# Beer Production Forecast

February 18, 2025

[1]:
```python
import pandas  as pd
import numpy  as np
import matplotlib.pyplot as plt
```

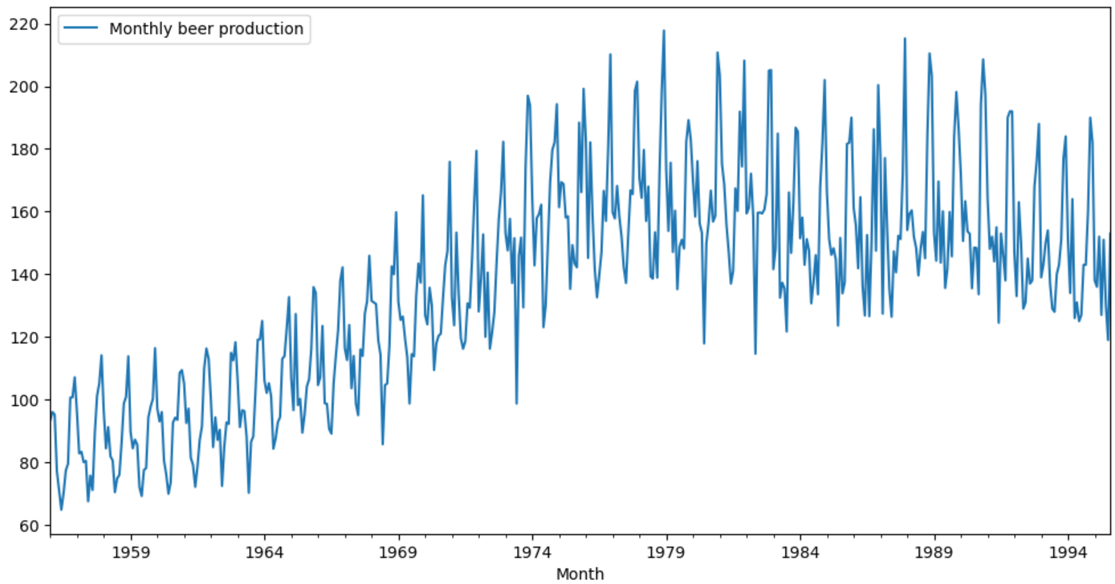
[2]:
```python
df = pd.read_csv(r'C:\Users\User\Desktop\monthly-beer-production.csv',index_col␣
↪= 'Month', parse_dates = True)
df.index.freq='MS'
```

[3]:
```python
df.head()
```

[3]:
```
            Monthly beer production
Month
1956-01-01                     93.2
1956-02-01                     96.0
1956-03-01                     95.2
1956-04-01                     77.1
1956-05-01                     70.9
```

