use the single exponential smoothing because it is mainly␣
↪useful for short-term \
forecasting and when the data has a gradual or linear trend that needs to be␣
↪captured. \
Likewise, we skip the double exponential smoothing because it refers to␣
↪timeseries \
with a trend. We have a look at the triplpe exponential smoothing that refers␣
↪to \
timeseries with trend and seasonality. There is no significant trend in our␣
↪data though.")
```

```
We will forecast the last 24 hours of the indoors temperature using:
```

1. Simple Average Smoothing
2. Triple Exponential Smoothing

We won't use the single exponential smoothing because it is mainly useful for short-term forecasting and when the data has a gradual or linear trend that needs to be captured. Likewise, we skip the double exponential smoothing because it refers to timeseries with a trend. We have a look at the triplpe exponential smoothing that refers to timeseries with trend and seasonality. There is no significant trend in our data though.

[48]:
```
train = Tair_hr_values[:-24]
test = Tair_hr_values[-24:]
train[3900:-24],test
```

[48]:
```
(array([[31.16666667],
        [31.86666667],
        [29.38333333],
        [28.18333333],
        [29.00833333],
        [27.44166667],
        [25.00833334],
        [22.73333333],
        [21.7       ],
        [21.01666667],
        [20.34583333],
        [20.66666666],
        [20.74166667],
        [20.48333333],
        [20.70833333],
        [20.74166667],
        [20.275     ],
        [19.88333333],
        [20.58333333],
        [22.55833333],
        [24.4       ],
        [26.49166666],
        [27.73333333],
        [29.75      ],
        [30.6       ],
        [30.70833333],
        [29.89166666],
        [28.61666667],
        [28.65000002],
        [27.93333334],
        [25.39166667],
        [22.75000001],
        [21.39166666],
        [21.10833333],
```

```
        [21.06666666],
        [20.86666667]]), array([[20.31666667],
        [20.23333333],
        [20.325     ],
        [20.43333333],
        [20.45      ],
        [20.075     ],
        [20.85      ],
        [22.1       ],
        [24.54166666],
        [26.75      ],
        [28.275     ],
        [29.125     ],
        [30.66666667],
        [31.01666667],
        [30.875     ],
        [29.82500001],
        [28.15000001],
        [26.40833333],
        [24.55833334],
        [22.91666667],
        [21.44166667],
        [19.8       ],
        [18.77916666],
        [18.35833334]]))
```

[49]:

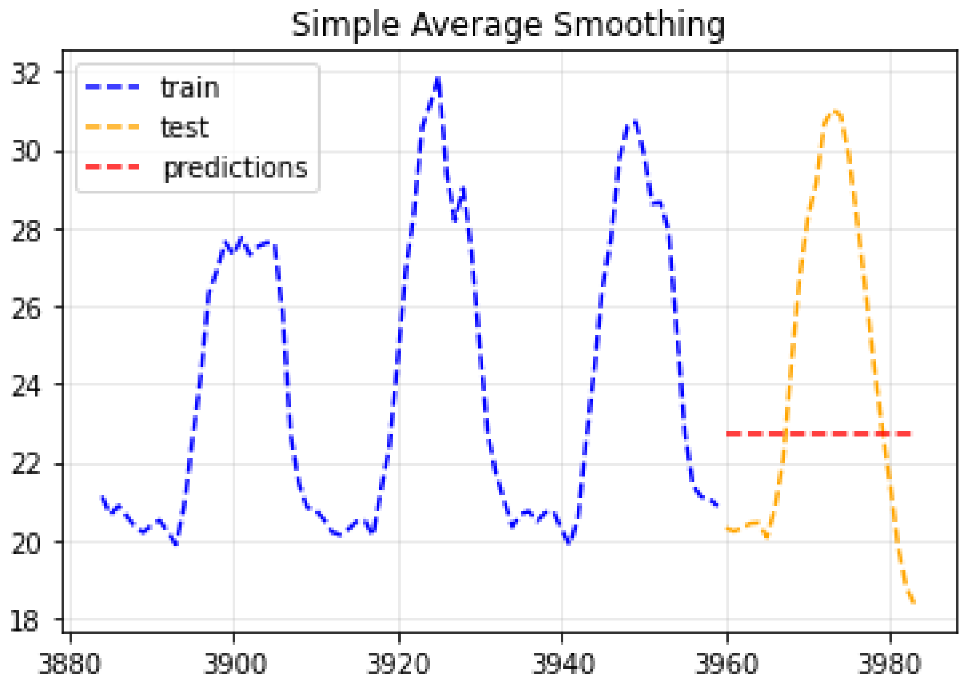
```
def mse(observations, estimates):
    '''
    INPUT:
        observations - numpy array of values indicating observed values
        estimates - numpy array of values indicating an estimate of values
    OUTPUT:
        Mean Square Error value
    '''
    # check arg types
    assert type(observations) == type(np.array([])), "'observations' must be a␣
↪numpy array"
    assert type(estimates) == type(np.array([])), "'estimates' must be a numpy␣
↪array"
    # check length of arrays equal
    assert len(observations) == len(estimates), "Arrays must be of equal length"

    # calculations
    difference = observations - estimates
    sq_diff = difference ** 2
    mse = sum(sq_diff)
```

```
    return mse
```

[50]:
```
# find mean of series
trend_seasonal_avg = np.mean(Tair_hr_values)

# create array of mean value equal to length of time array
simple_avg_preds = np.full(shape=len(test), fill_value=trend_seasonal_avg,␣
↪dtype='float')

# mse
simple_mse = mse(test, simple_avg_preds)

# results
print("Predictions: ", simple_avg_preds)
print("MSE: ", simple_mse)
```

```
Predictions:  [22.71656505 22.71656505 22.71656505 22.71656505 22.71656505
22.71656505
 22.71656505 22.71656505 22.71656505 22.71656505 22.71656505 22.71656505
 22.71656505 22.71656505 22.71656505 22.71656505 22.71656505 22.71656505
 22.71656505 22.71656505 22.71656505 22.71656505 22.71656505 22.71656505]
MSE:  [470.80015169 470.80015169 470.80015169 470.80015169 470.80015169
 470.80015169 470.80015169 470.80015169 470.80015169 470.80015169
 470.80015169 470.80015169 470.80015169 470.80015169 470.80015169
 470.80015169 470.80015169 470.80015169 470.80015169 470.80015169
 470.80015169 470.80015169 470.80015169 470.80015169]
```

[51]:
```
time = np.arange(3984)
train_subset = train[-100:].flatten()
plt.plot(time[-100:-24], train_subset[:-24], 'b--', label="train")
plt.plot(time[-24:], test, color='orange', linestyle="--", label="test")
plt.plot(time[-24:], simple_avg_preds, 'r--', label="predictions")
plt.legend(loc='upper left')
plt.title("Simple Average Smoothing")
plt.grid(alpha=0.3)
```

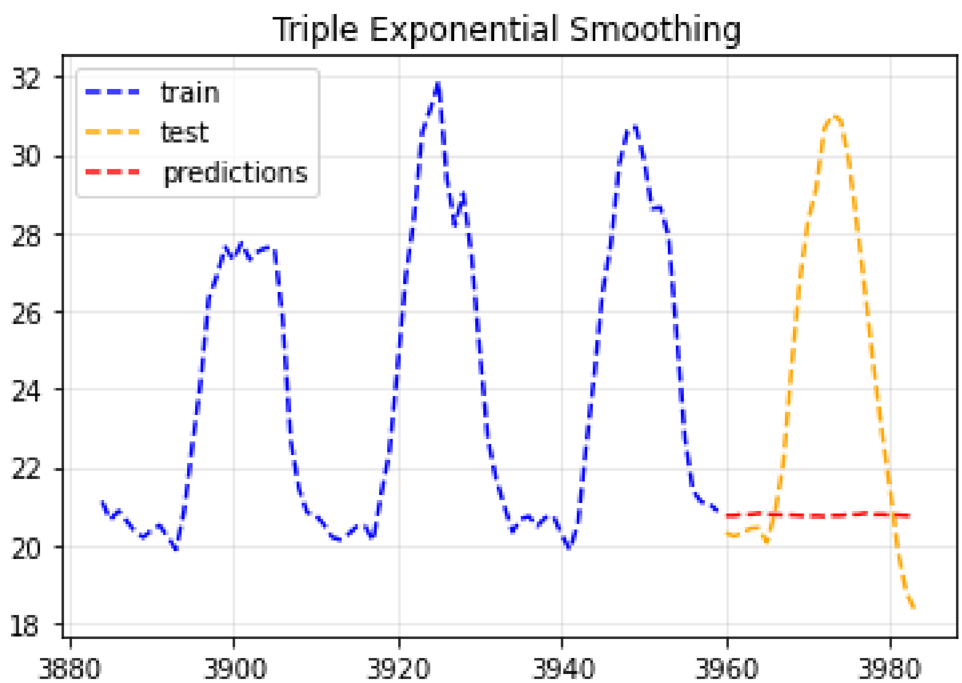


[ ]:

[52]:
```
from statsmodels.tsa.api import ExponentialSmoothing

triple = ExponentialSmoothing(train,
                              trend="additive",
                              seasonal="additive",
                              seasonal_periods=13).fit(optimized=True)
triple_preds = triple.forecast(len(test))
triple_mse = mse(test, triple_preds)
print("Predictions: ", triple_preds)
print("MSE: ", triple_mse)
```

```
Predictions:  [20.75802878 20.75785392 20.79466218 20.7856051  20.82008972
20.78557375
 20.78921815 20.77163693 20.77400625 20.75883463 20.74187863 20.75390028
 20.74171441 20.75807602 20.75790117 20.79470943 20.78565234 20.82013697
 20.78562099 20.7892654  20.77168417 20.7740535  20.75888188 20.74192588]
MSE:  [684.57715711 684.60446223 678.88882858 680.28919212 674.9783876
 680.29404666 679.73008658 682.45660366 682.08830084 684.45133315
 687.10536361 685.22225721 687.13113646 684.56977963 684.59708436
 678.88153418 680.28187718 674.97115086 680.28673164 679.72277983
 682.44925704 682.08095959 684.4439575  687.09794951]
```

[53]:
```
time = np.arange(3984)
train_subset = train[-100:].flatten()
plt.plot(time[-100:-24], train_subset[:-24], 'b--', label="train")
plt.plot(time[-24:], test, color='orange', linestyle="--", label="test")
plt.plot(time[-24:], triple_preds, 'r--', label="predictions")
plt.legend(loc='upper left')
plt.title("Triple Exponential Smoothing")
plt.grid(alpha=0.3);
```



[54]:
```
print ("Indeed it does not do a very good job at predicting temperature values.
↪")
```

```
Indeed it does not do a very good job at predicting temperature values.
```

[55]:
```
print("COMPARISON")
data_dict = {'MSE':[np.mean(simple_mse), np.mean(triple_mse)]}
df = pd.DataFrame(data_dict, index=['simple', 'triple'])
print(df)
```

```
COMPARISON
             MSE
simple 470.80015
triple 682.13334
```

[56]:
```
comment = "**5. Univariate Temperature forecasting using SARIMA Model**"
font_size = "20px"

Markdown(f"<span style='font-weight:bold; font-size:{font_size}'>{comment}</
↪span>")
```

[56]:

5. Univariate Temperature forecasting using SARIMA Model

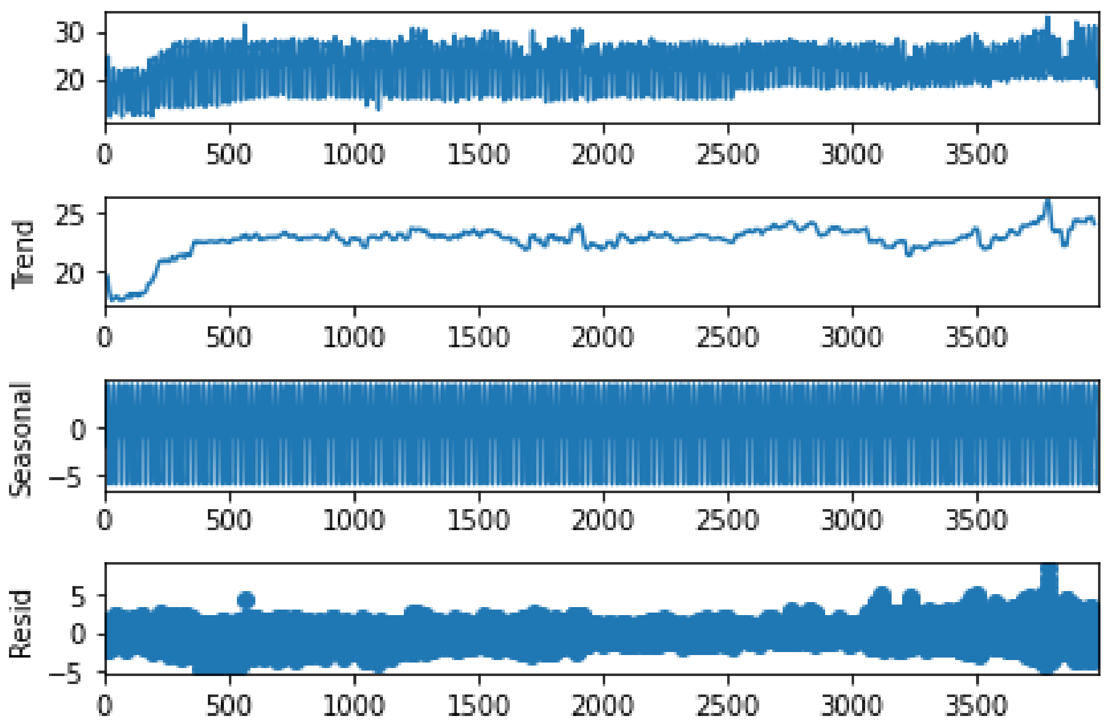
[57]:
```
print ("We are going to use a SARIMA model to predict indoors temperature. The␣
↪SARIMA stands \
for Seasonal Autoregressive Integrated Moving Average Model.")
```

```
We are going to use a SARIMA model to predict indoors temperature. The SARIMA
stands for Seasonal Autoregressive Integrated Moving Average Model.
```

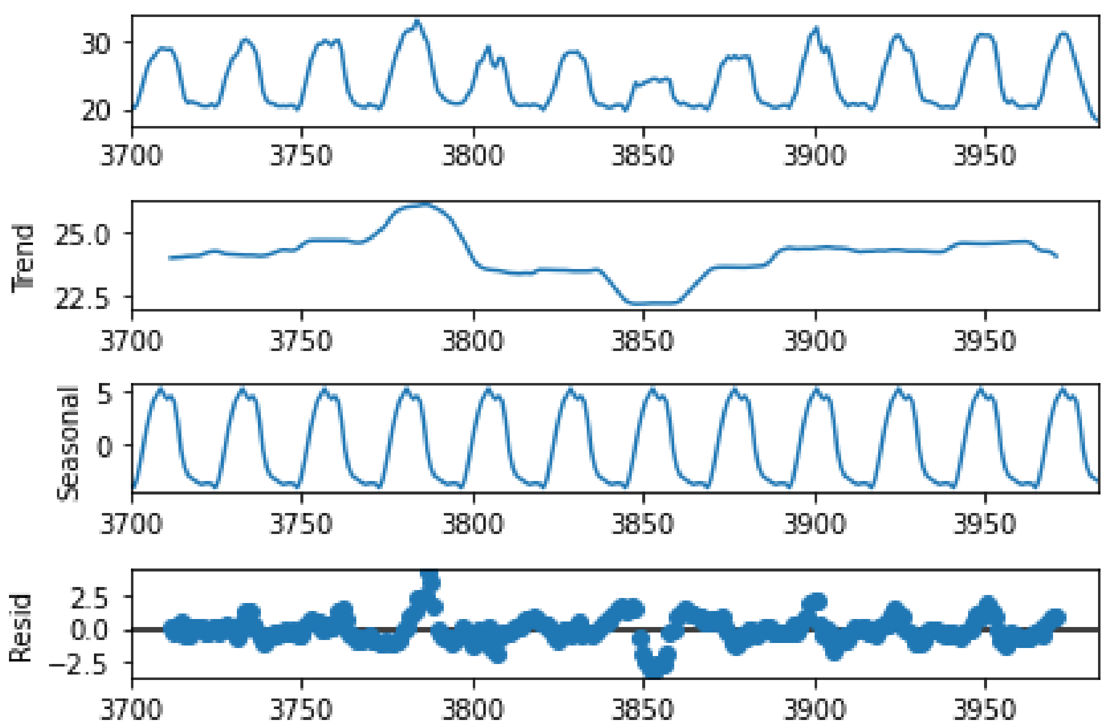
[58]:
```
"""
order(p,d,q):
p is number of AR terms
d is number of times that we would difference our data
q is number of MA terms
When we work with SARIMA models 'S' refers to 'seasonal' and we have the␣
↪additional
standard inputs:

seasonal order(p,d,q):
p is number of AR terms in regards to seasonal lag
d is number of times that we would difference our seasonal lag (as seen above)
q is number of MA terms in regards to seasonal lag
s is number of periods in a season
"""
```

[58]:
```
"\norder(p,d,q):\np is number of AR terms\nd is number of times that we would
difference our data\nq is number of MA terms\nWhen we work with SARIMA models
'S' refers to 'seasonal' and we have the additional \nstandard
inputs:\n\nseasonal order(p,d,q):\np is number of AR terms in regards to
seasonal lag\nd is number of times that we would difference our seasonal lag (as
seen above)\nq is number of MA terms in regards to seasonal lag\ns is number of
periods in a season\n"
```

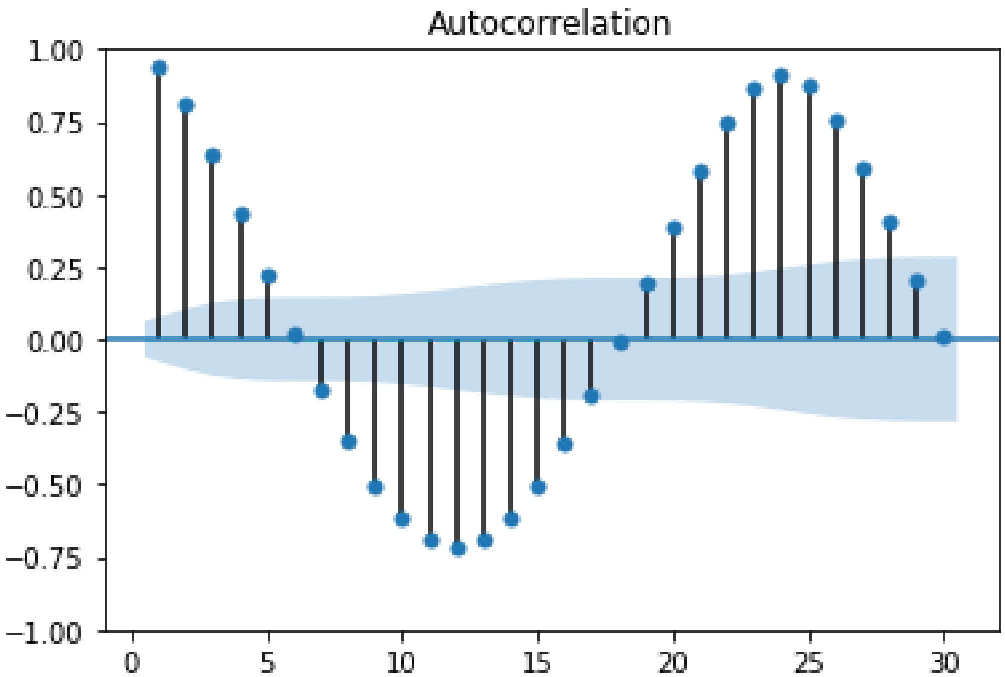
[59]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
seasonal_decompose(Tair_hr[:],period=24).plot();
```

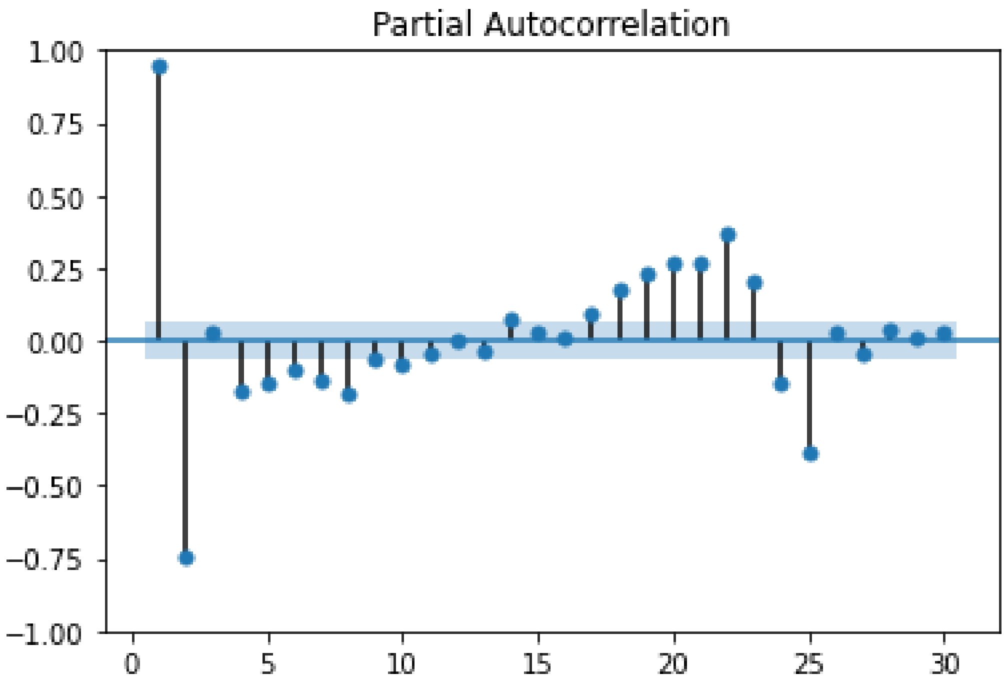


[60]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
seasonal_decompose(Tair_hr[3700:],period=24).plot();
```



[61]:
```
import statsmodels.api as sm

sm.tsa.graphics.plot_acf(Tair_hr[3000:],zero=False)
sm.tsa.graphics.plot_pacf(Tair_hr[3000:],zero = False);
```



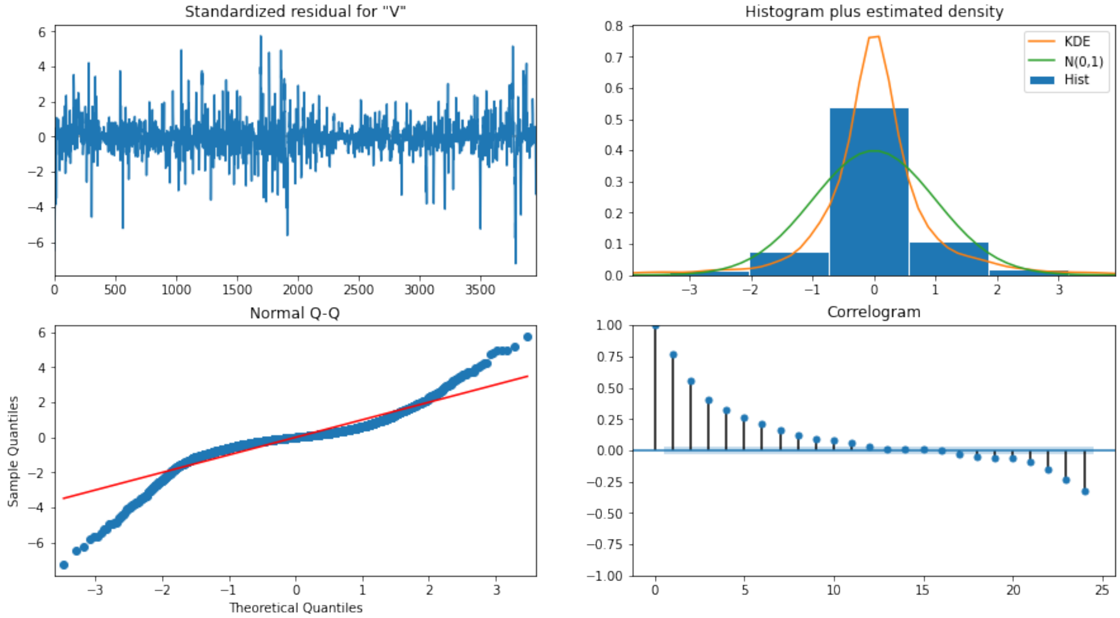


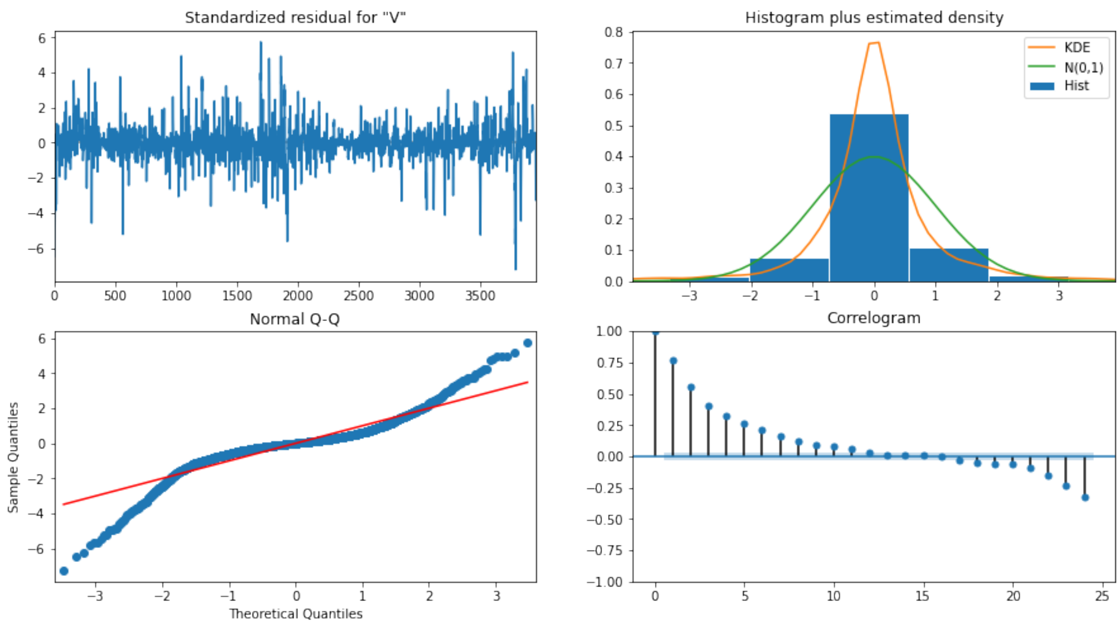
[62]:
```
print ("Now let's start with the most basic model, with no auto correlation and␣
 ↪we just \
difference the values and predict moving foreward.")

sar = sm.tsa.statespace.SARIMAX(Tair_hr.iloc[:, 0],
                                order=(0,0,0),
                                seasonal_order=(0,1,0,24),
                                trend='c').fit()
```

Now let's start with the most basic model, with no auto correlation and we just difference the values and predict moving foreward.

[63]:
```
sar.plot_diagnostics(figsize = (15,8),lags=24)
```

[63]:





[64]:
```
print ("The pattern in the residuals suggests that the model can be further
 ↪improved. \
The histogram suggests that the standardized residuals follow to some
 ↪approximation the \
normal distribution. The plot compares the quantiles of the observed data
 ↪against the \
```

```
quantiles of a theoretical standard normal distribution. We see some skewness␣
 ↪and some \
outliers. The correlogram suggests significant autocorrelation because the␣
 ↪autocorrelation \
falls really outside the confidence intervals.")
```

The pattern in the residuals suggests that the model can be further improved. The histogram suggests that the standardized residuals follow to some approximation the normal distribution. The plot compares the quantiles of the observed data against the quantiles of a theoretical standard normal distribution. We see some skewness and some outliers. The correlogram suggests significant autocorrelation because the autocorrelation falls really outside the confidence intervals.

[65]:
```
Tair_hr_values = Tair_hr.values
Tair_hr.iloc[2000:, 0]
```

[65]:
```
2000    23.24167
2001    24.37500
2002    24.10833
2003    24.58333
2004    25.39167
          …
3979    22.91667
3980    21.44167
3981    19.80000
3982    18.77917
3983    18.35833
Name: Value, Length: 1984, dtype: float64
```

[66]:
```
Tair_hr.index
```

[66]:
```
RangeIndex(start=0, stop=3984, step=1)
```

[67]:
```
print ("for the next steps we need to set a datetime to the data")
start_date = '2013-01-01'
end_date = '2023-11-28'
step = pd.DateOffset(days=1)

Tair_hr_index = pd.date_range(start=start_date, end=end_date, freq=step)

# Print the first few values
print(Tair_hr_index[:5])
```

```
for the next steps we need to set a datetime to the data
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05'],
```

```
              dtype='datetime64[ns]', freq='<DateOffset: days=1>')
```

[69]:
```
Tair_hr.index = Tair_hr_index
Tair_hr.index
```

[69]:
```
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06', '2013-01-07', '2013-01-08',
               '2013-01-09', '2013-01-10',
               …
               '2023-11-19', '2023-11-20', '2023-11-21', '2023-11-22',
               '2023-11-23', '2023-11-24', '2023-11-25', '2023-11-26',
               '2023-11-27', '2023-11-28'],
              dtype='datetime64[ns]', length=3984, freq='<DateOffset: days=1>')
```

[70]:
```
df_train = Tair_hr.iloc[3500:-24, 0]
df_test = Tair_hr.iloc[-24:, 0]
df_train.tail()
```

[70]:
```
2023-10-31   23.13333
2023-11-01   21.36667
2023-11-02   20.79167
2023-11-03   21.26667
2023-11-04   20.74167
Freq: <DateOffset: days=1>, Name: Value, dtype: float64
```

[71]:
```
df_test.head()
```

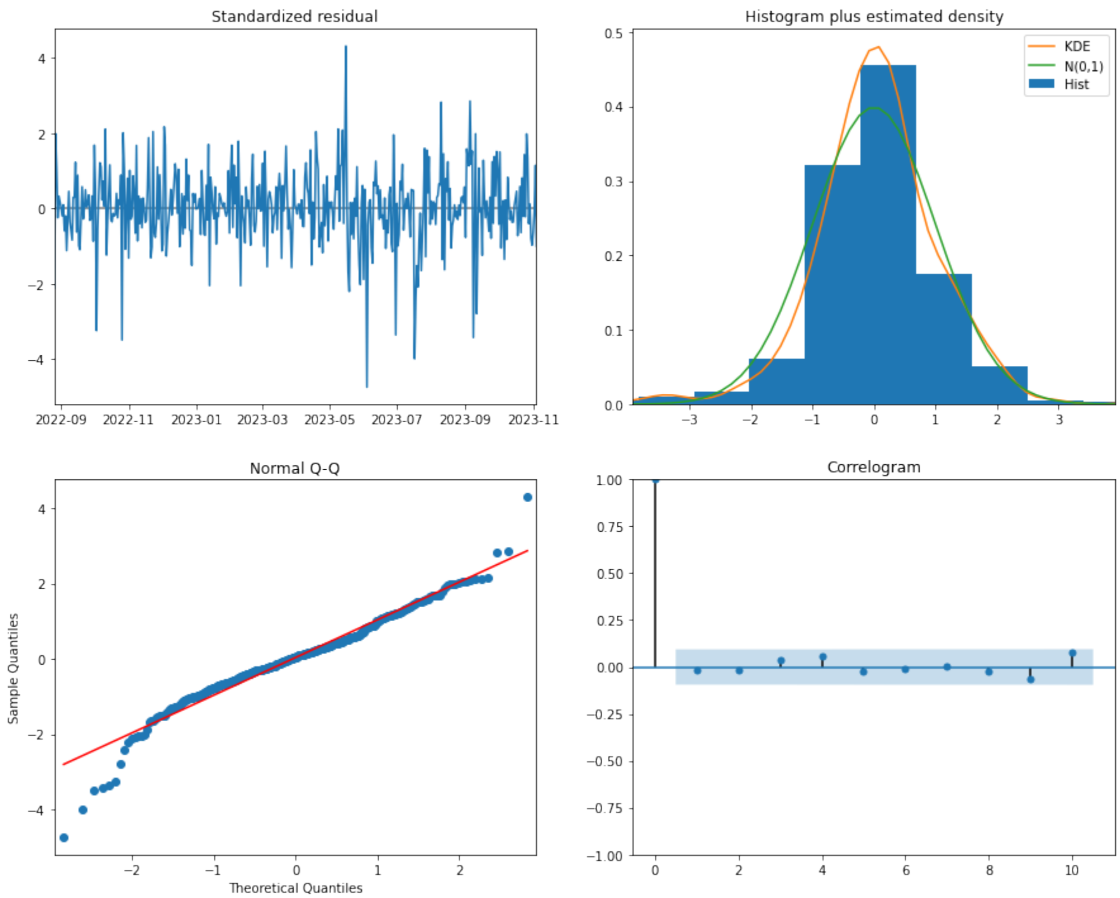
[71]:
```
2023-11-05   20.31667
2023-11-06   20.23333
2023-11-07   20.32500
2023-11-08   20.43333
2023-11-09   20.45000
Freq: <DateOffset: days=1>, Name: Value, dtype: float64
```

[72]:
```
print ("Let's run auto ARIMA that will give us the best fitting terms that␣
 ↪result in the \
smallest AIC (Akaike Information Criterion, a metric used to compare the␣
 ↪performance \
of different models).")
print("I have commented out the lines below because it takes minutes to run \
the script and we don't want to wait during the interview :)")
import pmdarima as pm
# Seasonal - fit stepwise auto-ARIMA
SARIMA_model = pm.auto_arima(df_train, start_p=0, start_q=0,
                         test='adf',
                         max_p=3, max_q=3,
                         m=24, #12 is the frequncy of the cycle
```

```
                          start_P=0,
                          seasonal=True, #set to seasonal
                          d=None,
                          D=1, #order of the seasonal differencing
                          trace=False,
                          error_action='ignore',
                          suppress_warnings=True,
                          stepwise=True)
print("Best Parameters (p, d, q, P, D, Q, s):", SARIMA_model.order,␣
 ↪SARIMA_model.seasonal_order)
print(SARIMA_model.aic())
```

Let's run auto ARIMA that will give us the best fitting terms that result in the smallest AIC (Akaike Information Criterion, a metric used to compare the performance of different models).
I have commented out the lines below because it takes minutes to run the script and we don't want to wait during the interview :)
Best Parameters (p, d, q, P, D, Q, s): (2, 0, 1) (2, 1, 0, 24)
735.4039780741509

[75]:
```
SARIMA_model.plot_diagnostics(figsize=(15,12))
plt.show()
```

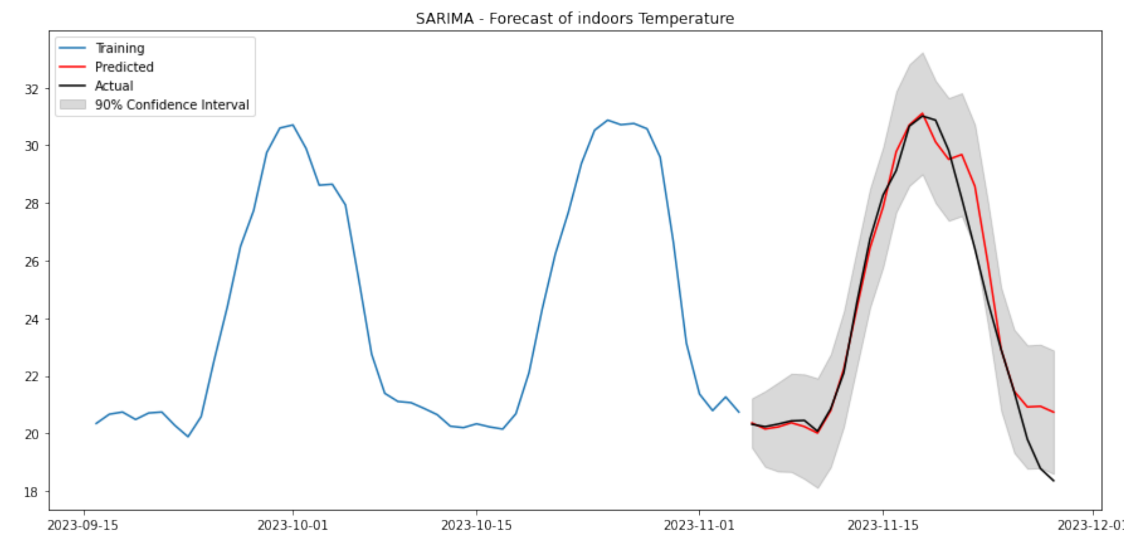


[76]:
```
print ("Here we see more like a random noise in the residuals, a faily normal␣
↪distribution \
and almost no autocorrelation.")
```

Here we see more like a random noise in the residuals, a faily normal distribution and almost no autocorrelation.

[77]:
```
def forecast(SARIMA_model, periods=24):
    # Forecast
    n_periods = periods
    fitted, confint = SARIMA_model.predict(n_periods=n_periods,␣
↪return_conf_int=True)
    index_of_fc = pd.date_range(df_train.index[-1] + pd.DateOffset(days=1),␣
↪periods = n_periods, freq='D')

    forecast_values_auto = fitted
    #confidence_intervals_auto = conf_int_auto
```

```
    # make series for plotting purpose
    fitted_series = pd.Series(fitted, index=index_of_fc)
    lower_series = pd.Series(confint[:, 0], index=index_of_fc)
    upper_series = pd.Series(confint[:, 1], index=index_of_fc)
    forecast_auto = fitted_series.values
    lower_percentile = np.percentile(confint, 10, axis=1)
    upper_percentile = np.percentile(confint, 90, axis=1)


    # Plot
    plt.figure(figsize=(15,7))
    plt.plot(df_train[-50:], color='#1f76b4', label='Training')
    plt.plot(fitted_series, color='red', label='Predicted')
    plt.plot(df_test, color='black', label='Actual')
    plt.fill_between(lower_series.index, lower_percentile, upper_percentile,␣
↪color='k', alpha=.15, label='90% Confidence Interval')

    plt.title("SARIMA - Forecast of indoors Temperature")
    plt.legend(loc='upper left')
    plt.show()

forecast(SARIMA_model)
```



[78]:
```
SARIMA_model.summary()
```

[78]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                     SARIMAX Results
==============================================================================
```

```
===========
Dep. Variable:                                   y   No. Observations:
460
Model:             SARIMAX(2, 0, 1)x(2, 1, [], 24)   Log Likelihood
-361.702
Date:                             Sun, 09 Jul 2023   AIC
735.404
Time:                                     14:50:39   BIC
759.870
Sample:                                 08-02-2022   HQIC
745.059
                                      - 11-04-2023
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.6469      0.134      4.826      0.000       0.384       0.910
ar.L2          0.1994      0.123      1.616      0.106      -0.042       0.441
ma.L1          0.5068      0.119      4.255      0.000       0.273       0.740
ar.S.L24      -0.5121      0.036    -14.065      0.000      -0.583      -0.441
ar.S.L48      -0.2994      0.046     -6.535      0.000      -0.389      -0.210
sigma2         0.3004      0.014     21.221      0.000       0.273       0.328
================================================================================
===
Ljung-Box (L1) (Q):                   0.16   Jarque-Bera (JB):
158.97
Prob(Q):                              0.68   Prob(JB):
0.00
Heteroskedasticity (H):               1.34   Skew:
-0.43
Prob(H) (two-sided):                  0.08   Kurtosis:
5.83
================================================================================
===

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

[79]:
```
# Predicted values and actual values
forecast_auto, conf_int_auto = SARIMA_model.predict(n_periods=24,
                                                    return_conf_int=True)
predicted_values_auto = forecast_auto.values
actual_values = df_test.values.flatten()

# Mean Absolute Error (MAE)
```

```
maeSA = np.mean(np.abs(predicted_values_auto - actual_values))
print("MAE:", maeSA)

# Root Mean Squared Error (RMSE)
mseSA = np.mean((predicted_values_auto - actual_values) ** 2)
rmseSA = np.sqrt(mseSA)
print("MSE:", rmseSA)
print("RMSE:", rmseSA)

# Mean Absolute Percentage Error (MAPE)
mapeSA = np.mean(np.abs((predicted_values_auto - actual_values) /␣
↪actual_values)) * 100
print("MAPE:", mapeSA)
```

```
MAE: 0.5940614094719291
MSE: 0.9558774709361916
RMSE: 0.9558774709361916
MAPE: 2.6084199193111255
```

[80]:
```
comment = "**6. Multivariate Temperature forecasting using SARIMAX Model**"
font_size = "20px"

Markdown(f"<span style='font-weight:bold; font-size:{font_size}'>{comment}</
↪span>")
```

[80]:

6. Multivariate Temperature forecasting using SARIMAX Model

[81]:
```
print("SARIMAX(Seasonal Auto-Regressive Integrated Moving Average with␣
↪eXogenous factors) \
is an updated version of the ARIMA model. ARIMA includes an autoregressive␣
↪integrated moving \
average, while SARIMAX includes seasonal effects and eXogenous factors with the␣
↪\
autoregressive and moving average component in the model.")
```

```
SARIMAX(Seasonal Auto-Regressive Integrated Moving Average with eXogenous
factors) is an updated version of the ARIMA model. ARIMA includes an
autoregressive integrated moving average, while SARIMAX includes seasonal
effects and eXogenous factors with the autoregressive and moving average
component in the model.
```

[82]:
```
print ("we have lots of variables that could influence the indoors temperature.␣
↪Some of \
them are clearly not important (eg drain pH and drain EC). For the rest we can␣
↪to a feauture \
importance analysis, to see which among the variables explain most of the␣
↪variance")
```

we have lots of variables that could influence the indoors temperature. Some of them are clearly not important (eg drain pH and drain EC). For the rest we can to a feauture importance analysis, to see which among the variables explain most of the variance

[83]:
```
df_outd.head()
```

[83]:
```
          time  AbsHumOut   Iglob  PARout    Pyrgeo    RadSum    Rain  \
0 43,815.00000    6.22095 0.00000 0.00000 -72.00000 215.00000 0.00000
1 43,815.00347    6.22095 0.00000 0.00000 -73.00000   0.00000 0.00000
2 43,815.00694    6.20556 0.00000 0.00000 -76.00000   0.00000 0.00000
3 43,815.01042    6.19017 0.00000 0.00000 -77.00000   0.00000 0.00000
4 43,815.01389    6.16262 0.00000 0.00000 -75.00000   0.00000 0.00000

     Rhout    Tout  Winddir  Windsp
0 80.60000 6.90000 32.00000 4.70000
1 80.60000 6.90000 32.00000 4.70000
2 80.40000 6.90000 32.00000 4.70000
3 80.20000 6.90000 32.00000 4.70000
4 80.90000 6.70000 32.00000 4.70000
```

[84]:
```
df_ind.head()
```

[84]:
```
          time  AssimLight  BlackScr    CO2air  Cum_irr  EC_drain_PC  \
0 43,815.00000     0.00000  35.00000 472.00000  0.35480      3.98000
1 43,815.00347     0.00000  85.00000 501.00000  0.53220      3.99000
2 43,815.00694     0.00000  96.00000 489.00000  0.53220      3.99000
3 43,815.01042     0.00000  96.00000 497.00000  0.53220      4.00000
4 43,815.01389     0.00000  96.00000 477.00000  0.53220      4.00000

      EnScr  HumDef  PipeGrow  PipeLow    Rhair     Tair  Tot_PAR  \
0 100.00000 7.17000   0.00000 45.20000 60.60000 20.90000  0.00000
1 100.00000 6.94000   0.00000 43.60000 61.40000 20.70000  0.00000
2 100.00000 7.24000   0.00000 42.30000 60.90000 21.20000  0.00000
3 100.00000 6.74000   0.00000 41.20000 62.50000 20.70000  0.00000
4 100.00000 6.71000   0.00000 41.20000 62.70000 20.70000  0.00000

   Tot_PAR_Lamps  VentLee  Ventwind  assim_sp  assim_vip  co2_dos  co2_sp  \
0        0.00000  0.80000   0.00000       NaN    0.00000      NaN     NaN
1        0.00000  0.80000   0.00000       NaN    0.00000  0.00034     NaN
2        0.00000  0.80000   0.00000       NaN    0.00000  0.00036     NaN
3        0.00000  0.80000   0.00000       NaN    0.00000  0.00201     NaN
4        0.00000  0.80000   0.00000       NaN    0.00000  0.00155     NaN

    co2_vip  dx_sp  dx_vip  int_blue_sp  int_blue_vip  int_farred_sp  \
0 400.00000    NaN 2.20000          NaN           NaN            NaN
1 400.00000    NaN 2.20000      0.00000           NaN        0.00000
```

```
2 400.00000    NaN 2.20000      0.00000           NaN        0.00000
3 400.00000    NaN 2.20000      0.00000           NaN        0.00000
4 400.00000    NaN 2.20000      0.00000           NaN        0.00000

   int_farred_vip  int_red_sp  int_red_vip  int_white_sp  int_white_vip  \
0             NaN         NaN          NaN           NaN            NaN
1             NaN     0.00000          NaN       0.00000            NaN
2             NaN     0.00000          NaN       0.00000            NaN
3             NaN     0.00000          NaN       0.00000            NaN
4             NaN     0.00000          NaN       0.00000            NaN

   pH_drain_PC  scr_blck_sp  scr_blck_vip  scr_enrg_sp  scr_enrg_vip  \
0      6.27000          NaN      96.00000          NaN     100.00000
1      6.28000          NaN      96.00000          NaN     100.00000
2      6.28000          NaN      96.00000          NaN     100.00000
3      6.27000          NaN      96.00000          NaN     100.00000
4      6.28000          NaN      96.00000          NaN     100.00000

   t_grow_min_sp  t_grow_min_vip  t_heat_sp  t_heat_vip  t_rail_min_sp  \
0            NaN        10.00000        NaN    21.00000            NaN
1            NaN        10.00000        NaN    21.00000            NaN
2            NaN        10.00000        NaN    21.00000            NaN
3            NaN        10.00000        NaN    21.00000            NaN
4            NaN        10.00000        NaN    21.00000            NaN

   t_rail_min_vip  t_vent_sp  t_ventlee_vip  t_ventwind_vip  water_sup  \
0         0.00000        NaN       25.00000        26.00000    4.00000
1         0.00000        NaN       25.00000        26.00000    6.00000
2         0.00000        NaN       25.00000        26.00000    6.00000
3         0.00000        NaN       25.00000        26.00000    6.00000
4         0.00000        NaN       25.00000        26.00000    6.00000

   water_sup_intervals_sp_min  water_sup_intervals_vip_min  window_pos_lee_sp  \
0                         NaN                  1,000.00000                NaN
1                         NaN                  1,000.00000                NaN
2                         NaN                  1,000.00000                NaN
3                         NaN                  1,000.00000                NaN
4                         NaN                  1,000.00000                NaN

   window_pos_lee_vip
0             1.20000
1             1.20000
2             1.20000
3             1.20000
4             1.20000
```

[85]:
```python
print ("we have to combine the dataframes:")
df_combined = pd.concat([df_outd, df_ind], axis=1)
df_combined.head()
```

```
we have to combine the dataframes:
```

[85]:
```
           time  AbsHumOut   Iglob  PARout    Pyrgeo    RadSum    Rain  \
0 43,815.00000    6.22095 0.00000 0.00000 -72.00000 215.00000 0.00000
1 43,815.00347    6.22095 0.00000 0.00000 -73.00000   0.00000 0.00000
2 43,815.00694    6.20556 0.00000 0.00000 -76.00000   0.00000 0.00000
3 43,815.01042    6.19017 0.00000 0.00000 -77.00000   0.00000 0.00000
4 43,815.01389    6.16262 0.00000 0.00000 -75.00000   0.00000 0.00000

     Rhout    Tout  Winddir  Windsp          time  AssimLight  BlackScr  \
0 80.60000 6.90000 32.00000 4.70000 43,815.00000     0.00000  35.00000
1 80.60000 6.90000 32.00000 4.70000 43,815.00347     0.00000  85.00000
2 80.40000 6.90000 32.00000 4.70000 43,815.00694     0.00000  96.00000
3 80.20000 6.90000 32.00000 4.70000 43,815.01042     0.00000  96.00000
4 80.90000 6.70000 32.00000 4.70000 43,815.01389     0.00000  96.00000

     CO2air  Cum_irr  EC_drain_PC     EnScr  HumDef  PipeGrow  PipeLow  \
0 472.00000  0.35480      3.98000 100.00000 7.17000   0.00000 45.20000
1 501.00000  0.53220      3.99000 100.00000 6.94000   0.00000 43.60000
2 489.00000  0.53220      3.99000 100.00000 7.24000   0.00000 42.30000
3 497.00000  0.53220      4.00000 100.00000 6.74000   0.00000 41.20000
4 477.00000  0.53220      4.00000 100.00000 6.71000   0.00000 41.20000

     Rhair     Tair  Tot_PAR  Tot_PAR_Lamps  VentLee  Ventwind  assim_sp  \
0 60.60000 20.90000  0.00000        0.00000  0.80000   0.00000       NaN
1 61.40000 20.70000  0.00000        0.00000  0.80000   0.00000       NaN
2 60.90000 21.20000  0.00000        0.00000  0.80000   0.00000       NaN
3 62.50000 20.70000  0.00000        0.00000  0.80000   0.00000       NaN
4 62.70000 20.70000  0.00000        0.00000  0.80000   0.00000       NaN

   assim_vip  co2_dos  co2_sp   co2_vip  dx_sp  dx_vip  int_blue_sp  \
0    0.00000      NaN     NaN 400.00000    NaN 2.20000          NaN
1    0.00000  0.00034     NaN 400.00000    NaN 2.20000      0.00000
2    0.00000  0.00036     NaN 400.00000    NaN 2.20000      0.00000
3    0.00000  0.00201     NaN 400.00000    NaN 2.20000      0.00000
4    0.00000  0.00155     NaN 400.00000    NaN 2.20000      0.00000

   int_blue_vip  int_farred_sp  int_farred_vip  int_red_sp  int_red_vip  \
0           NaN            NaN             NaN         NaN          NaN
1           NaN        0.00000             NaN     0.00000          NaN
2           NaN        0.00000             NaN     0.00000          NaN
3           NaN        0.00000             NaN     0.00000          NaN
4           NaN        0.00000             NaN     0.00000          NaN
```

```
   int_white_sp  int_white_vip  pH_drain_PC  scr_blck_sp  scr_blck_vip  \
0           NaN            NaN      6.27000          NaN      96.00000
1       0.00000            NaN      6.28000          NaN      96.00000
2       0.00000            NaN      6.28000          NaN      96.00000
3       0.00000            NaN      6.27000          NaN      96.00000
4       0.00000            NaN      6.28000          NaN      96.00000

   scr_enrg_sp  scr_enrg_vip  t_grow_min_sp  t_grow_min_vip  t_heat_sp  \
0          NaN     100.00000            NaN        10.00000        NaN
1          NaN     100.00000            NaN        10.00000        NaN
2          NaN     100.00000            NaN        10.00000        NaN
3          NaN     100.00000            NaN        10.00000        NaN
4          NaN     100.00000            NaN        10.00000        NaN

   t_heat_vip  t_rail_min_sp  t_rail_min_vip  t_vent_sp  t_ventlee_vip  \
0    21.00000            NaN         0.00000        NaN       25.00000
1    21.00000            NaN         0.00000        NaN       25.00000
2    21.00000            NaN         0.00000        NaN       25.00000
3    21.00000            NaN         0.00000        NaN       25.00000
4    21.00000            NaN         0.00000        NaN       25.00000

   t_ventwind_vip  water_sup  water_sup_intervals_sp_min  \
0        26.00000    4.00000                         NaN
1        26.00000    6.00000                         NaN
2        26.00000    6.00000                         NaN
3        26.00000    6.00000                         NaN
4        26.00000    6.00000                         NaN

   water_sup_intervals_vip_min  window_pos_lee_sp  window_pos_lee_vip
0                  1,000.00000                NaN             1.20000
1                  1,000.00000                NaN             1.20000
2                  1,000.00000                NaN             1.20000
3                  1,000.00000                NaN             1.20000
4                  1,000.00000                NaN             1.20000
```

[86]:
```python
print ("drop variables with many NaN values and then drop the Nan lines. Then␣
↪take the \
hourly values")
df_combined_filtered = df_combined.dropna(axis=1, thresh=df_combined.
↪shape[0]-150)
df_combined_filtered = df_combined_filtered.dropna()
num_groups = len(df_combined_filtered) // 12

# Take the average every 12 rows
df_combined_hr = df_combined_filtered.iloc[:num_groups*12].
↪groupby(df_combined_filtered.index // 12).mean()
```

```
df_combined_hr
```

drop variables with many NaN values and then drop the Nan lines. Then take the hourly values

[86]:

```
                time  AbsHumOut     Iglob    PARout      Pyrgeo      RadSum  \
0     43,815.02083    6.22694   0.00000   0.00000   -72.09091     0.00000
1     43,815.06076    6.23459   0.00000   0.00000   -75.33333     0.00000
2     43,815.10243    6.28361   0.00000   0.00000   -59.16667     0.00000
3     43,815.14410    6.45165   0.00000   0.00000   -52.75000     0.00000
4     43,815.18576    6.56769   0.00000   0.00000   -53.33333     0.00000
…              …          …         …         …           …           …
3979 43,980.81076    7.10976 276.75000 526.83333 -104.33333 2,896.75000
3980 43,980.85243    7.47256 121.66667 235.33333  -99.83333 2,966.66667
3981 43,980.89410    9.34072  20.41667  44.91667  -89.33333 2,989.83333
3982 43,980.93576    9.40363   0.00000   1.00000  -85.25000 2,992.00000
3983 43,980.97743    9.38771   0.00000   0.33333  -84.75000 2,992.00000

         Rain    Rhout     Tout  Winddir  Windsp         time  AssimLight  \
0     0.00000 81.30909  6.78182 24.72727 4.06364 43,815.02083     0.00000
1     0.00000 84.04167  6.30000 16.00000 2.90833 43,815.06076     0.00000
2     0.00000 85.59167  6.14167 16.00000 3.20000 43,815.10243     0.00000
3     0.00000 88.22500  6.08333 16.00000 3.32500 43,815.14410     0.00000
4     0.00000 90.16667  6.02500 16.00000 3.61667 43,815.18576     0.00000
…         …        …        …        …       …            …
3979 0.00000 40.16667 20.14167  2.00000 4.20000 43,980.81076     0.00000
3980 0.00000 44.49167 19.29167  2.00000 3.99167 43,980.85243     0.00000
3981 0.00000 62.33333 17.42500  2.00000 4.07500 43,980.89410     0.00000
3982 0.00000 68.09167 16.07500  2.00000 4.30000 43,980.93576     0.00000
3983 0.00000 71.32500 15.29167  2.00000 4.21667 43,980.97743     0.00000

      BlackScr    CO2air  Cum_irr  EC_drain_PC     EnScr   HumDef  PipeGrow  \
0     95.00000 493.36364  0.53220      3.98909 100.00000  6.89000   0.00000
1     96.00000 498.66667  0.53220      3.97583 100.00000  6.95917   0.00000
2     96.00000 494.91667  0.04435      3.97417 100.00000  7.04167   0.00000
3     96.00000 494.00000  0.00000      3.96750 100.00000  7.03167   0.00000
4     96.00000 500.00000  0.00000      3.96917 100.00000  7.02000   0.00000
…           …         …       …           …         …        …
3979   0.00000 424.50000  1.59660     10.17083   0.00000 12.19417   0.00000
3980   0.00000 431.33333  1.59660     10.19667   0.00000 10.38667   0.00000
3981   0.00000 435.66667  1.59660     10.26417   0.00000  6.93167   0.00000
3982   0.00000 449.54167  1.59660     10.29583   0.00000  4.89917   0.00000
3983   0.00000 464.00000  1.59660     10.32750   0.83333  3.05000   0.00000

      PipeLow    Rhair     Tair  Tot_PAR  Tot_PAR_Lamps  VentLee  Ventwind  \
0    43.03636 61.82727 20.76364  0.00000        0.00000  0.80000   0.00000
```

1	46.88333	61.39167	20.74167	0.00000	0.00000	0.80000	0.00000
2	46.84167	61.33333	20.92500	0.00000	0.00000	0.80000	0.00000
3	47.13333	61.57500	21.00833	0.00000	0.00000	0.80000	0.00000
4	47.37500	61.88333	21.11667	0.00000	0.00000	0.80000	0.00000
…	…	…	…	…	…	…	…
3979	0.00000	40.37500	22.91667	263.41667	0.00000	100.00000	78.05000
3980	0.00000	44.72500	21.44167	117.66667	0.00000	100.00000	57.86667
3981	0.00000	59.48333	19.80000	22.45833	0.00000	87.56667	8.66667
3982	0.00000	69.52500	18.77917	0.50000	0.00000	39.54167	0.00000
3983	0.00000	80.54167	18.35833	0.16667	0.00000	0.00000	0.00000

	assim_vip	co2_dos	co2_vip	dx_vip	int_farred_sp	int_white_sp \
0	0.00000	0.00078	400.00000	2.20000	0.00000	0.00000
1	0.00000	0.00034	400.00000	2.20000	0.00000	0.00000
2	0.00000	0.00006	400.00000	2.20000	0.00000	0.00000
3	0.00000	0.00012	400.00000	2.20000	0.00000	0.00000
4	0.00000	0.00018	400.00000	2.20000	0.00000	0.00000
…	…	…	…	…	…	…
3979	0.00000	0.00125	400.00000	2.20000	0.00000	0.00000
3980	0.00000	0.00113	400.00000	2.20000	0.00000	0.00000
3981	0.00000	0.00088	400.00000	2.20000	0.00000	0.00000
3982	0.00000	0.00056	400.00000	2.20000	0.00000	0.00000
3983	0.00000	0.00023	400.00000	2.20000	0.00000	0.00000

	pH_drain_PC	scr_blck_vip	scr_enrg_vip	t_grow_min_vip	t_heat_vip \
0	6.27909	96.00000	100.00000	10.00000	21.00000
1	6.27917	96.00000	100.00000	10.00000	21.00000
2	6.27833	96.00000	100.00000	10.00000	21.00000
3	6.27667	96.00000	100.00000	10.00000	21.00000
4	6.28000	96.00000	100.00000	10.00000	21.00000
…	…	…	…	…	…
3979	4.42833	96.00000	100.00000	0.00000	10.00000
3980	4.44000	96.00000	85.00000	0.00000	10.00000
3981	4.45250	96.00000	80.00000	0.00000	10.00000
3982	4.46833	96.00000	98.33333	0.00000	10.00000
3983	4.47583	96.00000	100.00000	0.00000	10.00000

	t_rail_min_vip	t_ventlee_vip	t_ventwind_vip	water_sup \
0	0.00000	25.00000	26.00000	6.00000
1	0.00000	25.00000	26.00000	6.00000
2	0.00000	25.00000	26.00000	0.50000
3	0.00000	25.00000	26.00000	0.00000
4	0.00000	25.00000	26.00000	0.00000
…	…	…	…	…
3979	0.00000	18.00000	20.00000	18.00000
3980	0.00000	18.00000	20.00000	18.00000
3981	0.00000	18.00000	20.00000	18.00000

```
3982          0.00000       18.00000        20.00000   18.00000
3983          0.00000       18.00000        20.00000   18.00000

      water_sup_intervals_vip_min  window_pos_lee_vip
0                      1,000.00000             1.20000
1                      1,000.00000             1.20000
2                      1,000.00000             1.20000
3                      1,000.00000             1.20000
4                      1,000.00000             1.20000
…                                …                   …
3979                      30.00000             0.00000
3980                      30.00000             0.00000
3981                      30.00000             0.00000
3982                      30.00000             0.00000
3983                      30.00000             0.00000

[3983 rows x 44 columns]
```

[87]:

```
start_date = '2013-01-01'
end_date = '2023-11-27'
step = pd.DateOffset(days=1)

df_combined_hr_index = pd.date_range(start=start_date, end=end_date, freq=step)
df_combined_hr.index = df_combined_hr_index
```

[ ]:

[88]:

```
from sklearn.feature_selection import SelectKBest, f_classif

target_variable = df_combined_hr['Tair']

# Selecting the features using SelectKBest and f_classif
selector = SelectKBest(f_classif, k=23)
X_new = selector.fit_transform(df_combined_hr, target_variable)
names = df_combined_hr.columns.values[selector.get_support()]
scores = selector.scores_[selector.get_support()]
names_scores = list(zip(names, scores))
ns_df = pd.DataFrame(data=names_scores, columns=['Feat_names', 'F_Scores'])
ns_df_sorted = ns_df.sort_values(['F_Scores', 'Feat_names'], ascending =␣
↪[False, True])
print(ns_df_sorted)
```

```
                 Feat_names  F_Scores
9                      Tair       inf
15                   dx_vip       inf
18               t_heat_vip  15.86973
19            t_ventlee_vip  11.24211
```

```
20                t_ventwind_vip   9.18111
10                       Tot_PAR   4.62515
17                  scr_enrg_vip   3.63696
12                      Ventwind   3.45646
4                       BlackScr   2.99139
5                        Cum_irr   2.79312
21                     water_sup   2.79312
1                         PARout   2.68716
0                          Iglob   2.65395
6                         HumDef   2.50714
13                     assim_vip   2.13078
22  water_sup_intervals_vip_min   2.12508
3                     AssimLight   2.12007
11                       VentLee   1.99755
7                       PipeGrow   1.94458
16                int_farred_sp   1.86257
8                          Rhair   1.83319
2                         RadSum   1.75383
14                       co2_vip   1.74156
```

[89]:

```
print ("Most influential variables: dx_vip: Humidity deficit VIP (Vapor␣
↪Pressure Deficit ), \
t_ventlee_vip: Ventilation temperature VIP (leeward vents, temperature of the␣
↪incoming air) \
t_ventwind_vip: Ventilation temperature VIP (windward side), t_heat_vip:␣
↪Heating temperature VIP")
```

```
Most influential variables: dx_vip: Humidity deficit VIP (Vapor Pressure Deficit
), t_ventlee_vip: Ventilation temperature VIP (leeward vents, temperature of the
incoming air) t_ventwind_vip: Ventilation temperature VIP (windward side),
t_heat_vip: Heating temperature VIP
```

[90]:

```
print ("The dx_vip is directly related to the temperature, and actually is the␣
↪temperature \
that influences the dx_vip. So I won't use this variable for the predition of␣
↪Tair.")
```

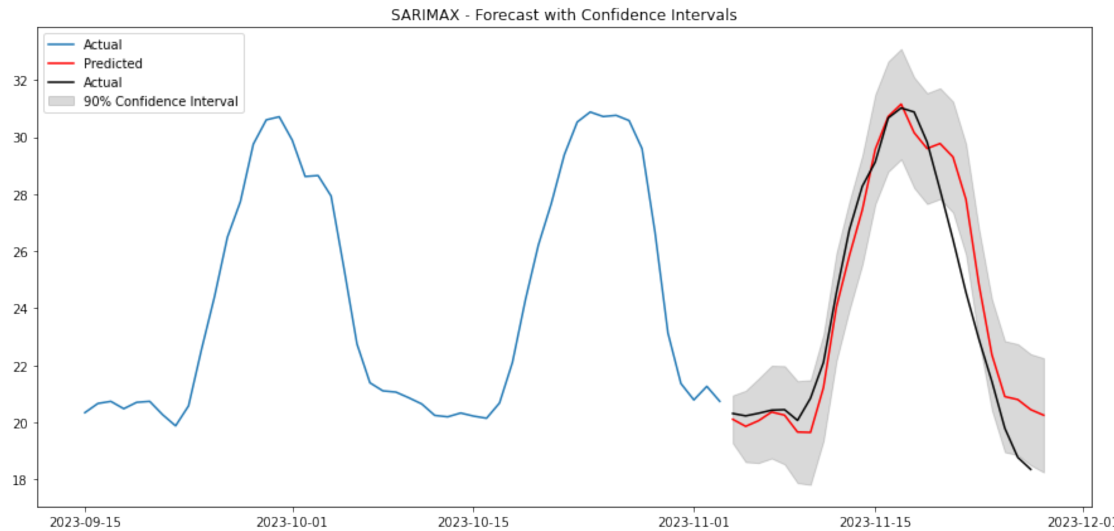
```
The dx_vip is directly related to the temperature, and actually is the
temperature that influences the dx_vip. So I won't use this variable for the
predition of Tair.
```

[91]:

```
combined_train = df_combined_hr.iloc[-500:-24]

# Create the test set
combined_test = df_combined_hr.iloc[-24:]
```

[92]:
```
from statsmodels.tsa.statespace.sarimax import SARIMAX
endog = combined_train['Tair']

# Define exogenous variables
exog_train = combined_train[['t_ventlee_vip', 't_ventwind_vip', 't_heat_vip']]

# Set the start index for prediction
start_date = combined_train.index[-1] + timedelta(days=1)  # Assuming your data␣
↪has hourly frequency

# Set the end index for prediction
end_date = start_date + timedelta(days=24)

# Specify the SARIMAX model with exogenous variables
sarimax_model = SARIMAX(endog, exog=exog_train, order=(1, 0, 1),␣
↪seasonal_order=(2, 1, 0, 24))

# Fit the model
results = sarimax_model.fit()

# Obtain summary statistics
summary = results.summary()

# Create exogenous variables for prediction
exog_pred = exog_train[-25:]  # Get the last 25 rows of exogenous variables

# Make predictions with confidence intervals
predictions = results.get_prediction(start=start_date, end=end_date,␣
↪exog=exog_pred, dynamic=False)
predicted_values = predictions.predicted_mean
confidence_intervals = predictions.conf_int()
lower_percentile = np.percentile(confidence_intervals, 10, axis=1)
upper_percentile = np.percentile(confidence_intervals, 90, axis=1)


# Plotting the predictions with confidence intervals
plt.figure(figsize=(15, 7))
plt.plot(combined_train['Tair'].tail(50), label='Actual')
plt.plot(predicted_values, color='red', label='Predicted')
plt.plot(combined_test['Tair'], color='black', label='Actual')
#plt.fill_between(confidence_intervals.index, confidence_intervals.iloc[:, 0],␣
↪confidence_intervals.iloc[:, 1], color='gray', alpha=0.3)
plt.fill_between(confidence_intervals.index, lower_percentile,␣
↪upper_percentile, color='k', alpha=.15, label='90% Confidence Interval')

plt.title("SARIMAX - Forecast with Confidence Intervals")
plt.legend()
```

```
plt.show()
```



[93]:
```
print ("summary statistics")
print (summary)
```

```
summary statistics
                                      SARIMAX Results
================================================================================
===========
Dep. Variable:                              Tair   No. Observations:
476
Model:             SARIMAX(1, 0, 1)x(2, 1, [], 24)   Log Likelihood
-362.862
Date:                           Sun, 09 Jul 2023   AIC
741.723
Time:                                   14:51:03   BIC
774.633
Sample:                               07-16-2022   HQIC
754.692
                                    - 11-03-2023
Covariance Type:                             opg
================================================================================
==
                     coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
--
t_ventlee_vip    -0.2946      0.423     -0.697      0.486      -1.123
0.533
```

```
t_ventwind_vip     0.4813      0.069      6.963      0.000       0.346
0.617
t_heat_vip         0.6565      0.452      1.451      0.147      -0.230
1.543
ar.L1              0.8485      0.020     41.974      0.000       0.809
0.888
ma.L1              0.2613      0.047      5.571      0.000       0.169
0.353
ar.S.L24          -0.4731      0.037    -12.897      0.000      -0.545
-0.401
ar.S.L48          -0.3199      0.045     -7.183      0.000      -0.407
-0.233
sigma2             0.2851      0.014     20.639      0.000       0.258
0.312
================================================================================
===
Ljung-Box (L1) (Q):                   0.08   Jarque-Bera (JB):
99.87
Prob(Q):                              0.78   Prob(JB):
0.00
Heteroskedasticity (H):               1.33   Skew:
-0.14
Prob(H) (two-sided):                  0.08   Kurtosis:
5.29
================================================================================
===

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

[94]:
```python
from sklearn.metrics import mean_absolute_error, mean_squared_error

# Define the actual values
actual_values = combined_test['Tair']

# Calculate the MAE
maeSX1 = mean_absolute_error(actual_values, predicted_values[-24:])

# Calculate the MSE
mseSX1 = mean_squared_error(actual_values, predicted_values[-24:])

# Calculate the RMSE (using mseSX1 instead of mse)
rmseSX1 = np.sqrt(mseSX1)

# Calculate the MAPE
```

```
mapeSX1 = np.mean(np.abs((actual_values - predicted_values[-24:]) /␣
↪actual_values)) * 100

# Print the metrics
print("MAE:", maeSX1)
print("MSE:", mseSX1)
print("RMSE:", rmseSX1)
print("MAPE:", mapeSX1)
```

```
MAE: 0.8501748698533372
MSE: 1.055535696933144
RMSE: 1.0273926693008588
MAPE: 4.356218604685104
```

[95]:
```
comment = "**7. Final Comparison of Models Using MSE**"
font_size = "20px"

Markdown(f"<span style='font-weight:bold; font-size:{font_size}'>{comment}</
↪span>")
```

[95]:

7. Final Comparison of Models Using MSE

[96]:
```
print("FINAL COMPARISON")
data_dict = {'MSE':[np.mean(simple_mse), np.mean(triple_mse), maeSA, maeSX1]}
df = pd.DataFrame(data_dict, index=['simple averaged smoothing','triple␣
↪exponential smoothing'\
                                    , 'SARIMA', 'SARIMAX'])
print(df)
```

```
FINAL COMPARISON
                                  MSE
simple averaged smoothing    470.80015
triple exponential smoothing 682.13334
SARIMA                         0.59406
SARIMAX                        0.85017
```

[ ]: