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Лабораторная работа по эконометрике

Анализ временного ряда

In [1]:
```
import yfinance as yf
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import numpy as np
from IPython.display import clear_output
%matplotlib inline
```

Загрузка данных

Я решил взять данные акций Apple в период 2019-2020 (за этот период картинка лучше всего) и прогнозировать признак Close - цена акции в момент закрытия торогов.

In [2]:
```
df = yf.download('AAPL','2019-01-02','2020-02-01')
df.sort_index(inplace=True)
df.head()
```

```
[*********************100%***********************]  1 of 1 completed
```

Out[2]:

Date	Open	High	Low	Close	Adj Close	Volume
2019-01-02	38.722500	39.712502	38.557499	39.480000	38.505024	148158800
2019-01-03	35.994999	36.430000	35.500000	35.547501	34.669640	365248800
2019-01-04	36.132500	37.137501	35.950001	37.064999	36.149662	234428400
2019-01-07	37.174999	37.207500	36.474998	36.982498	36.069202	219111200
2019-01-08	37.389999	37.955002	37.130001	37.687500	36.756794	164101200

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 273 entries, 2019-01-02 to 2020-01-31
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Open       273 non-null    float64
 1   High       273 non-null    float64
 2   Low        273 non-null    float64
 3   Close      273 non-null    float64
 4   Adj Close  273 non-null    float64
 5   Volume     273 non-null    int64  
dtypes: float64(5), int64(1)
memory usage: 14.9 KB
```

In [4]:
```
df_close = df[['Close']].copy()
```

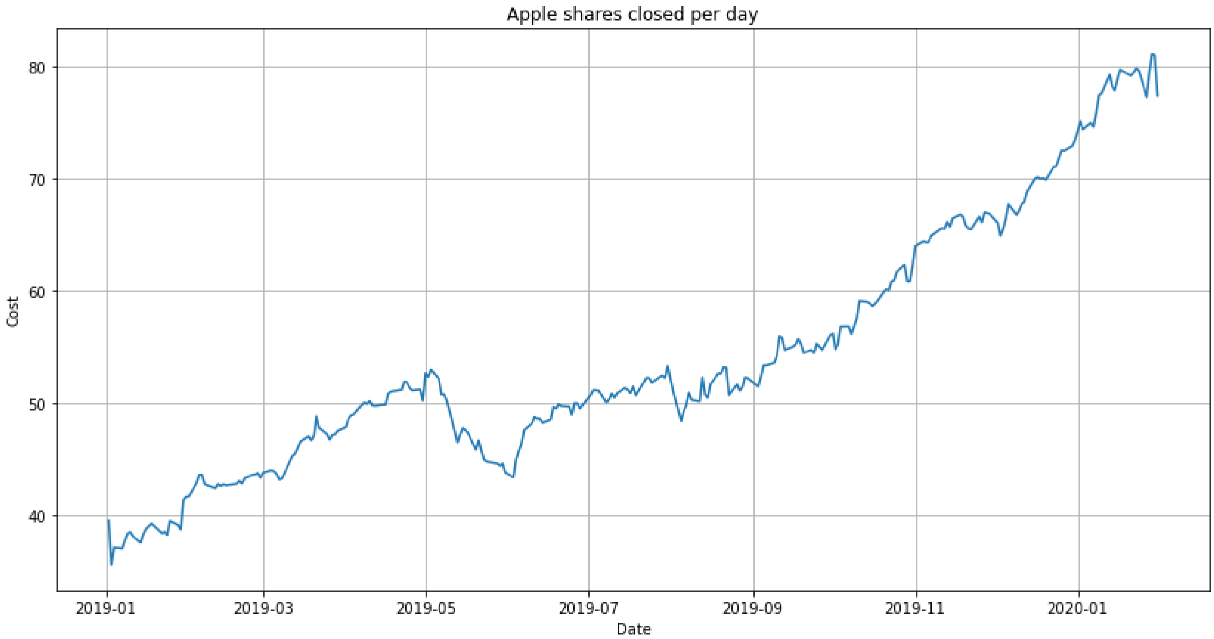
```
df_close.head()
```

Out[4]:

Date	Close
2019-01-02	39.480000
2019-01-03	35.547501
2019-01-04	37.064999
2019-01-07	36.982498
2019-01-08	37.687500

In [5]:

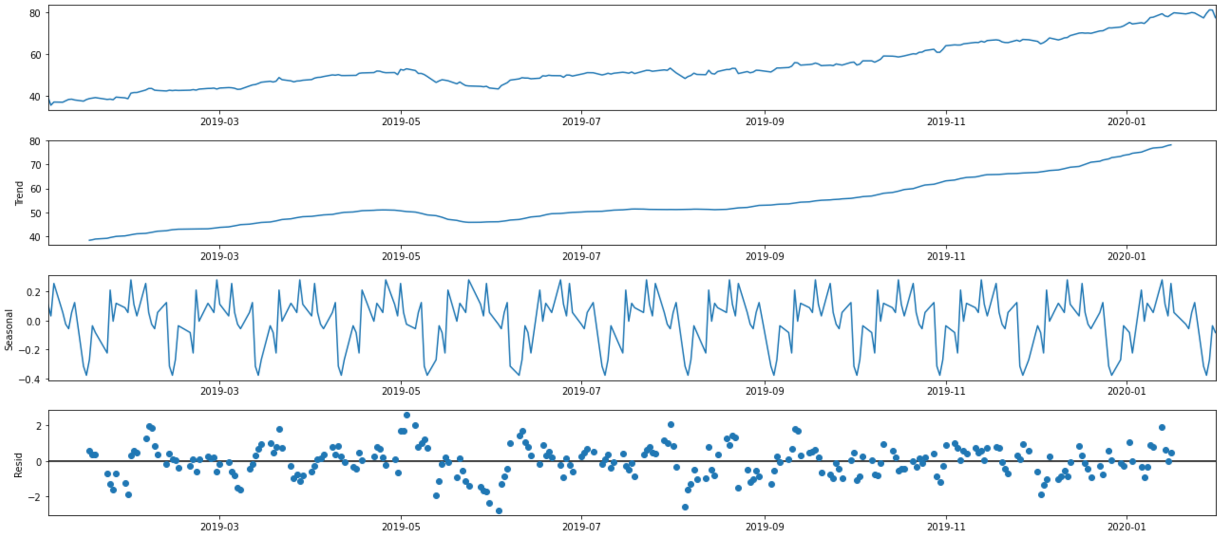
```
plt.figure(figsize=(14,7))
plt.title('Apple shares closed per day')
plt.plot(df_close)
plt.xlabel('Date')
plt.ylabel('Cost')
plt.grid()
```



statsmodels.tsa.seasonal.seasonal_decompose выделят трендовую и сезонную составляющую временного ряда:

In [6]:

```
# 5, 20 ,253
from pylab import rcParams
from statsmodels.tsa.seasonal import seasonal_decompose
rcParams['figure.figsize'] = (18, 8)
decomposition = seasonal_decompose(df_close, model='additive',
period=20)
fig = decomposition.plot()
```



In [7]:
```
df_close = df_close.reset_index(drop=True)
df_close.head()
```

Out[7]:

	Close
0	39.480000
1	35.547501
2	37.064999
3	36.982498
4	37.687500

Train-test split

Здесь я делаю train-test split в соотношении 80 на 20 %

In [8]:
```
df_train = df_close[:int(len(df) * 0.8)]
print(len(df_train))
df_train.head()
```

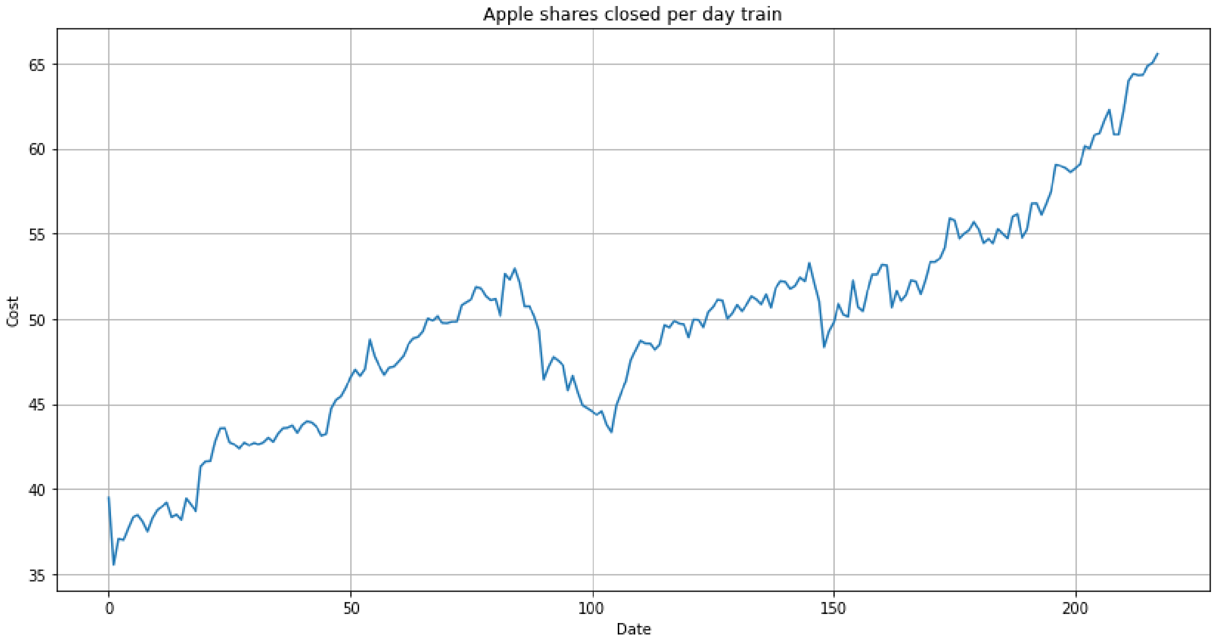
218

Out[8]:

	Close
0	39.480000
1	35.547501
2	37.064999
3	36.982498
4	37.687500

In [9]:
```
plt.figure(figsize=(14,7))
plt.title('Apple shares closed per day train')
plt.plot(df_train)
plt.xlabel('Date')
```

```
plt.ylabel('Cost')
plt.grid()
```



In [10]:

```
df_test = df_close[int(len(df) * 0.8):]
print(len(df_test))
df_test.head()
```

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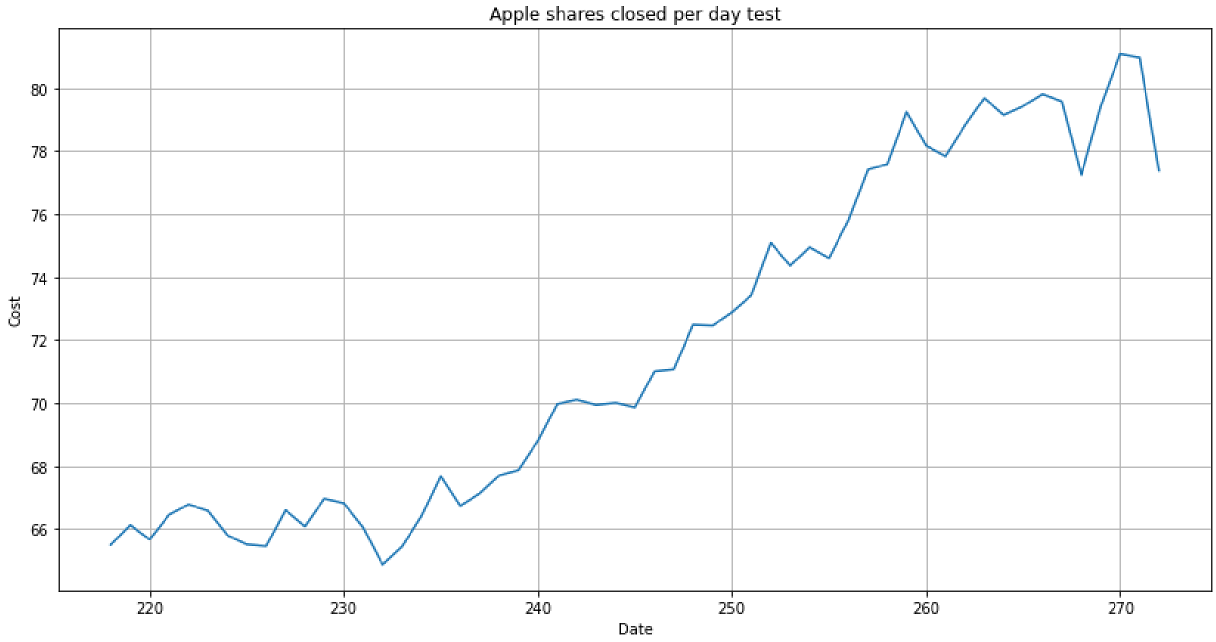
Out[10]:

	Close
218	65.489998
219	66.117500
220	65.660004
221	66.440002
222	66.775002

In [11]:

```
plt.figure(figsize=(14,7))
plt.title('Apple shares closed per day test')
plt.plot(df_test)
plt.xlabel('Date')
plt.ylabel('Cost')
plt.grid()
```



Реализация Grid Search (перебор параметров)

Grid Search SARIMA

Из модели SARIMA можно получить AR, MA, ARMA, ARIMA модели, поэтому была реализована функция перебора параметров для statsmodels.tsa.statespace.sarimax.SARIMAX

In [12]:

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_absolute_percentage_error
from warnings import catch_warnings
from warnings import filterwarnings

# Прогноз
def sarima_forecast(train, test, config):
    order, sorder, trend = config
    model = SARIMAX(train, order=order, seasonal_order=sorder,
trend=trend, enforce_stationarity=False, enforce_invertibility=False)
    model_fit = model.fit(disp=False)
    preds = model_fit.predict(len(train), len(train) + len(test) - 1)
    return preds

# Вычисление MAPE
def get_score(train,test, cfg):
    predictions = sarima_forecast(train,test, cfg)
    error = mean_absolute_percentage_error(test, predictions)
    return error

# Оценивание модели по MAPE
```

```
def score_model(train,test, cfg):
    result = None
    key = str(cfg)
    try:
        with catch_warnings():
            filterwarnings("ignore")
            result = get_score(train,test, cfg)
    except:
        error = None

    if result is not None:
        print(f'> Model {key},    MAPE {result}')
    return (key, result)

# grid search
def grid_search(train, test, cfg_list):
    scores = [score_model(train, test, cfg) for cfg in cfg_list]
    scores = [r for r in scores if r[1] != None]
    scores.sort(key=lambda tup: tup[1])
    return scores
```

Grid Search HWES

Тут я реализовал перебор параметров для сглаживания Хольтса - Винтерса с целью поиска наилучшей модели.

In [13]:

```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from sklearn.metrics import mean_absolute_percentage_error
from warnings import catch_warnings
from warnings import filterwarnings

# Прогноз
def smothing_forecast(train, test, config):
    trend, seasonal, seasonal_periods, sm  = config
    model = ExponentialSmoothing(train, trend=trend,  seasonal=seasonal,
seasonal_periods=seasonal_periods)
    model_fit = model.fit(smoothing_level= sm)
    preds = model_fit.predict(len(train), len(train) + len(test) - 1)
    return preds

# Вычисление MAPE
def get_score_sm(train,test, cfg):
    predictions = smothing_forecast(train,test, cfg)
    error = mean_absolute_percentage_error(test, predictions)
```

```
    return error

# Оценивание модели по MAPE
def score_model_sm(train,test, cfg):
    result = None
    key = str(cfg)
    try:
        with catch_warnings():
            filterwarnings("ignore")
            result = get_score_sm(train,test, cfg)
    except:
        error = None

    if result is not None:
        print(f'> Model {key},    MAPE {result}')
    return (key, result)

# grid search
def grid_search_sm(train, test, cfg_list):
    scores = [score_model_sm(train, test, cfg) for cfg in cfg_list]
    scores = [r for r in scores if r[1] != None]
    scores.sort(key=lambda tup: tup[1])
    return scores
```

Предсказание временного ряда

AR model

autoregressive models: AR(p) - все параметры кроме p зануляем, перебираем p и trend

In [14]:

```
def AR_config(seasonal=[0]):
        models = []
        p_params = [1, 2, 3 ,4 ,5]
        d_params = [0]
        q_params = [0]
        t_params = ['n','c','t','ct']
        P_params = [0]
        D_params = [0]
        Q_params = [0]
        m_params = seasonal
        for p in p_params:
                for d in d_params:
                        for q in q_params:
```

```
                                    for t in t_params:
                                        for P in P_params:
                                            for D in D_params:
                                                for Q in
Q_params:
                                                    for m in
m_params:

cfg = [(p,d,q), (P,D,Q,m), t]

models.append(cfg)
    return models
```

In [15]:

```
cfg_list = AR_config()
scores = grid_search(df_train['Close'].to_numpy(),
df_test['Close'].to_numpy(), cfg_list)
clear_output(wait=True)
print('done\n')
print('TOP 3 scores : \n')
for cfg, res in scores[:3]:
    print(f'> Model {cfg},    MAPE {res}')
```

```
done

TOP 3 scores :

> Model [(1, 0, 0), (0, 0, 0, 0), 't'],    MAPE 0.02342426253238507
> Model [(5, 0, 0), (0, 0, 0, 0), 't'],    MAPE 0.0253005303567747
> Model [(3, 0, 0), (0, 0, 0, 0), 't'],    MAPE 0.025469170704316917
```

Лучшие параметры модели: [(1, 0, 0), (0, 0, 0, 0), 't'], то есть AR(1)

при этом MAPE = 0.02342426253238507

Построим данную модель

In [16]:

```
model = SARIMAX(df_train['Close'].to_numpy(), order=(1, 0, 0),
seasonal_order=(0, 0, 0, 0), trend='t', enforce_stationarity=False,
enforce_invertibility=False)
res = model.fit()
print(res.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  218
Model:               SARIMAX(1, 0, 0)   Log Likelihood                -264.454
Date:                Wed, 21 Apr 2021   AIC                            534.908
Time:                        13:45:48   BIC                            545.048
Sample:                             0   HQIC                           539.004
                                - 218
Covariance Type:                  opg
==============================================================================
```

```
                    coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
drift             0.0009      0.001      0.842      0.400      -0.001       0.003
ar.L1             1.0003      0.003    364.337      0.000       0.995       1.006
sigma2            0.6700      0.041     16.393      0.000       0.590       0.750
===================================================================================
Ljung-Box (L1) (Q):                   0.86   Jarque-Bera (JB):               137.58
Prob(Q):                              0.35   Prob(JB):                         0.00
Heteroskedasticity (H):               1.33   Skew:                            -0.73
Prob(H) (two-sided):                  0.23   Kurtosis:                         6.62
===================================================================================

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

Из SARIMAX result выделим критерии AIC (Информационный критерий Акаике) и BIC (Байесовский информационный критерий).

AIC = 534.908

BIC = 545.048

Тренировочная выборка:

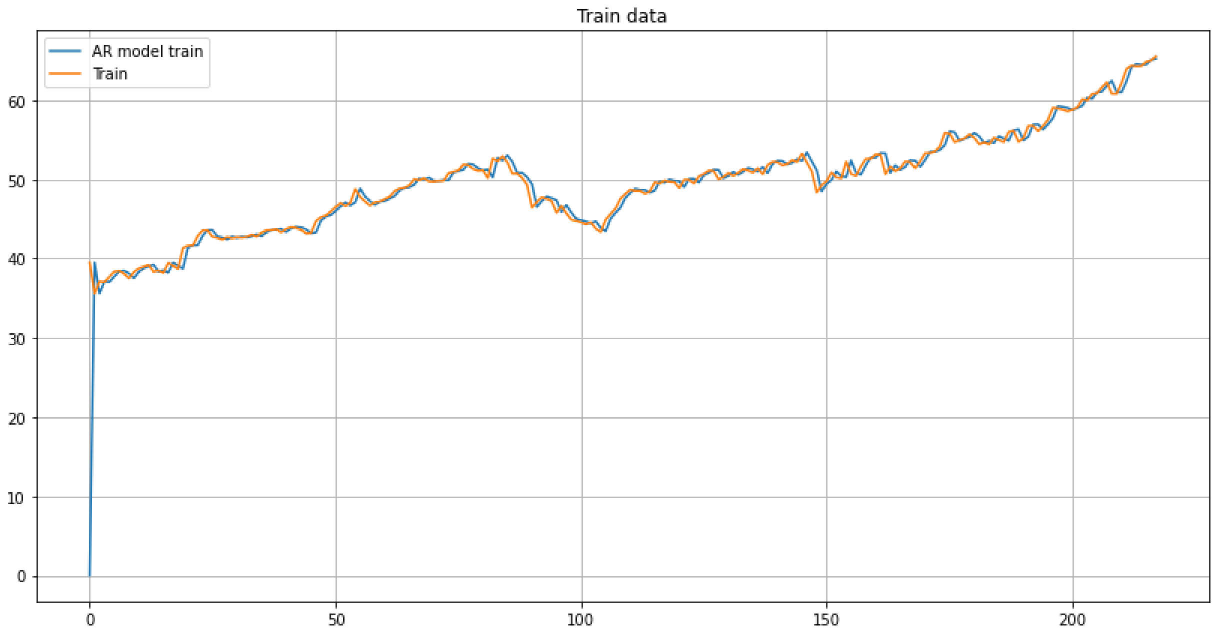
In [17]:

```
print('train data MAPE:
',mean_absolute_percentage_error(df_train['Close'].to_numpy(),
res.predict()))
```

```
train data MAPE:  0.01660565549473924
```

In [18]:

```
plt.figure(figsize=(14,7))
plt.title('Train data')
plt.plot (res.predict(), label= 'AR model train')
plt.plot(df_train.reset_index(drop=True), label = 'Train')
plt.legend(loc='upper left')
plt.grid()
```



Сделаем прогноз на весь тестовый датасет

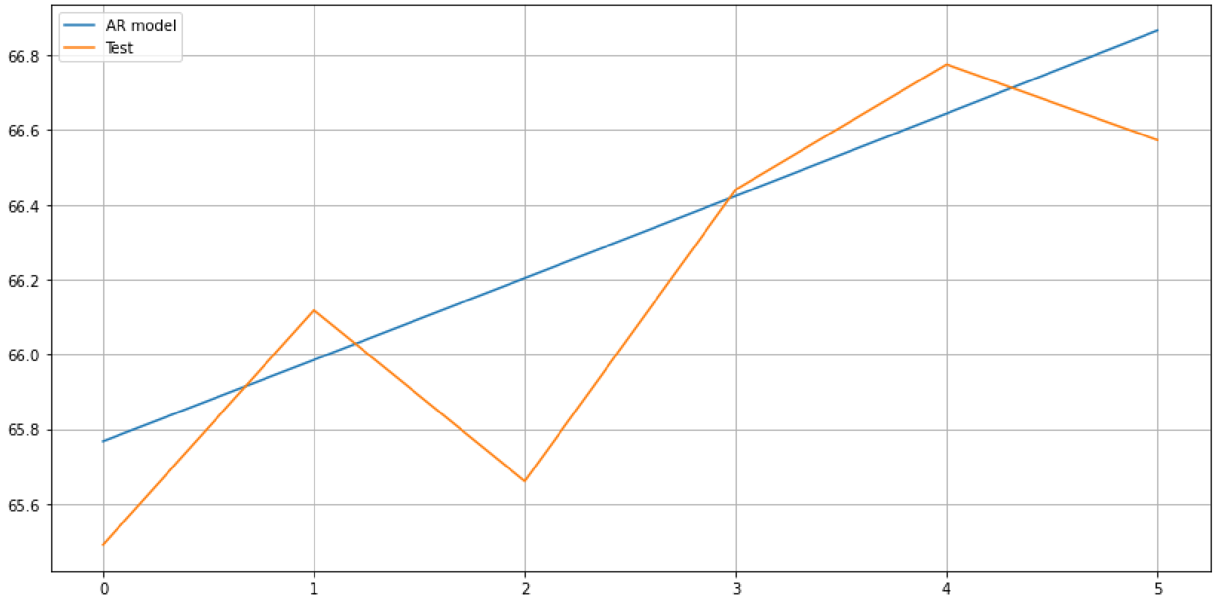
In [19]:
```
print('test data MAPE:
',mean_absolute_percentage_error(df_test['Close'].to_numpy(),
res.predict(len(df_train), len(df_train) + len(df_test) - 1)))
```

```
test data MAPE:  0.02342426253238507
```

In [20]:
```
plt.figure(figsize=(14,7))
plt.title('Test data')
plt.plot(res.predict(len(df_train), len(df_train) + len(df_test) - 1),
label= 'AR model test')
plt.plot(df_test.reset_index(drop=True), label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```

Сделаем короткий прогноз (на 6 дней)

In [21]:
```
plt.figure(figsize=(14,7))
plt.plot(res.predict(len(df_train), len(df_train)+5), label= 'AR model')
plt.plot(df_test.reset_index(drop=True)[:6], label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```



MA model

moving average models: MA(q) - все параметры кроме q зануляем, перебираем q и trend

In [45]:
```
def MA_config(seasonal=[0]):
        models = []
        p_params = [0]
        d_params = [0]
        q_params = [1, 2, 3 ,4 ,5]
        t_params = ['n','c','t','ct']
        P_params = [0]
        D_params = [0]
        Q_params = [0]
        m_params = seasonal
        for p in p_params:
                for d in d_params:
                        for q in q_params:
                                for t in t_params:
                                        for P in P_params:
                                                for D in D_params:
                                                        for Q in
Q_params:
                                                                for m in
m_params:

cfg = [(p,d,q), (P,D,Q,m), t]

models.append(cfg)
        return models
```

In [47]:
```
cfg_list = MA_config()
scores = grid_search(df_train['Close'].to_numpy(),
df_test['Close'].to_numpy(), cfg_list)
clear_output(wait=True)
print('done\n')
print('TOP 3 scores : \n')
for cfg, res in scores[:3]:
    print(f'> Model {cfg},    MAPE {res}')
```

```
done

TOP 3 scores :

> Model [(0, 0, 5), (0, 0, 0, 0), 'ct'],    MAPE 0.12726102167754255
> Model [(0, 0, 3), (0, 0, 0, 0), 'ct'],    MAPE 0.13052905465327297
> Model [(0, 0, 2), (0, 0, 0, 0), 'ct'],    MAPE 0.13167416556351777
```

Лучшие параметры модели: [(0, 0, 5), (0, 0, 0, 0), 't'], то есть MA(5)

при этом MAPE = 0.12726102167754255

Построим данную модель

In [24]:
```
model = SARIMAX(df_train['Close'].to_numpy(), order=(0, 0, 5),
seasonal_order=(0, 0, 0, 0), trend='ct', enforce_stationarity=False,
enforce_invertibility=False)
res = model.fit()
print(res.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  218
Model:               SARIMAX(0, 0, 5)   Log Likelihood                -278.303
Date:                Wed, 21 Apr 2021   AIC                            572.606
Time:                        13:45:57   BIC                            599.459
Sample:                             0   HQIC                           583.459
                                - 218
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     39.8295      0.746     53.390      0.000      38.367      41.292
drift          0.0910      0.005     16.817      0.000       0.080       0.102
ma.L1          1.0934      0.067     16.418      0.000       0.963       1.224
ma.L2          0.9226      0.083     11.134      0.000       0.760       1.085
ma.L3          0.8803      0.083     10.637      0.000       0.718       1.043
ma.L4          0.7462      0.088      8.486      0.000       0.574       0.919
ma.L5          0.4432      0.064      6.880      0.000       0.317       0.569
sigma2         0.8004      0.065     12.395      0.000       0.674       0.927
===================================================================================
Ljung-Box (L1) (Q):                   4.19   Jarque-Bera (JB):                10.27
Prob(Q):                              0.04   Prob(JB):                         0.01
Heteroskedasticity (H):               2.03   Skew:                            -0.01
Prob(H) (two-sided):                  0.00   Kurtosis:                         4.08
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-ste
p).
D:\conda\lib\site-packages\statsmodels\base\model.py:568: ConvergenceWarning: Maximu
```

```
m Likelihood optimization failed to converge. Check mle_retvals
  ConvergenceWarning)
```

Из SARIMAX result выделим критерии AIC (Информационный критерий Акаике) и BIC (Байесовский информационный критерий).

AIC = 572.606

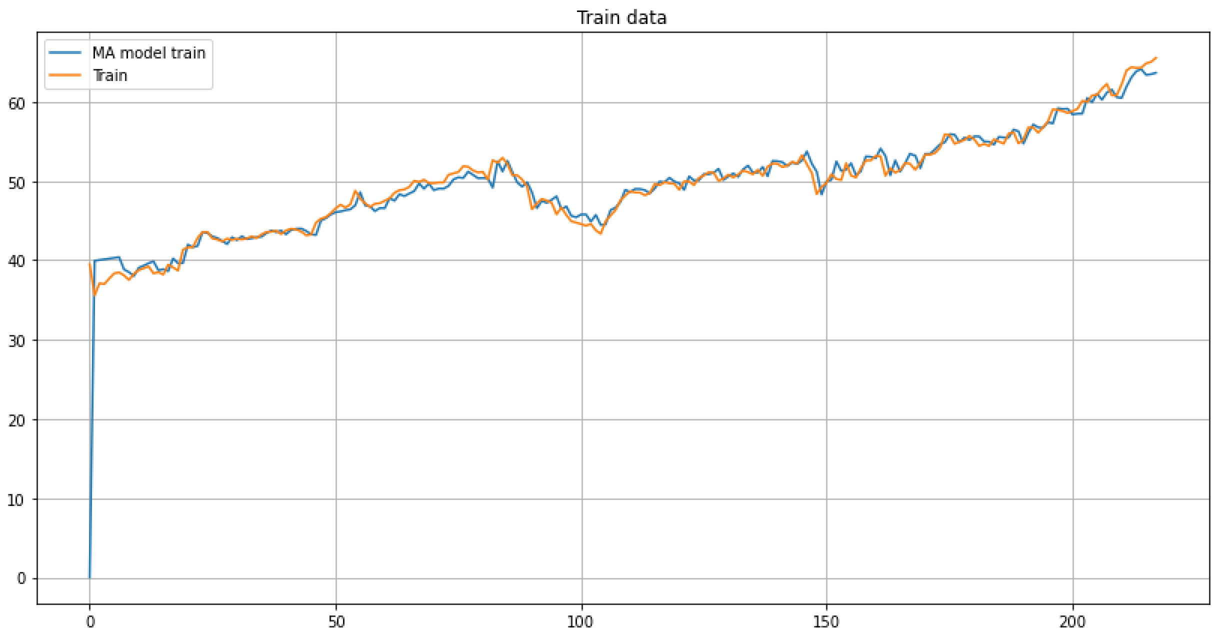
BIC = 599.459

Тренировочная выборка:

In [25]:
```
print('train data MAPE:
',mean_absolute_percentage_error(df_train['Close'].to_numpy(),
res.predict()))
```

```
train data MAPE:  0.019875968025944258
```

In [26]:
```
plt.figure(figsize=(14,7))
plt.title('Train data')
plt.plot (res.predict(), label= 'MA model train')
plt.plot(df_train.reset_index(drop=True), label = 'Train')
plt.legend(loc='upper left')
plt.grid()
```



Сделаем прогноз на весь тестовый датасет

In [27]:
```
print('test data MAPE:
',mean_absolute_percentage_error(df_test['Close'].to_numpy(),
res.predict(len(df_train), len(df_train) + len(df_test) - 1)))
```

```
test data MAPE:  0.12726102167754255
```

In [28]:
```
plt.figure(figsize=(14,7))
plt.title('Test data')
plt.plot(res.predict(len(df_train), len(df_train) + len(df_test) - 1),
```

```
label= 'MA model test')
plt.plot(df_test.reset_index(drop=True), label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```

ARMA model

mixed autoregressive moving average models: ARMA(p, q) - все параметры кроме p и q зануляем, перебираем p, q и trend

In [29]:
```
def ARMA_config(seasonal=[0]):
        models = []
        # define config lists
        p_params = [1, 2, 3]
        d_params = [0]
        q_params = [1, 2, 3]
        t_params = ['n','c','t','ct']
        P_params = [0]
        D_params = [0]
        Q_params = [0]
        m_params = seasonal
        for p in p_params:
                for d in d_params:
                        for q in q_params:
                                for t in t_params:
                                        for P in P_params:
                                                for D in D_params:
                                                        for Q in
Q_params:
                                                                for m in
```

```
m_params:

cfg = [(p,d,q), (P,D,Q,m), t]

models.append(cfg)
        return models
```

In [30]:

```
cfg_list = ARMA_config()
scores = grid_search(df_train['Close'].to_numpy(),
df_test['Close'].to_numpy(), cfg_list)
clear_output(wait=True)
print('done\n')
print('TOP 3 scores : \n')
for cfg, res in scores[:3]:
    print(f'> Model {cfg},    MAPE {res}')
```

```
done

TOP 3 scores :

> Model [(3, 0, 2), (0, 0, 0, 0), 't'],    MAPE 0.02549486570867855
> Model [(3, 0, 1), (0, 0, 0, 0), 't'],    MAPE 0.025640667172609342
> Model [(1, 0, 3), (0, 0, 0, 0), 't'],    MAPE 0.025669254054550818
```

Лучшие параметры модели: [(3, 0, 2), (0, 0, 0, 0), 't'], то есть ARMA(3,2)

при этом MAPE = 0.02549486570867855

Построим данную модель

In [31]:

```
model = SARIMAX(df_train['Close'].to_numpy(), order=(3, 0, 2),
seasonal_order=(0, 0, 0, 0), trend='t', enforce_stationarity=False,
enforce_invertibility=False)
res = model.fit()
print(res.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  218
Model:               SARIMAX(3, 0, 2)   Log Likelihood                -247.826
Date:                Wed, 21 Apr 2021   AIC                            509.652
Time:                        13:46:10   BIC                            533.246
Sample:                             0   HQIC                           519.185
                                - 218
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
drift          0.0003      0.001      0.378      0.706      -0.001       0.002
ar.L1          1.3427      0.522      2.573      0.010       0.320       2.366
ar.L2         -0.3144      0.504     -0.624      0.533      -1.301       0.673
ar.L3         -0.0273      0.304     -0.090      0.928      -0.623       0.569
ma.L1         -0.3649      0.518     -0.704      0.481      -1.380       0.650
ma.L2         -0.0998      0.292     -0.341      0.733      -0.673       0.473
sigma2         0.5857      0.041     14.270      0.000       0.505       0.666
===================================================================================
```

```
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                58.85
Prob(Q):                              0.94   Prob(JB):                         0.00
Heteroskedasticity (H):               2.19   Skew:                            -0.39
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.44
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-ste
p).
D:\conda\lib\site-packages\statsmodels\base\model.py:568: ConvergenceWarning: Maximu
m Likelihood optimization failed to converge. Check mle_retvals
  ConvergenceWarning)
```

Из SARIMAX result выделим критерии AIC (Информационный критерий Акаике) и BIC (Байесовский информационный критерий).

AIC = 509.652

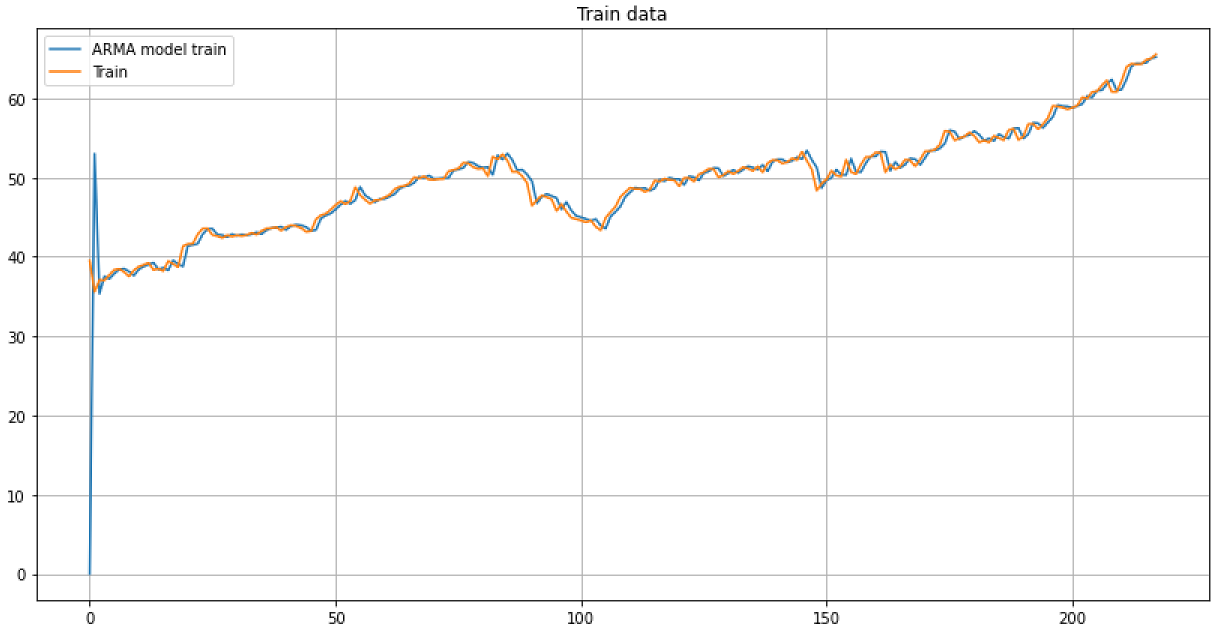
BIC = 533.246

Тренировочная выборка:

In [32]:
```
print('train data MAPE:
',mean_absolute_percentage_error(df_train['Close'].to_numpy(),
res.predict()))
```

```
train data MAPE:  0.018292091495712565
```

In [33]:
```
plt.figure(figsize=(14,7))
plt.title('Train data')
plt.plot (res.predict(), label= 'ARMA model train')
plt.plot(df_train.reset_index(drop=True), label = 'Train')
plt.legend(loc='upper left')
plt.grid()
```



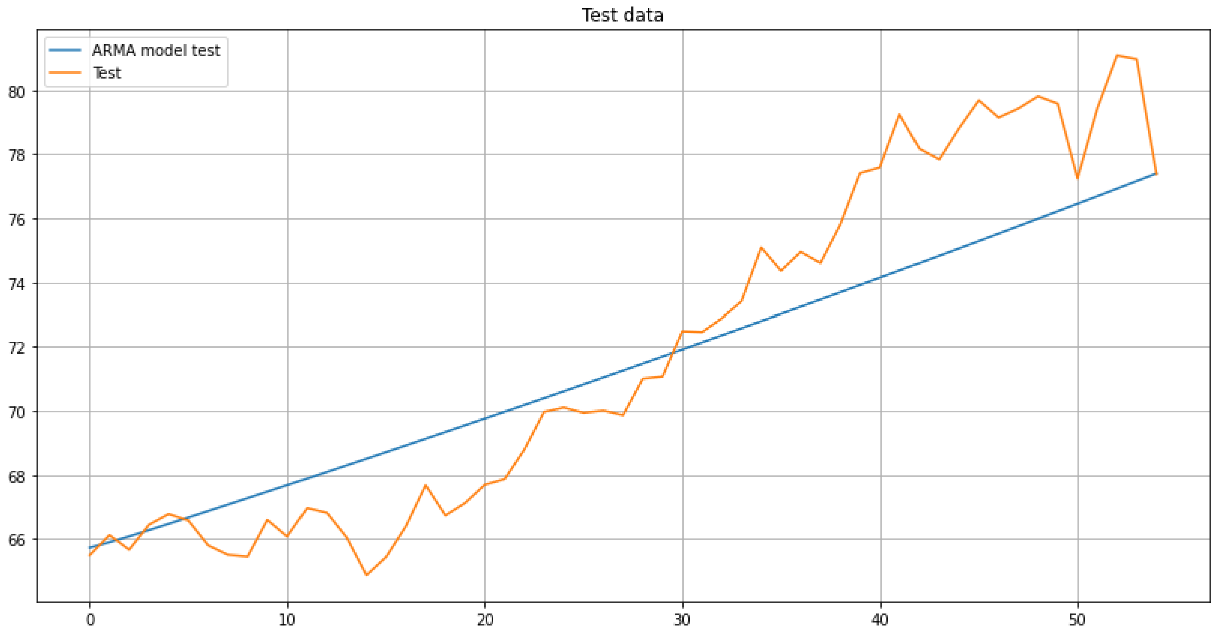
Сделаем прогноз на весь тестовый датасет

In [34]:
```
print('test data MAPE:
```

```
',mean_absolute_percentage_error(df_test['Close'].to_numpy(),
res.predict(len(df_train), len(df_train) + len(df_test) - 1)))
```

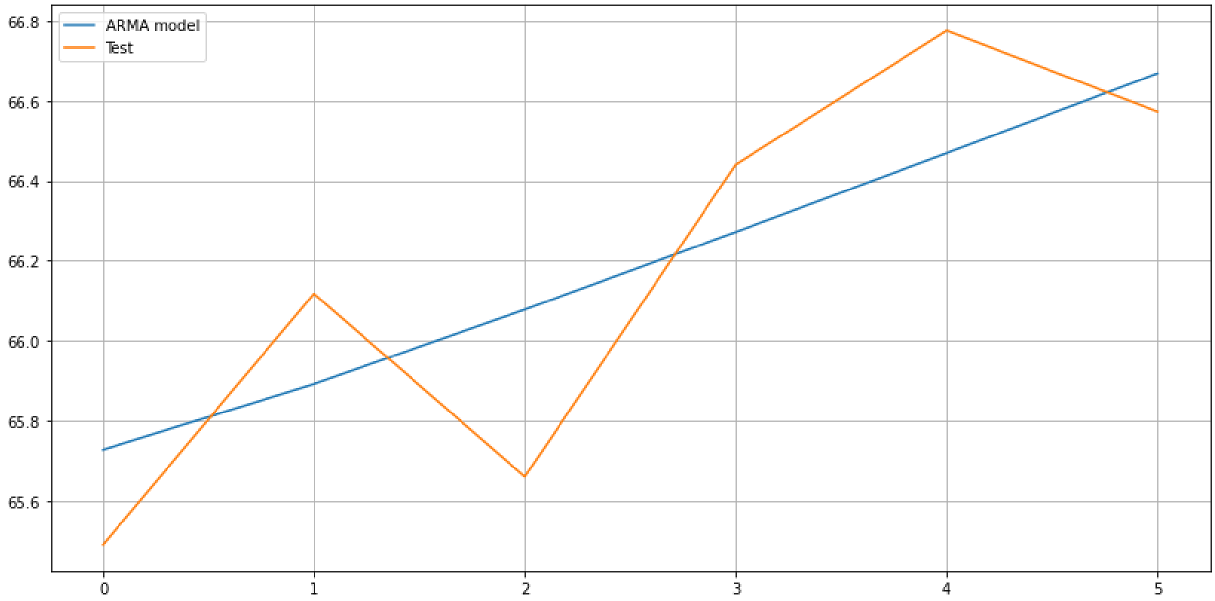
```
test data MAPE:  0.02549486570867855
```

In [35]:
```
plt.figure(figsize=(14,7))
plt.title('Test data')
plt.plot(res.predict(len(df_train), len(df_train) + len(df_test) - 1),
label= 'ARMA model test')
plt.plot(df_test.reset_index(drop=True), label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```



Сделаем короткий прогноз на 6 дней

In [36]:
```
plt.figure(figsize=(14,7))
plt.plot(res.predict(len(df_train), len(df_train) + 5), label= 'ARMA
model')
plt.plot(df_test.reset_index(drop=True)[:6], label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```



ARIMA model

integration models: ARIMA(p, d, q) - все параметры кроме p, d, q зануляем, перебираем p, d, q и trend

In [37]:
```
def ARIMA_config(seasonal=[0]):
        models = []
        # define config lists
        p_params = [1, 2, 3]
        d_params = [1,2]
        q_params = [1, 2, 3]
        t_params = ['n','c','t','ct']
        P_params = [0]
        D_params = [0]
        Q_params = [0]
        m_params = seasonal
        for p in p_params:
                for d in d_params:
                        for q in q_params:
                                for t in t_params:
                                        for P in P_params:
                                                for D in D_params:
                                                        for Q in
Q_params:
                                                                for m in
m_params:

cfg = [(p,d,q), (P,D,Q,m), t]
```

```
models.append(cfg)
        return models
```

In [38]:

```
cfg_list = ARIMA_config()
scores = grid_search(df_train['Close'].to_numpy(),
df_test['Close'].to_numpy(), cfg_list)
clear_output(wait=True)
print('done\n')
print('TOP 3 scores : \n')
for cfg, res in scores[:3]:
    print(f'> Model {cfg},    MAPE {res}')
```

```
done

TOP 3 scores :

> Model [(3, 2, 2), (0, 0, 0, 0), 't'],    MAPE 0.023060497871810182
> Model [(2, 1, 2), (0, 0, 0, 0), 't'],    MAPE 0.023114822121800084
> Model [(1, 1, 2), (0, 0, 0, 0), 't'],    MAPE 0.023116655637654467
```

Лучшие параметры модели: [(3, 2, 2), (0, 0, 0, 0), 't'], то есть ARIMA(3,2,2)

при этом MAPE = 0.023060497871810182

Построим данную модель

In [39]:

```
model = SARIMAX(df_train['Close'].to_numpy(), order=(3, 2, 2),
seasonal_order=(0, 0, 0, 0), trend='t', enforce_stationarity=False,
enforce_invertibility=False)
res = model.fit()
print(res.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  218
Model:               SARIMAX(3, 2, 2)   Log Likelihood                -248.602
Date:                Wed, 21 Apr 2021   AIC                            511.203
Time:                        13:46:35   BIC                            534.732
Sample:                             0   HQIC                           520.712
                                - 218
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
drift       1.168e-05   2.56e-05      0.456      0.648   -3.85e-05    6.18e-05
ar.L1         -1.0245      0.160     -6.412      0.000      -1.338      -0.711
ar.L2         -0.2634      0.106     -2.486      0.013      -0.471      -0.056
ar.L3         -0.1054      0.082     -1.279      0.201      -0.267       0.056
ma.L1         -0.0812      0.161     -0.504      0.614      -0.397       0.235
ma.L2         -0.9146      0.144     -6.339      0.000      -1.197      -0.632
sigma2         0.6090      0.071      8.533      0.000       0.469       0.749
===================================================================================
Ljung-Box (L1) (Q):                   1.36   Jarque-Bera (JB):                52.47
Prob(Q):                              0.24   Prob(JB):                         0.00
Heteroskedasticity (H):               2.19   Skew:                            -0.43
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.27
===================================================================================
```

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

Из SARIMAX result выделим критерии AIC (Информационный критерий Акаике) и BIC (Байесовский информационный критерий).

AIC = 511.203

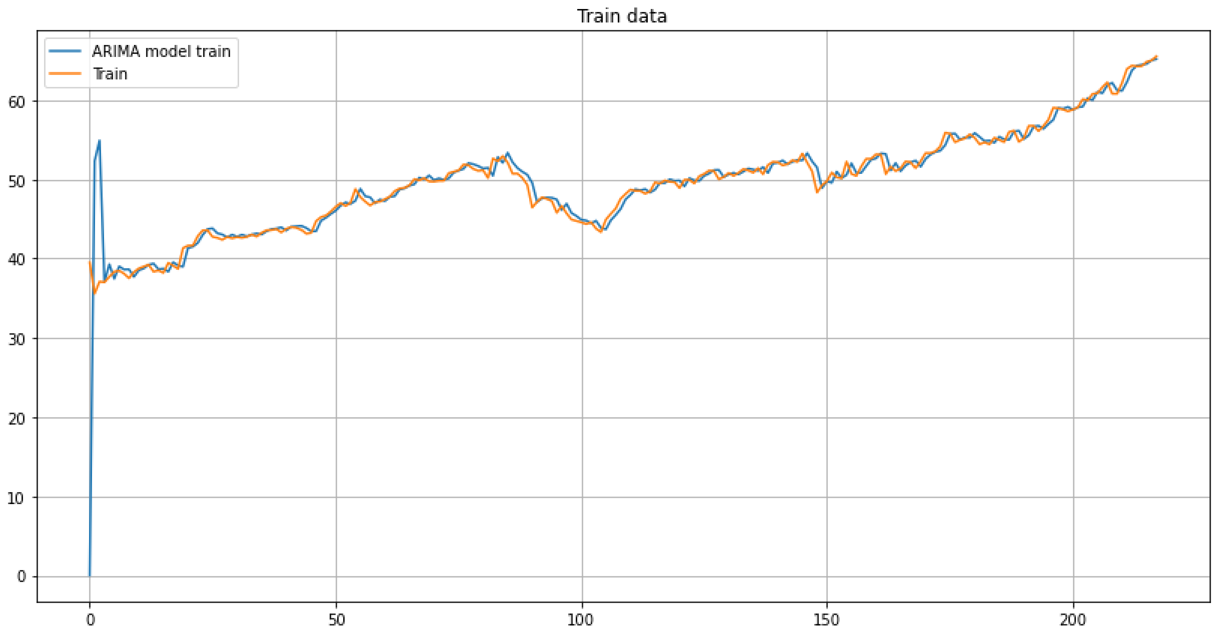
BIC = 534.732

Тренировочная выборка:

In [40]:
```
print('train data MAPE: ',mean_absolute_percentage_error(df_train['Close'].to_numpy(), res.predict()))
```

```
train data MAPE:  0.020463763628766004
```

In [41]:
```
plt.figure(figsize=(14,7))
plt.title('Train data')
plt.plot (res.predict(), label= 'ARIMA model train')
plt.plot(df_train.reset_index(drop=True), label = 'Train')
plt.legend(loc='upper left')
plt.grid()
```



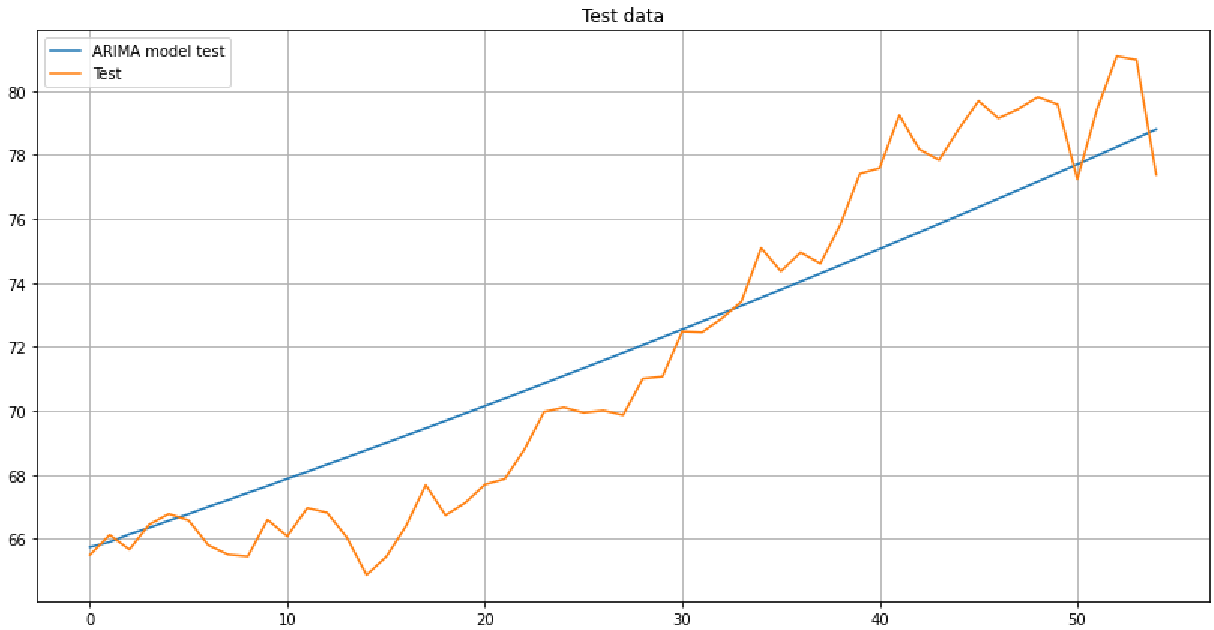
Построим прогноз на весь тестовый датасет

In [42]:
```
print('test data MAPE: ',mean_absolute_percentage_error(df_test['Close'].to_numpy(), res.predict(len(df_train), len(df_train) + len(df_test) - 1)))
```

```
test data MAPE:  0.023060497871810182
```

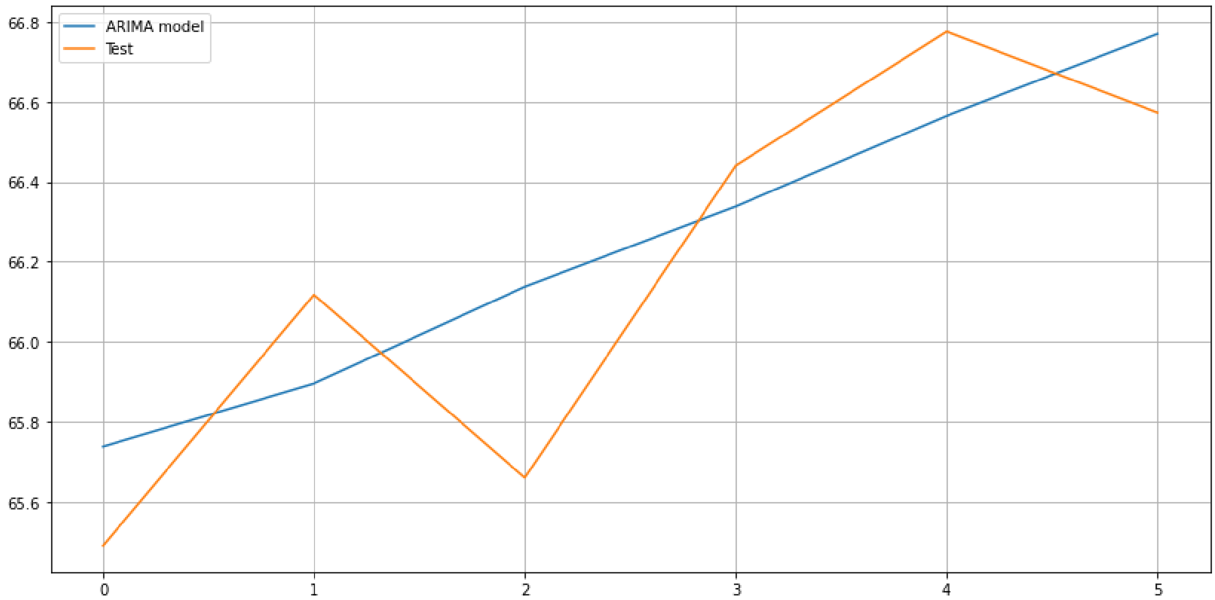
In [43]:
```
plt.figure(figsize=(14,7))
plt.title('Test data')
```

```
plt.plot(res.predict(len(df_train), len(df_train) + len(df_test) - 1),
label= 'ARIMA model test')
plt.plot(df_test.reset_index(drop=True), label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```



Сделаем короткий прогноз на 6 дней

In [44]:
```
plt.figure(figsize=(14,7))
plt.plot(res.predict(len(df_train), len(df_train) + 5), label= 'ARIMA
model')
plt.plot(df_test.reset_index(drop=True)[:6], label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```



SARIMA model

И наконец, самая мощная модель из рассмотренных - SARIMA(p,q,d,P,Q,D,s)

Теперь перебираем все параметры, даже 0 , чтобы наконец определить самую точную модель на наших данных

In [52]:

```
def SARIMA_config(seasonal=[0]):
        models = list()
        # define config lists
        p_params = [0, 1, 2]
        d_params = [0,1]
        q_params = [0, 1, 2]
        t_params = ['n','c','t','ct']
        P_params = [0, 1, 2]
        D_params = [0, 1]
        Q_params = [0, 1, 2]
        m_params = seasonal
        # create config instances
        for p in p_params:
                for d in d_params:
                        for q in q_params:
                                for t in t_params:
                                        for P in P_params:
                                                for D in D_params:
                                                        for Q in
Q_params:
                                                                for m in
m_params:

cfg = [(p,d,q), (P,D,Q,m), t]

models.append(cfg)
        return models
```

In [53]:

```
cfg_list = SARIMA_config(seasonal=[0,6,12])
# grid search
scores = grid_search(df_train['Close'].to_numpy(),
df_test['Close'].to_numpy(), cfg_list)
clear_output(wait=True)
print('done\n')
print('TOP 3 scores : \n')
for cfg, res in scores[:3]:
    print(f'> Model {cfg},    MAPE {res}')
```

done

```
TOP 3 scores :

> Model [(1, 0, 1), (2, 1, 1, 12), 'ct'],    MAPE 0.01775834516985734
> Model [(2, 0, 0), (2, 1, 1, 12), 'ct'],    MAPE 0.018217943739792398
> Model [(1, 0, 0), (2, 1, 1, 12), 'ct'],    MAPE 0.019390754523184395
```

Лучшие параметры модели: [(1, 0, 1), (2, 1, 1, 12), 'ct'], то есть SARIMA(1, 0 , 1, 2, 1 , 1, 12)

при этом MAPE = 0.01775834516985734

Построим данную модель

In [54]:
```
model = SARIMAX(df_train['Close'].to_numpy(), order=(1, 0, 1),
seasonal_order=(2, 1, 1, 12), trend='ct', enforce_stationarity=False,
enforce_invertibility=False)
res = model.fit()
print(res.summary())
```

```
                                   SARIMAX Results
=====================================================================================
======
Dep. Variable:                                   y   No. Observations:
218
Model:             SARIMAX(1, 0, 1)x(2, 1, 1, 12)   Log Likelihood                   -2
27.032
Date:                             Wed, 21 Apr 2021   AIC                               4
70.064
Time:                                     13:05:12   BIC                               4
95.652
Sample:                                          0   HQIC                              4
80.438
                                             - 218
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -0.0655      0.078     -0.842      0.400      -0.218       0.087
drift          0.0009      0.001      1.560      0.119      -0.000       0.002
ar.L1          0.9719      0.026     37.727      0.000       0.921       1.022
ma.L1         -0.0351      0.091     -0.384      0.701      -0.214       0.144
ar.S.L12      -0.1631      0.089     -1.827      0.068      -0.338       0.012
ar.S.L24      -0.2014      0.095     -2.122      0.034      -0.387      -0.015
ma.S.L12      -0.8362      0.098     -8.542      0.000      -1.028      -0.644
sigma2         0.7036      0.078      9.042      0.000       0.551       0.856
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                24.54
Prob(Q):                              0.98   Prob(JB):                         0.00
Heteroskedasticity (H):               0.94   Skew:                            -0.57
Prob(H) (two-sided):                  0.81   Kurtosis:                         4.39
===================================================================================

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

D:\conda\lib\site-packages\statsmodels\base\model.py:568: ConvergenceWarning: Maximu
m Likelihood optimization failed to converge. Check mle_retvals
  ConvergenceWarning)
```

Из SARIMAX result выделим критерии AIC (Информационный критерий Акаике) и BIC (Байесовский информационный критерий).

AIC = 470.06

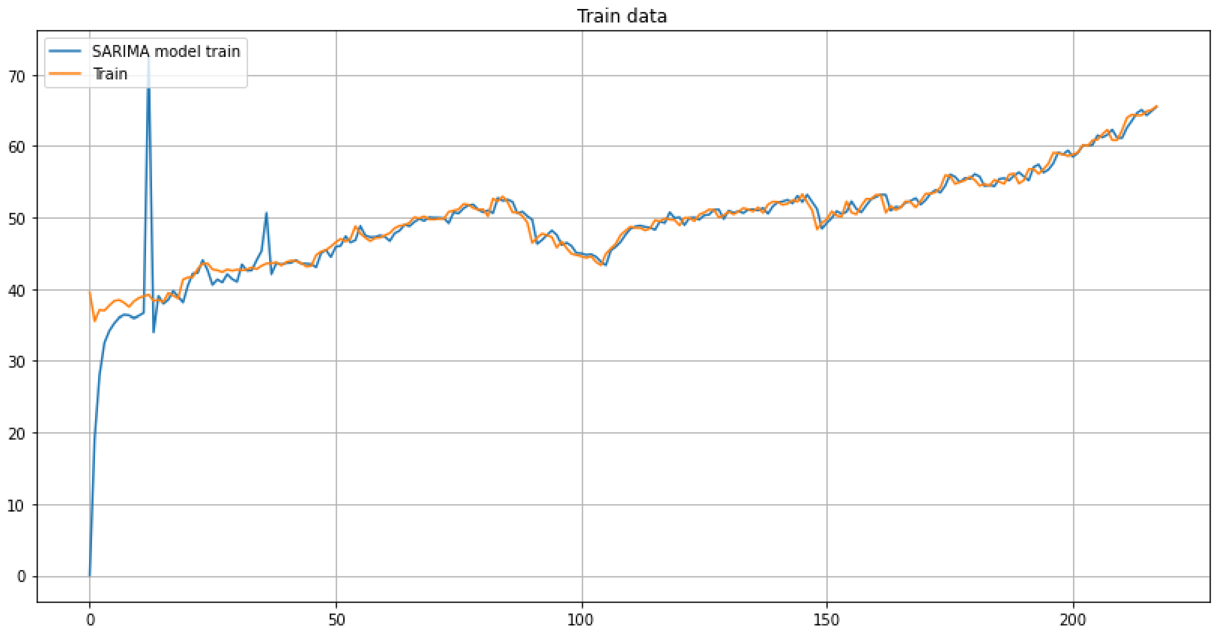
BIC = 495.652

Тренировочная выборка:

In [55]:
```
print('train data MAPE:
',mean_absolute_percentage_error(df_train['Close'].to_numpy(),
res.predict()))
```

```
train data MAPE:  0.028722370927469765
```

In [56]:
```
plt.figure(figsize=(14,7))
plt.title('Train data')
plt.plot (res.predict(), label= 'SARIMA model train')
plt.plot(df_train.reset_index(drop=True), label = 'Train')
plt.legend(loc='upper left')
plt.grid()
```

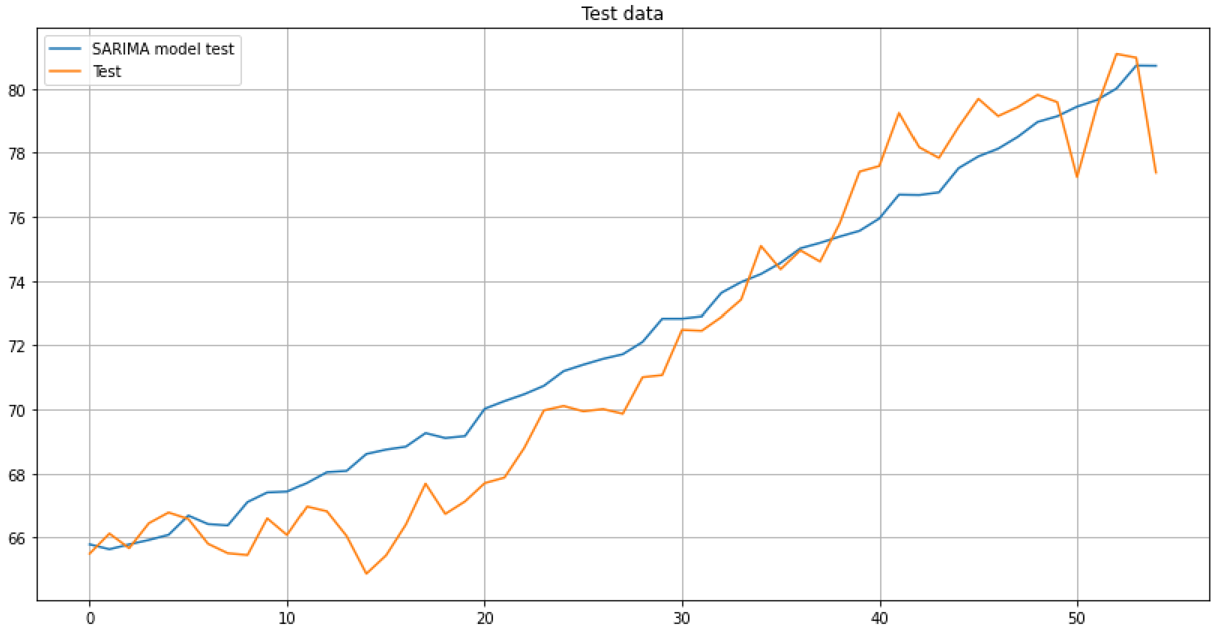


Сделаем прогноз на весь тестовый датасет

In [57]:
```
print('test data MAPE:
',mean_absolute_percentage_error(df_test['Close'].to_numpy(),
res.predict(len(df_train), len(df_train) + len(df_test) - 1)))
```

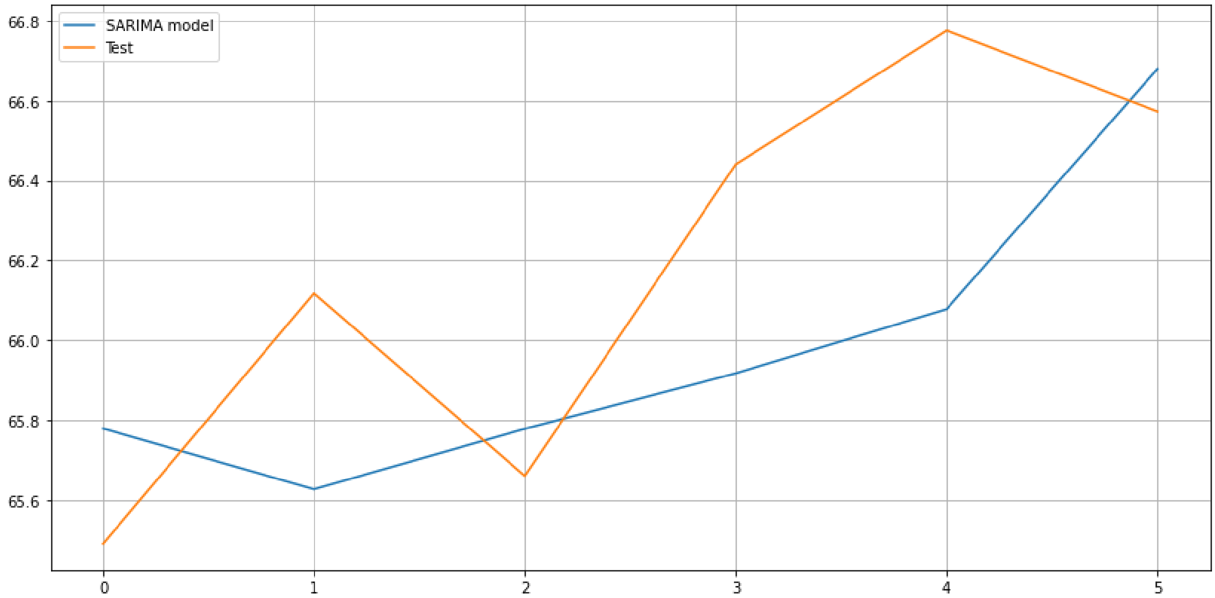
```
test data MAPE:  0.017758345169857 34
```

In [58]:
```
plt.figure(figsize=(14,7))
plt.title('Test data')
plt.plot(res.predict(len(df_train), len(df_train) + len(df_test) - 1),
label= 'SARIMA model test')
plt.plot(df_test.reset_index(drop=True), label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```



Короткий прогноз на 6 дней:

In [59]:
```
plt.figure(figsize=(14,7))
plt.plot(res.predict(len(df_train), len(df_train) + 5), label= 'SARIMA model')
plt.plot(df_test.reset_index(drop=True)[:6], label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```



Длинный прогноз очень впечатляет, действиетльно самый точный из выше упомянутых моделей, однако короткий прогноз не самый точный.

Simple Exponential Smoothing (SES)

Обратимся к более простым моделям - Простое экспоненциальное сглаживание.

In [110…
```
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
```

```
model = SimpleExpSmoothing(df_train['Close'].to_numpy())
res = model.fit(smoothing_level=0.8)
print(res.summary())
```

```
                       SimpleExpSmoothing Model Results
==============================================================================
Dep. Variable:                    endog   No. Observations:                  218
Model:               SimpleExpSmoothing   SSE                            151.504
Optimized:                         True   AIC                            -75.326
Trend:                             None   BIC                            -68.557
Seasonal:                          None   AICC                           -75.138
Seasonal Periods:                  None   Date:                 Wed, 21 Apr 2021
Box-Cox:                          False   Time:                         13:40:46
Box-Cox Coeff.:                    None
==============================================================================
                       coeff                 code              optimized
------------------------------------------------------------------------------
smoothing_level            0.8000000                alpha                False
initial_level              38.754874                  1.0                 True
------------------------------------------------------------------------------
D:\conda\lib\site-packages\statsmodels\tsa\holtwinters\model.py:429: FutureWarning:
After 0.13 initialization must be handled at model creation
  FutureWarning,
```

Из SimpleExpSmoothing Model Results выделим критерии AIC (Информационный критерий Акаике) и BIC (Байесовский информационный критерий).

AIC = -75.326

BIC = -68.557

Тренировочная выборка:

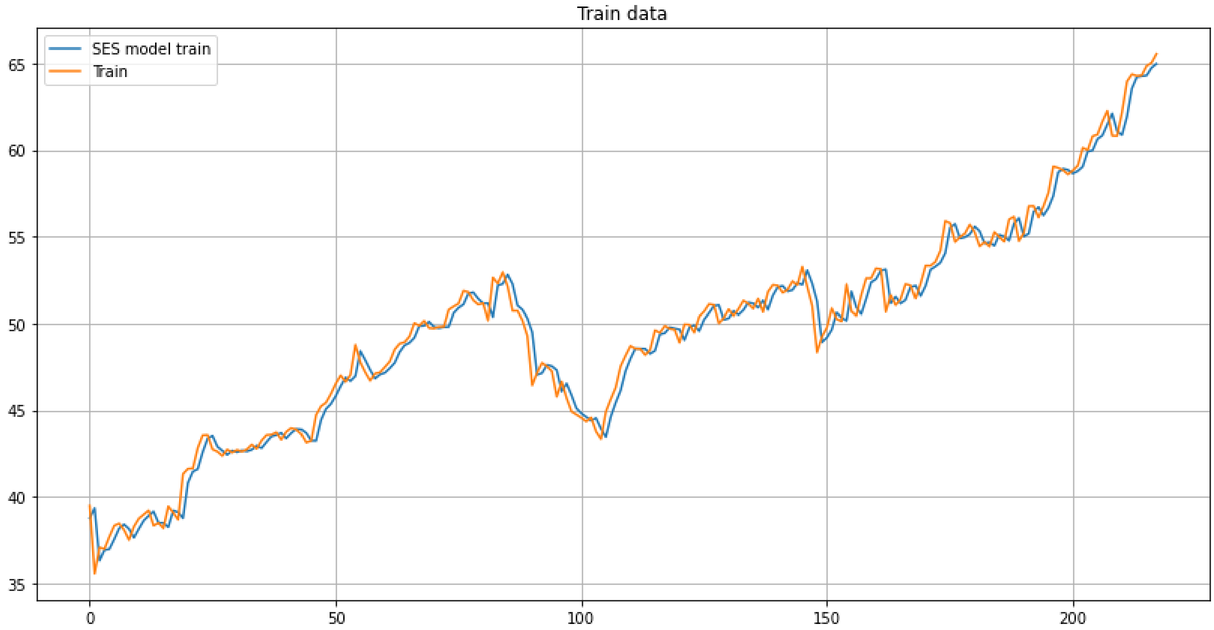
In [111…

```
print('train data MAPE: ',mean_absolute_percentage_error(df_train['Close'].to_numpy(), res.fittedvalues))
```

```
train data MAPE:  0.012429849347971346
```

In [112…

```
plt.figure(figsize=(14,7))
plt.title('Train data')
plt.plot (res.fittedvalues, label= 'SES model train')
plt.plot(df_train.reset_index(drop=True), label = 'Train')
plt.legend(loc='upper left')
plt.grid()
```



Сделаем прогноз на весь тестовый датасет

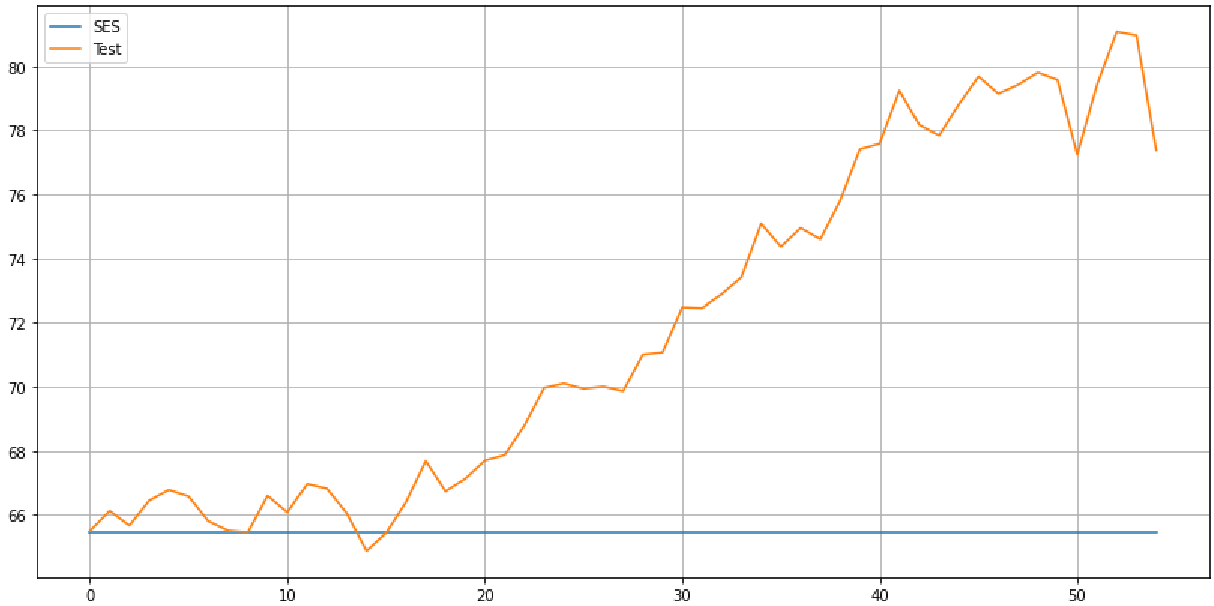
In [114…

```
print('test data MAPE: ',mean_absolute_percentage_error(df_test['Close'].to_numpy(), res.predict(len(df_train), len(df_train) + len(df_test) - 1)))
```

```
test data MAPE:  0.08408885919719841
```

In [115…

```
plt.figure(figsize=(14,7))
plt.plot(res.predict(len(df_train), len(df_train) + len(df_test) - 1), label= 'SES')
plt.plot(df_test.reset_index(drop=True), label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```



Holt Winter's Exponential Smoothing (HWES)

Сглаживание Хольтса - Винтерса

In [102…

```
def SmoothingHW_config():
    models = []
    t_params = ['add', 'mul', 'additive', 'multiplicative']
    s_params =['add', 'mul', 'additive', 'multiplicative']
    sp_params = [0, 6, 12]
    sm_params = [0.2, 0.4, 0.6]
    for t in t_params:
        for s in s_params:
            for sp in sp_params:
                for sm in sm_params:
                    cfg = [t, s, sp, sm]
                    models.append(cfg)
    return models
```

In [103…

```
cfg_list = SmoothingHW_config()
# grid search
scores = grid_search_sm(df_train['Close'].to_numpy(),
df_test['Close'].to_numpy(), cfg_list)
clear_output(wait=True)
print('done\n')
print('TOP 3 scores : \n')
for cfg, res in scores[:3]:
    print(f'> Model {cfg},    MAPE {res}')
```

```
done

TOP 3 scores :

> Model ['mul', 'mul', 6, 0.6],    MAPE 0.03238032624358724
> Model ['mul', 'multiplicative', 6, 0.6],    MAPE 0.03238032624358724
> Model ['multiplicative', 'mul', 6, 0.6],    MAPE 0.03238032624358724
```

Лучшие параметры модели:['mul', 'mul', 6, 0.6]

при этом MAPE = 0.03238032624358724

Построим данную модель

In [117…

```
model = ExponentialSmoothing(df_train['Close'].to_numpy(), trend='mul',
seasonal='mul', seasonal_periods=6)
res = model.fit(0.6)
print(res.summary())
```

```
                       ExponentialSmoothing Model Results
================================================================================
Dep. Variable:                    endog   No. Observations:                  218
Model:             ExponentialSmoothing   SSE                            154.463
Optimized:                         True   AIC                            -55.110
Trend:                   Multiplicative   BIC                            -21.265
```

```
Seasonal:                Multiplicative   AICC                        -53.588
Seasonal Periods:                     6   Date:              Wed, 21 Apr 2021
Box-Cox:                          False   Time:                      13:41:49
Box-Cox Coeff.:                    None
=================================================================================
                          coeff                 code              optimized
---------------------------------------------------------------------------------
smoothing_level             0.6000000                alpha                 False
smoothing_trend            7.9421e-10                 beta                  True
smoothing_seasonal          8.659e-11                gamma                  True
initial_level               47.025866                  l.0                  True
initial_trend               1.0025384                  b.0                  True
initial_seasons.0           0.8081157                  s.0                  True
initial_seasons.1           0.8090868                  s.1                  True
initial_seasons.2           0.8071435                  s.2                  True
initial_seasons.3           0.8046110                  s.3                  True
initial_seasons.4           0.8087328                  s.4                  True
initial_seasons.5           0.8076070                  s.5                  True
---------------------------------------------------------------------------------
D:\conda\lib\site-packages\statsmodels\tsa\holtwinters\model.py:429: FutureWarning:
After 0.13 initialization must be handled at model creation
  FutureWarning,
```

Из ExponentialSmoothing Model Results выделим критерии AIC (Информационный критерий Акаике) и BIC (Байесовский информационный критерий).

AIC = -55.110

BIC = -21.265

Тренировочная выборка

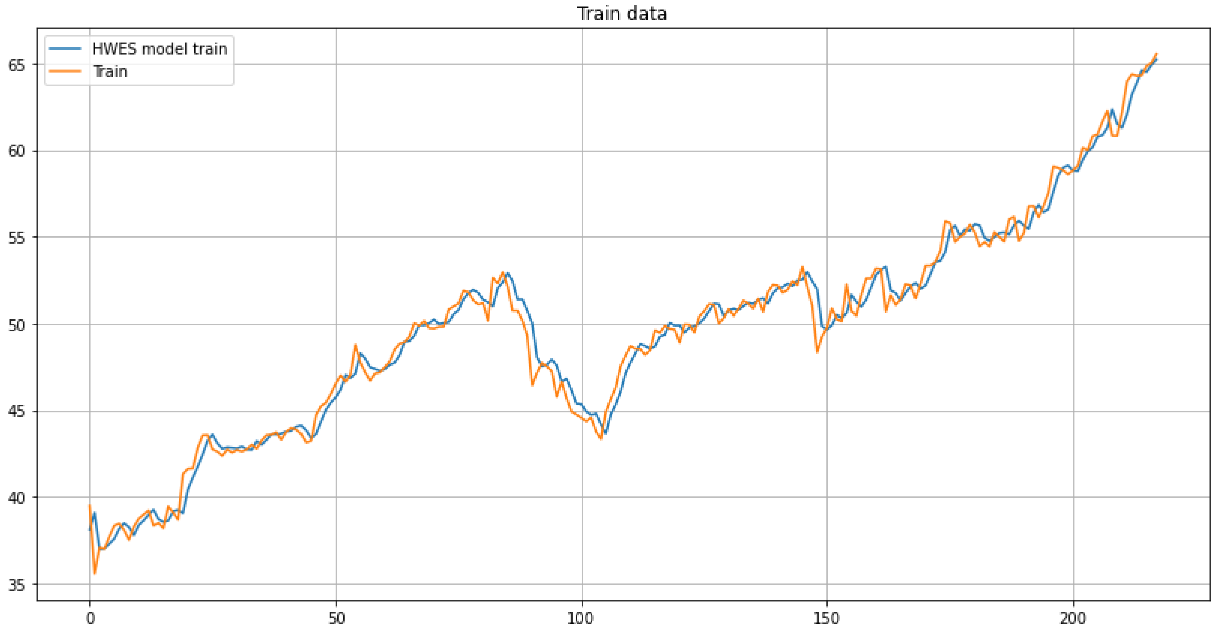
In [118…

```
print('train data MAPE: ',mean_absolute_percentage_error(df_train['Close'].to_numpy(), res.fittedvalues))
```

```
train data MAPE:  0.012645765504606847
```

In [119…

```
plt.figure(figsize=(14,7))
plt.title('Train data')
plt.plot (res.fittedvalues, label= 'HWES model train')
plt.plot(df_train.reset_index(drop=True), label = 'Train')
plt.legend(loc='upper left')
plt.grid()
```



Прогноз на тесте

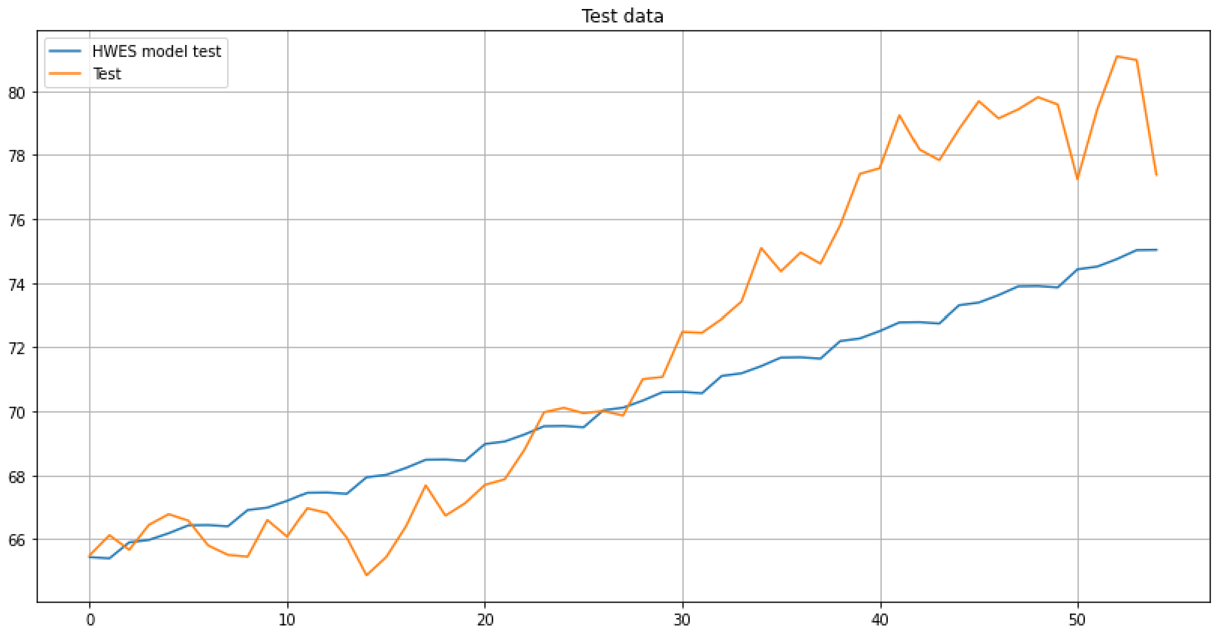
In [108…

```
print('test data MAPE: ',mean_absolute_percentage_error(df_test['Close'].to_numpy(), res.predict(len(df_train), len(df_train) + len(df_test) - 1)))
```

```
test data MAPE:  0.03238032624358724
```

In [120…

```
plt.figure(figsize=(14,7))
plt.title('Test data')
plt.plot(res.predict(len(df_train), len(df_train) + len(df_test) - 1), label= 'HWES model test')
plt.plot(df_test.reset_index(drop=True), label = 'Test')
plt.legend(loc='upper left')
plt.grid()
```



Вывод

Хуже всех сработала модель MA, затем модели : Простое экспоненциальное сглаживание и Сглаживание Хольтса - Винтерса.

Гораздо лучше себя показали ARMA, AR, ARIMA

Самый лучший прогноз получился при использовании SARIMA.

Результаты приведены в таблице ниже:

In [1]:
```
from IPython.display import Image
Image(filename='results.jpg')
```

Out[1]:

model	AIC	BIC	Train MAPE	Test MAPE	Forecast accuracy
SARIMA (1,0,1)x(2,1,1)_12	470.064	495.652	0.0287	0.0178	0.9822
ARIMA(3,2,2)	511.203	534.732	0.0205	0.0231	0.9769
AR(1)	534.908	545.048	0.0166	0.0234	0.9766
ARMA(3,2)	509.652	533.246	0.0183	0.0255	0.9745
HWES (smoothing = 0.6, seasonal periods = 6)	-55.110	-21.265	0.0126	0.0324	0.9679
SES (smoothing = 0.8)	-75.326	-68.557	0.0124	0.0841	0.9159
MA(5)	572.606	599.459	0.0199	0.1273	0.8727