[4]:
```python
df.plot(figsize=(12,6))
```

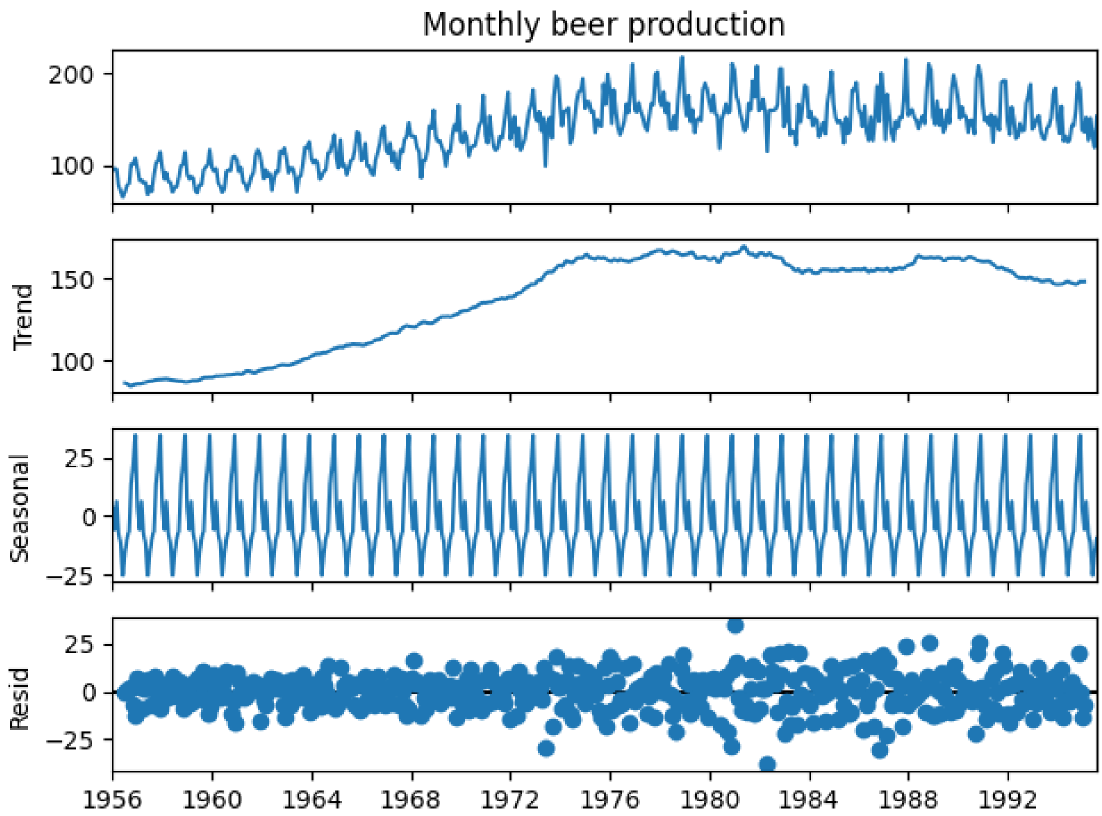
[4]: <Axes: xlabel='Month'>

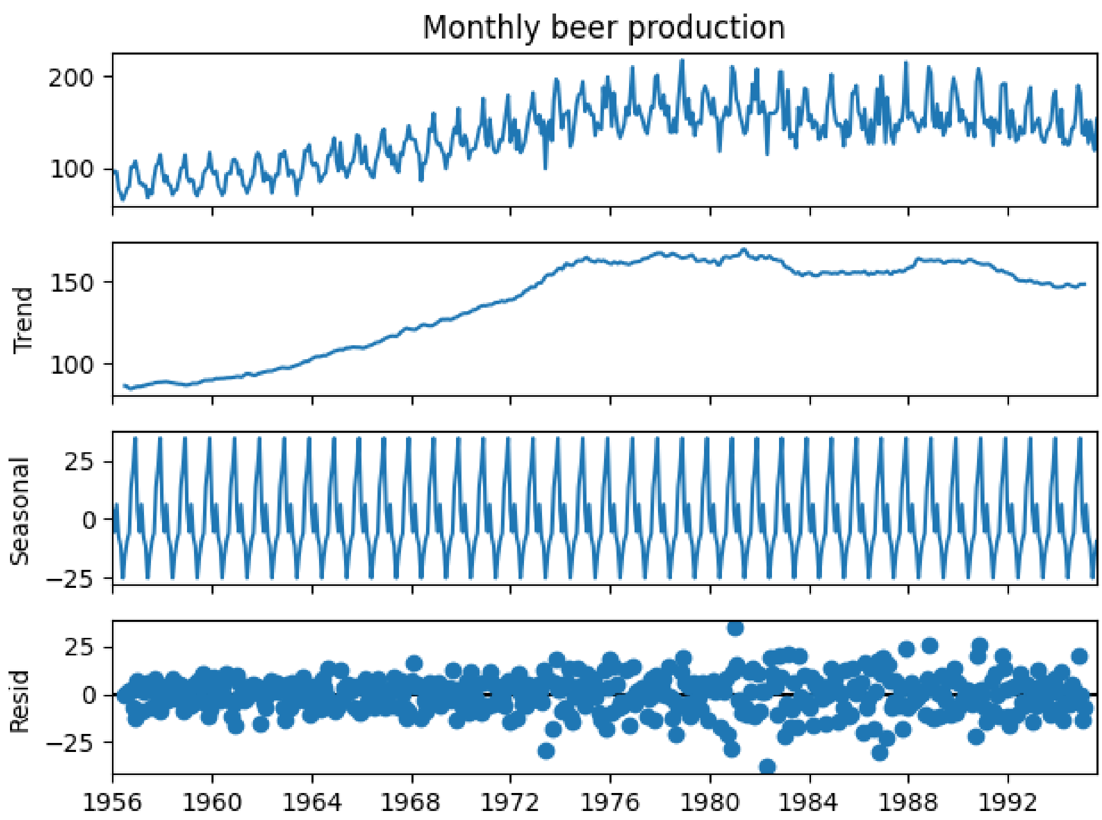


[5]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

[7]:
```
results = seasonal_decompose(df['Monthly beer production'])
results.plot()
```

[7]:






[8]:
```
len(df)
```

[8]:
```
476
```

[9]:
```
train = df.iloc[:464]
test = df.iloc[464:]
```

[10]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

[11]:
```
df.head(),df.tail()
```

[11]:
```
(             Monthly beer production
 Month
 1956-01-01                     93.2
 1956-02-01                     96.0
 1956-03-01                     95.2
 1956-04-01                     77.1
 1956-05-01                     70.9,
              Monthly beer production
 Month
```

```
1995-04-01                    127.0
1995-05-01                    151.0
1995-06-01                    130.0
1995-07-01                    119.0
1995-08-01                    153.0)
```

[12]:
```python
scaler.fit(train)
scaled_train = scaler.transform(train)
scaled_test = scaler.transform(test)
```

[15]:
```python
from tensorflow.keras.preprocessing.sequence import TimeseriesGenerator
```

[16]:
```python
#define generator
n_input = 3
n_features = 1
generator = TimeseriesGenerator(scaled_train, scaled_train, length=n_input,␣
 ↪batch_size=1)
```

[17]:
```python
x,y = generator[0]
print(f'Given the Array :\n{x.flatten()}')
print(f'Predict this Y:\n{y}')
```

```
Given the Array :
[0.18562092 0.20392157 0.19869281]
Predict this Y:
[[0.08039216]]
```

[18]:
```python
x.shape
```

[18]: (1, 3, 1)

[19]:
```python
n_input = 12
generator = TimeseriesGenerator(scaled_train, scaled_train, length=n_input,␣
 ↪batch_size=1)
```

[20]:
```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM
```

[21]:
```python
#define  model
model= Sequential()
model.add(LSTM(100,activation='relu', input_shape = (n_input ,  n_features)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
```

```
C:\Users\User\AppData\Local\Programs\Python\Python310\lib\site-
packages\keras\src\layers\rnn\rnn.py:200: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

[22]:
```
model.summary()
```

```
Model: "sequential"


 Layer (type)                          Output Shape
↪Param #

 lstm (LSTM)                           (None, 100)
↪40,800

 dense (Dense)                         (None, 1)
↪101



 Total params: 40,901 (159.77 KB)

 Trainable params: 40,901 (159.77 KB)

 Non-trainable params: 0 (0.00 B)
```

[23]:
```
model.fit(generator,epochs = 100)
```

```
Epoch 1/100
C:\Users\User\AppData\Local\Programs\Python\Python310\lib\site-
packages\keras\src\trainers\data_adapters\py_dataset_adapter.py:121:
UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in
its constructor. `**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will be
ignored.
  self._warn_if_super_not_called()
452/452              2s 2ms/step -
loss: 0.0539
Epoch 2/100
452/452              1s 2ms/step -
loss: 0.0173
Epoch 3/100
452/452              1s 2ms/step -
loss: 0.0143
Epoch 4/100
452/452              1s 2ms/step -
loss: 0.0099
Epoch 5/100
452/452              1s 2ms/step -
```

```
loss: 0.0071
Epoch 6/100
452/452                1s 2ms/step -
loss: 0.0082
Epoch 7/100
452/452                1s 2ms/step -
loss: 0.0079
Epoch 8/100
452/452                1s 2ms/step -
loss: 0.0070
Epoch 9/100
452/452                1s 3ms/step -
loss: 0.0067
Epoch 10/100
452/452                1s 3ms/step -
loss: 0.0088
Epoch 11/100
452/452                1s 2ms/step -
loss: 0.0069
Epoch 12/100
452/452                1s 2ms/step -
loss: 0.0063
Epoch 13/100
452/452                1s 2ms/step -
loss: 0.0082
Epoch 14/100
452/452                1s 2ms/step -
loss: 0.0073
Epoch 15/100
452/452                1s 2ms/step -
loss: 0.0057
Epoch 16/100
452/452                1s 2ms/step -
loss: 0.0061
Epoch 17/100
452/452                1s 2ms/step -
loss: 0.0060
Epoch 18/100
452/452                1s 2ms/step -
loss: 0.0060
Epoch 19/100
452/452                1s 3ms/step -
loss: 0.0058
Epoch 20/100
452/452                1s 2ms/step -
loss: 0.0066
Epoch 21/100
452/452                1s 2ms/step -
```

```
loss: 0.0057
Epoch 22/100
452/452              1s 2ms/step -
loss: 0.0056
Epoch 23/100
452/452              1s 3ms/step -
loss: 0.0063
Epoch 24/100
452/452              1s 2ms/step -
loss: 0.0057
Epoch 25/100
452/452              1s 2ms/step -
loss: 0.0053
Epoch 26/100
452/452              1s 2ms/step -
loss: 0.0060
Epoch 27/100
452/452              1s 2ms/step -
loss: 0.0058
Epoch 28/100
452/452              1s 3ms/step -
loss: 0.0072
Epoch 29/100
452/452              1s 3ms/step -
loss: 0.0068
Epoch 30/100
452/452              1s 2ms/step -
loss: 0.0057
Epoch 31/100
452/452              1s 3ms/step -
loss: 0.0059
Epoch 32/100
452/452              1s 3ms/step -
loss: 0.0065
Epoch 33/100
452/452              1s 3ms/step -
loss: 0.0055
Epoch 34/100
452/452              1s 2ms/step -
loss: 0.0059
Epoch 35/100
452/452              1s 2ms/step -
loss: 0.0063
Epoch 36/100
452/452              1s 2ms/step -
loss: 0.0063
Epoch 37/100
452/452              1s 3ms/step -
```

```
loss: 0.0060
Epoch 38/100
452/452              1s 3ms/step -
loss: 0.0057
Epoch 39/100
452/452              1s 3ms/step -
loss: 0.0057
Epoch 40/100
452/452              1s 2ms/step -
loss: 0.0047
Epoch 41/100
452/452              1s 3ms/step -
loss: 0.0056
Epoch 42/100
452/452              1s 2ms/step -
loss: 0.0054
Epoch 43/100
452/452              1s 2ms/step -
loss: 0.0061
Epoch 44/100
452/452              1s 2ms/step -
loss: 0.0063
Epoch 45/100
452/452              1s 2ms/step -
loss: 0.0055
Epoch 46/100
452/452              1s 2ms/step -
loss: 0.0061
Epoch 47/100
452/452              1s 2ms/step -
loss: 0.0055
Epoch 48/100
452/452              1s 3ms/step -
loss: 0.0059
Epoch 49/100
452/452              1s 2ms/step -
loss: 0.0051
Epoch 50/100
452/452              1s 2ms/step -
loss: 0.0055
Epoch 51/100
452/452              1s 3ms/step -
loss: 0.0049
Epoch 52/100
452/452              1s 2ms/step -
loss: 0.0062
Epoch 53/100
452/452              1s 2ms/step -
```

```
loss: 0.0059
Epoch 54/100
452/452              1s 3ms/step -
loss: 0.0060
Epoch 55/100
452/452              1s 2ms/step -
loss: 0.0048
Epoch 56/100
452/452              1s 2ms/step -
loss: 0.0057
Epoch 57/100
452/452              1s 2ms/step -
loss: 0.0053
Epoch 58/100
452/452              1s 2ms/step -
loss: 0.0051
Epoch 59/100
452/452              1s 2ms/step -
loss: 0.0055
Epoch 60/100
452/452              1s 3ms/step -
loss: 0.0050
Epoch 61/100
452/452              1s 2ms/step -
loss: 0.0054
Epoch 62/100
452/452              1s 2ms/step -
loss: 0.0052
Epoch 63/100
452/452              1s 3ms/step -
loss: 0.0059
Epoch 64/100
452/452              1s 2ms/step -
loss: 0.0063
Epoch 65/100
452/452              1s 2ms/step -
loss: 0.0065
Epoch 66/100
452/452              1s 2ms/step -
loss: 0.0056
Epoch 67/100
452/452              1s 3ms/step -
loss: 0.0048
Epoch 68/100
452/452              1s 3ms/step -
loss: 0.0051
Epoch 69/100
452/452              1s 2ms/step -
```

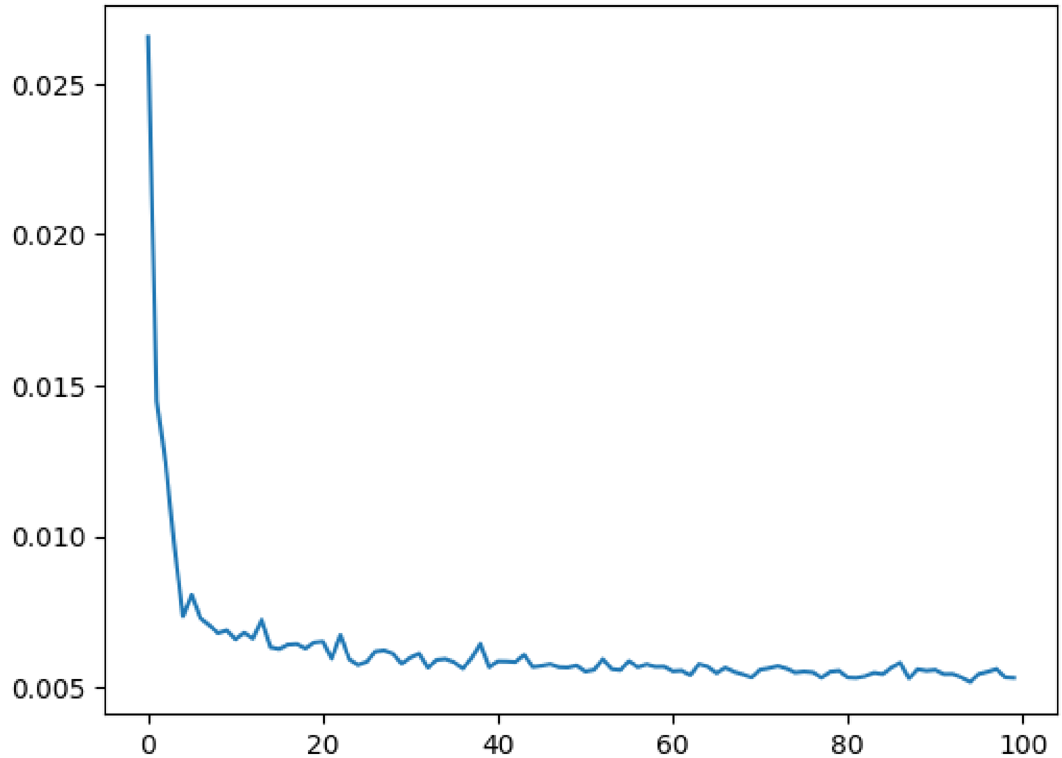
```
loss: 0.0059
Epoch 70/100
452/452           1s 2ms/step -
loss: 0.0052
Epoch 71/100
452/452           1s 3ms/step -
loss: 0.0053
Epoch 72/100
452/452           1s 3ms/step -
loss: 0.0060
Epoch 73/100
452/452           1s 3ms/step -
loss: 0.0058
Epoch 74/100
452/452           1s 2ms/step -
loss: 0.0053
Epoch 75/100
452/452           1s 3ms/step -
loss: 0.0057
Epoch 76/100
452/452           1s 3ms/step -
loss: 0.0055
Epoch 77/100
452/452           1s 2ms/step -
loss: 0.0058
Epoch 78/100
452/452           1s 3ms/step -
loss: 0.0059
Epoch 79/100
452/452           1s 2ms/step -
loss: 0.0056
Epoch 80/100
452/452           1s 3ms/step -
loss: 0.0057
Epoch 81/100
452/452           1s 2ms/step -
loss: 0.0050
Epoch 82/100
452/452           1s 3ms/step -
loss: 0.0047
Epoch 83/100
452/452           1s 2ms/step -
loss: 0.0052
Epoch 84/100
452/452           1s 3ms/step -
loss: 0.0051
Epoch 85/100
452/452           1s 2ms/step -
```

```
loss: 0.0048
Epoch 86/100
452/452              1s 3ms/step -
loss: 0.0052
Epoch 87/100
452/452              1s 2ms/step -
loss: 0.0055
Epoch 88/100
452/452              1s 3ms/step -
loss: 0.0051
Epoch 89/100
452/452              1s 2ms/step -
loss: 0.0055
Epoch 90/100
452/452              1s 3ms/step -
loss: 0.0047
Epoch 91/100
452/452              1s 2ms/step -
loss: 0.0049
Epoch 92/100
452/452              1s 3ms/step -
loss: 0.0060
Epoch 93/100
452/452              1s 2ms/step -
loss: 0.0058
Epoch 94/100
452/452              1s 3ms/step -
loss: 0.0044
Epoch 95/100
452/452              1s 3ms/step -
loss: 0.0044
Epoch 96/100
452/452              1s 2ms/step -
loss: 0.0055
Epoch 97/100
452/452              1s 3ms/step -
loss: 0.0056
Epoch 98/100
452/452              1s 2ms/step -
loss: 0.0049
Epoch 99/100
452/452              1s 3ms/step -
loss: 0.0051
Epoch 100/100
452/452              1s 2ms/step -
loss: 0.0049
```

[23]: <keras.src.callbacks.history.History at 0x2450ff6aec0>

[24]:
```
loss_per_epoch = model.history.history['loss']
plt.plot(range(len(loss_per_epoch)),loss_per_epoch)
```

[24]: [<matplotlib.lines.Line2D at 0x24513963070>]




[25]:
```
last_train_batch = scaled_train[-n_input:]
```

[26]:
```
last_train_batch = last_train_batch.reshape((1,n_input,n_features))
```

[27]:
```
model.predict(last_train_batch)
```

```
1/1              0s 164ms/step
```

[27]: array([[0.48843354]], dtype=float32)

[28]:
```
scaled_test[0]
```

[28]: array([0.51111111])

[29]:
```
test_predictions = []
first_eval_batch =scaled_train[-n_input:]
```

```
current_batch = first_eval_batch.reshape((1,n_input,n_features))

for i in range(len(test)):
    current_pred = model.predict(current_batch)[0]
    test_predictions.append(current_pred)
    current_batch = np.append(current_batch[:,1:,:],[[current_pred]],axis=1)
```

```
1/1             0s 40ms/step
1/1             0s 43ms/step
1/1             0s 31ms/step
1/1             0s 27ms/step
1/1             0s 26ms/step
1/1             0s 25ms/step
1/1             0s 40ms/step
1/1             0s 26ms/step
1/1             0s 26ms/step
1/1             0s 34ms/step
1/1             0s 28ms/step
1/1             0s 25ms/step
```

[30]:
```
test_predictions
```

[30]:
```
[array([0.48843354], dtype=float32),
 array([0.56507766], dtype=float32),
 array([0.69018567], dtype=float32),
 array([0.7062051], dtype=float32),
 array([0.5210469], dtype=float32),
 array([0.48929432], dtype=float32),
 array([0.57015634], dtype=float32),
 array([0.4155165], dtype=float32),
 array([0.4212395], dtype=float32),
 array([0.39995039], dtype=float32),
 array([0.42006385], dtype=float32),
 array([0.4685017], dtype=float32)]
```

[31]:
```
true_predictions =scaler.inverse_transform(test_predictions)
```

[32]:
```
test['predictions']=true_predictions
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_18820\2081619921.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  test['predictions']=true_predictions
```

[33]:
```
test.plot(figsize=(12,6))
```

[33]: <Axes: xlabel='Month'>


[37]:
```
future_predictions = []
future_steps = 36  # Number of future months to predict

# Start with the last known batch
current_batch = scaled_train[-n_input:].reshape((1, n_input, n_features))

for i in range(future_steps):
    # Predict the next value
    current_pred = model.predict(current_batch)[0]
    future_predictions.append(current_pred)

    # Update the batch (remove the oldest and add the new prediction)
    current_batch = np.append(current_batch[:, 1:, :], [[current_pred]], axis=1)

# Convert predictions back to original scale (if necessary)
future_predictions = scaler.inverse_transform(np.array(future_predictions).
 ↪reshape(-1, 1))
```

```
1/1              0s 44ms/step
1/1              0s 43ms/step
1/1              0s 25ms/step
1/1              0s 30ms/step
1/1              0s 28ms/step
1/1              0s 25ms/step
```

```
1/1              0s 26ms/step
1/1              0s 26ms/step
1/1              0s 26ms/step
1/1              0s 33ms/step
1/1              0s 31ms/step
1/1              0s 26ms/step
1/1              0s 25ms/step
1/1              0s 26ms/step
1/1              0s 26ms/step
1/1              0s 26ms/step
1/1              0s 25ms/step
1/1              0s 26ms/step
1/1              0s 26ms/step
1/1              0s 26ms/step
1/1              0s 25ms/step
1/1              0s 26ms/step
1/1              0s 35ms/step
1/1              0s 31ms/step
1/1              0s 31ms/step
1/1              0s 27ms/step
1/1              0s 25ms/step
1/1              0s 26ms/step
1/1              0s 25ms/step
1/1              0s 27ms/step
1/1              0s 25ms/step
1/1              0s 26ms/step
1/1              0s 26ms/step
1/1              0s 26ms/step
1/1              0s 26ms/step
1/1              0s 25ms/step
```

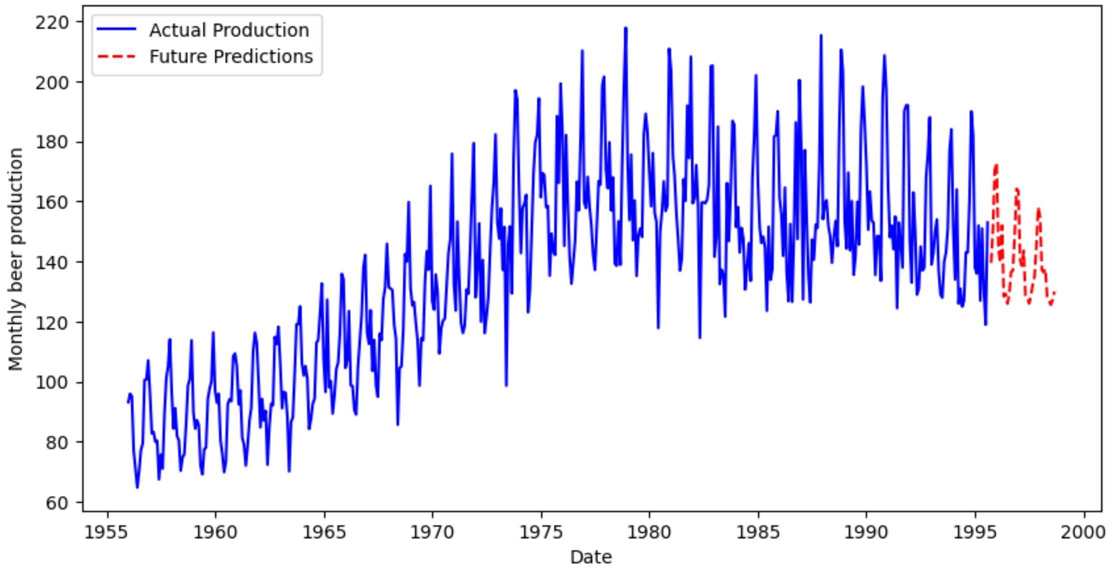
[38]:

```
# Create future dates
last_date = df.index[-1]  # Get last date in your dataset
future_dates = pd.date_range(start=last_date, periods=future_steps + 1,␣
 ↪freq='M')[1:]

# Plot the results
plt.figure(figsize=(10,5))
plt.plot(df.index, df['Monthly beer production'], label="Actual Production",␣
 ↪color="blue")
plt.plot(future_dates, future_predictions, label="Future Predictions",␣
 ↪color="red", linestyle="dashed")
plt.xlabel("Date")
plt.ylabel("Monthly beer production")
plt.legend()
plt.show()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_18820\1302364203.py:3: FutureWarning:
```

```
'M' is deprecated and will be removed in a future version, please use 'ME'
instead.
  future_dates = pd.date_range(start=last_date, periods=future_steps + 1,
freq='M')[1:]
```




[39]:
```
future_df = pd.DataFrame({
    "Date": future_dates,
    "Predicted Production": future_predictions.flatten()
})
```

[40]:
```
print(future_df)
```

```
          Date  Predicted Production
0   1995-09-30            139.530334
1   1995-10-31            151.256882
2   1995-11-30            170.398407
3   1995-12-31            172.849380
4   1996-01-31            144.520172
5   1996-02-29            139.662033
6   1996-03-31            152.033920
7   1996-04-30            128.374023
8   1996-05-31            129.249634
9   1996-06-30            125.992409
10  1996-07-31            129.069763
11  1996-08-31            136.480759
12  1996-09-30            137.061325
13  1996-10-31            148.938248
14  1996-11-30            164.203125
```

```
15 1996-12-31           163.456909
16 1997-01-31           140.542236
17 1997-02-28           138.597061
18 1997-03-31           143.589691
19 1997-04-30           128.607300
20 1997-05-31           127.953621
21 1997-06-30           126.059906
22 1997-07-31           128.496048
23 1997-08-31           132.584885
24 1997-09-30           135.072632
25 1997-10-31           145.555573
26 1997-11-30           158.043915
27 1997-12-31           154.931046
28 1998-01-31           137.313141
29 1998-02-28           136.453201
30 1998-03-31           137.564606
31 1998-04-30           128.062149
32 1998-05-31           126.895393
33 1998-06-30           125.608536
34 1998-07-31           127.277901
35 1998-08-31           130.028458
```

[ ]: