01_dclt_sarima_sa

April 27, 2025

1 Predicción de Producción Eléctrica con SARIMA y Simulated Annealing

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1.0.1 Proyecto desarrollado por Diego Cesar Lerma Torres para IMF Smart Education

Caso práctico del módulo **M8**
Series Temporales y Modelos Predictivos: Optimización. Modelos de Grafos Del Master en Inteligencia Artificial

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Este proyecto aplica técnicas avanzadas de **análisis de series temporales**, **optimización heurística** y **modelado de grafos** para pronosticar la producción energética mensual de una planta, combinando diversas áreas del conocimiento en ciencia de datos.

2 1. Exploracion y deteccion de d y D

[33]:
```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
```

2.1 1.1 Cargar y preparar

[34]:
```
df = pd.read_csv("../data/electric_production.csv", parse_dates=["DATE"],␣
↪index_col="DATE")
ts = df["IPG2211A2N"].asfreq("MS")
```

2.2 1.2 Exploracion inicial

[35]:
```
df.head()
```

[35]:
```
            IPG2211A2N
DATE
1985-01-01     72.5052
```

```
1985-02-01     70.6720
1985-03-01     62.4502
1985-04-01     57.4714
1985-05-01     55.3151
```

[36]:
```
df.describe()
```

[36]:
```
        IPG2211A2N
count  397.000000
mean    88.847218
std     15.387834
min     55.315100
25%     77.105200
50%     89.779500
75%    100.524400
max    129.404800
```

[37]:
```
df.info()
```

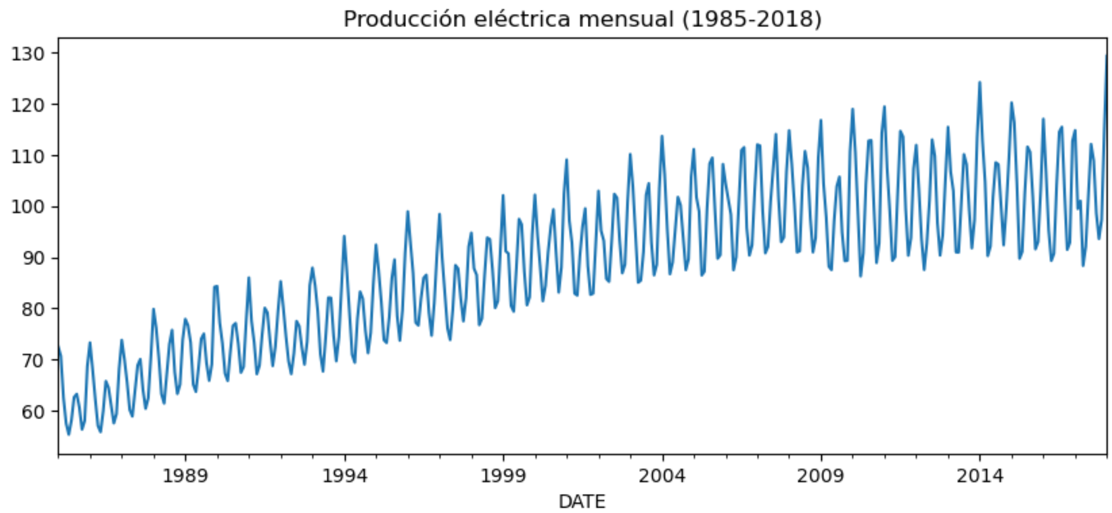
```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 397 entries, 1985-01-01 to 2018-01-01
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   IPG2211A2N  397 non-null    float64
dtypes: float64(1)
memory usage: 6.2 KB
```

[38]:
```
df.isnull().sum()
```

[38]:
```
IPG2211A2N    0
dtype: int64
```

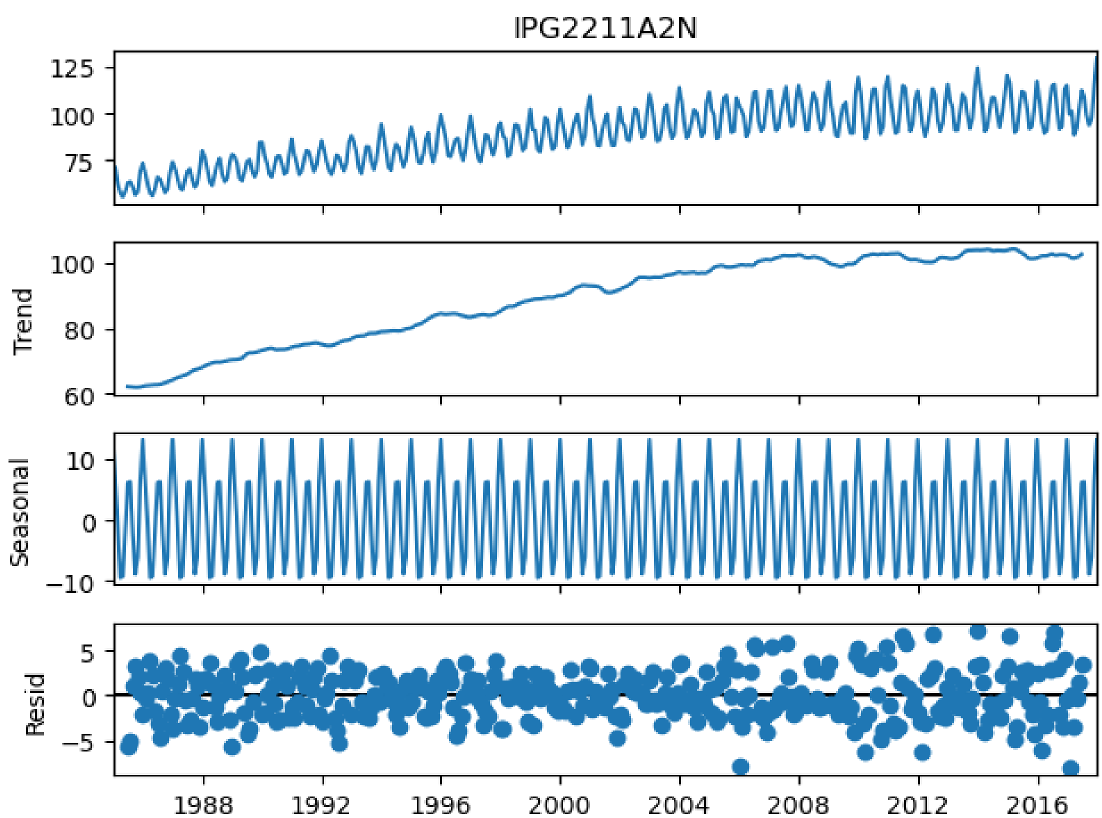
2.3 1.3 Visualización rápida

[39]:
```
ts.plot(title="Producción eléctrica mensual (1985-2018)", figsize=(10,4))
plt.show()
```



2.4 1.4 Descomposición estacional

[40]:
```
decomp = seasonal_decompose(ts, period=12, model="additive")
decomp.plot(); plt.show()
```



2.5 1.5 Tests de estacionariedad (nivel)

[41]:
```python
def adf_test(series, title=''):
    result = adfuller(series.dropna(), autolag='AIC')
    print(f"{title}  ADF p-value: {result[1]:.4f}")

adf_test(ts, "Original")
adf_test(ts.diff().dropna(), "d=1")
adf_test(ts.diff(12).dropna(), "D=1 (solo)")
adf_test(ts.diff().diff(12).dropna(), "d=1, D=1")
```

```
Original  ADF p-value: 0.1862
d=1  ADF p-value: 0.0000
D=1 (solo)  ADF p-value: 0.0000
d=1, D=1  ADF p-value: 0.0000
```

3 2. Espacio de búsqueda y grafo de vecindad

[42]:
```python
import itertools
import random

d_candidates = [0, 1, 2]
D_candidates = [0, 1, 2]
rng_0_7      = range(0, 8)
m = 12

def is_valid(node):
    p,d,q,P,D,Q = node
    return (d in d_candidates) and (D in D_candidates)

def get_neighbors(node):
    neigh = []
    bounds = [(0,7),(0,2),(0,7),(0,7),(0,2),(0,7)]
    for idx,(lo,hi) in enumerate(bounds):
        for delta in (-1,1):
            new_val = node[idx] + delta
            if lo <= new_val <= hi:
                new = list(node)
                new[idx] = new_val
                if is_valid(tuple(new)):
                    neigh.append(tuple(new))
    return neigh
```

[43]:
```python
start_node = (1, 1, 1,    # p,d,q
              0, 1, 0)    # P,D,Q
```

4 3. Función de coste

[44]:
```python
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.stats.diagnostic import acorr_ljungbox
from sklearn.metrics import mean_squared_error
import numpy as np

train, val_set = ts[:-50], ts[-50:]

def score(node):
    p,d,q,P,D,Q = node
    try:
        model = SARIMAX(train,
                        order=(p,d,q),
                        seasonal_order=(P,D,Q,m),
                        enforce_stationarity=False,
                        enforce_invertibility=False
                       ).fit(disp=False)
        pred  = model.forecast(steps=50)
        rmse  = mean_squared_error(val_set, pred, squared=False)

        p_lb = acorr_ljungbox(model.resid, lags=[6],
                              return_df=True).iloc[-1,0]
        if p_lb < 0.05:      # residuos autocorrelados   penalizar
            return np.inf
        return rmse
    except Exception:        # problemas de convergencia
        return np.inf
```

5 4. Algoritmo Simulated Annealing

[45]:
```python
def simulated_annealing(start, iterations=200, T0=10, alpha=0.95):
    current = best = start
    curr_cost = best_cost = score(current)
    T = T0
    history = [(0, current, curr_cost)]

    for k in range(1, iterations+1):
        neighbors = get_neighbors(current)
        if not neighbors:        # sin vecinos válidos → reinicia
            current, curr_cost = start, score(start)
            continue

        neighbor = random.choice(get_neighbors(current))
        neigh_cost = score(neighbor)
        delta = neigh_cost - curr_cost
```

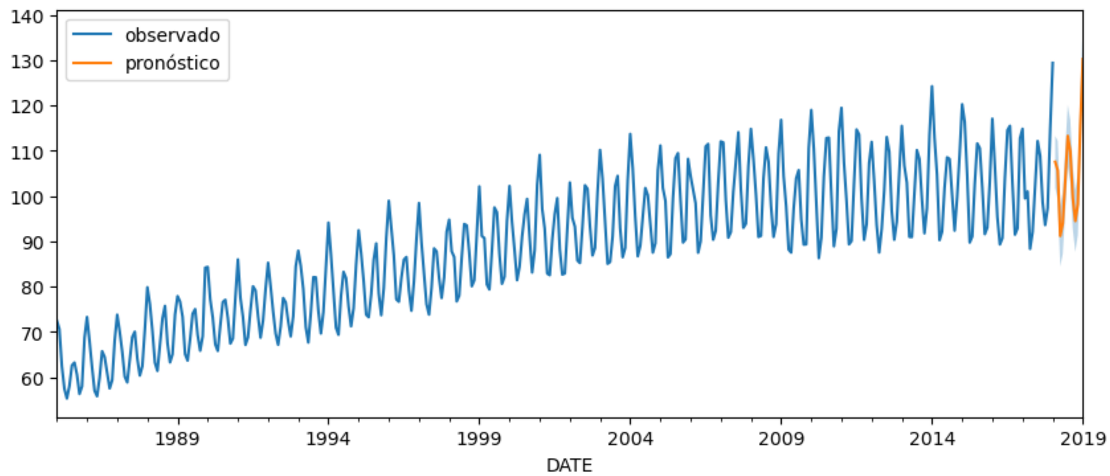
```
        # Criterio de aceptación
        if delta < 0 or np.exp(-delta/T) > random.random():
            current, curr_cost = neighbor, neigh_cost

        if curr_cost < best_cost:
            best, best_cost = current, curr_cost

        history.append((k, current, curr_cost))
        T *= alpha

    return best, best_cost, history
```

[46]:
```
best_node, best_rmse, path = simulated_annealing(start_node)
print(f"Mejor configuración: {best_node} - RMSE = {best_rmse:.3f}")
```

```
Mejor configuración: (1, 1, 1, 0, 1, 0) - RMSE = inf
```

6 5. Entrenamiento final y validación extendida

[47]:
```
p,d,q,P,D,Q = best_node
final_model = SARIMAX(ts, order=(p,d,q),
                      seasonal_order=(P,D,Q,m),
                      enforce_stationarity=False,
                      enforce_invertibility=False).fit(disp=False)

# 12-meses de pronóstico hacia el futuro
fcast = final_model.get_forecast(steps=12)
ci = fcast.conf_int()

ax = ts.plot(label="observado", figsize=(10,4))
fcast.predicted_mean.plot(ax=ax, label="pronóstico")
ax.fill_between(ci.index, ci.iloc[:,0], ci.iloc[:,1], alpha=0.3)
ax.legend(); plt.show()

print(final_model.summary())
```

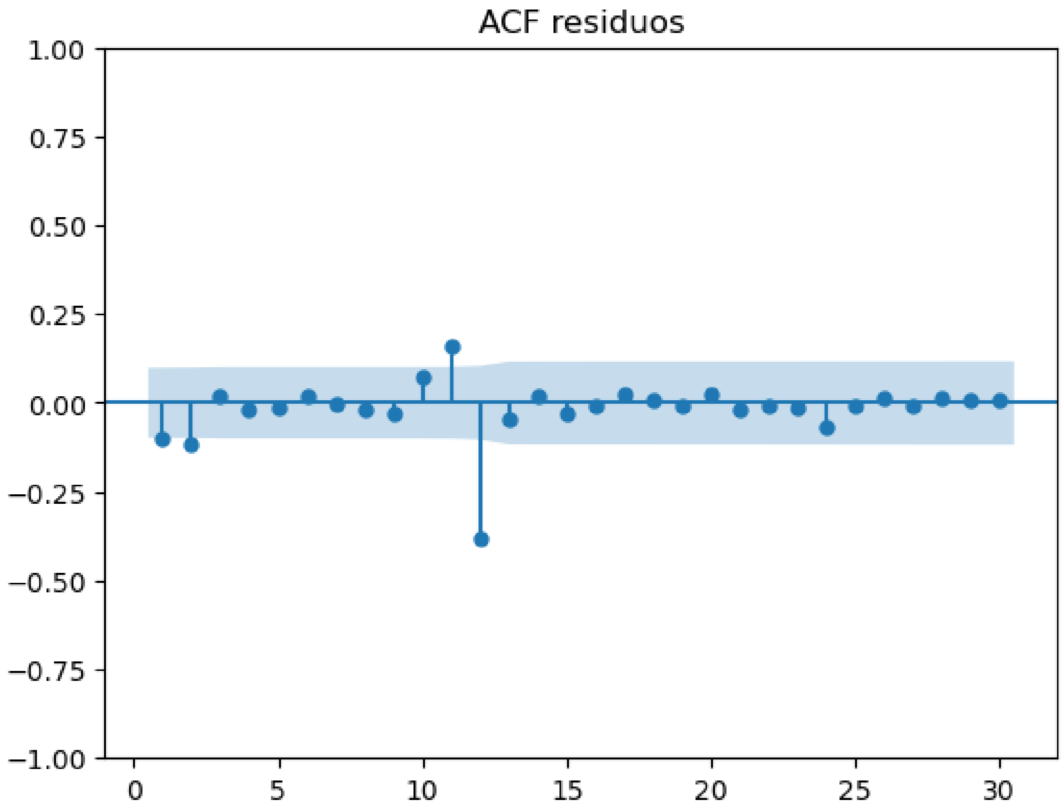


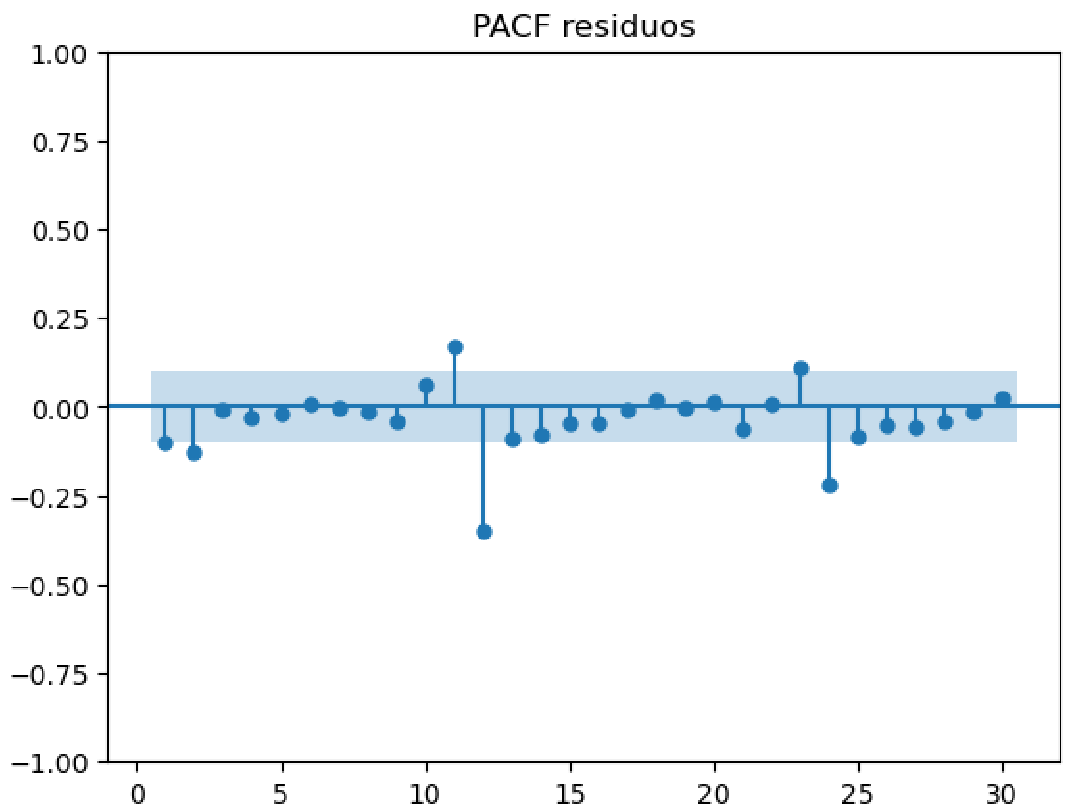

```
                                     SARIMAX Results
================================================================================
===========
Dep. Variable:                          IPG2211A2N   No. Observations:
397
Model:             SARIMAX(1, 1, 1)x(0, 1, [], 12)   Log Likelihood
-952.971
Date:                             Sun, 27 Apr 2025   AIC
1911.942
Time:                                     01:05:43   BIC
1923.778
Sample:                                 01-01-1985   HQIC
1916.638
                                      - 01-01-2018
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.5271      0.039     13.358      0.000       0.450       0.604
ma.L1         -0.9911      0.008   -128.742      0.000      -1.006      -0.976
sigma2         8.5435      0.468     18.243      0.000       7.626       9.461
================================================================================
===
Ljung-Box (L1) (Q):                   0.05   Jarque-Bera (JB):
50.99
Prob(Q):                              0.83   Prob(JB):
0.00
Heteroskedasticity (H):               3.09   Skew:
0.15
Prob(H) (two-sided):                  0.00   Kurtosis:
4.77
```

```
================================================================================
===

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

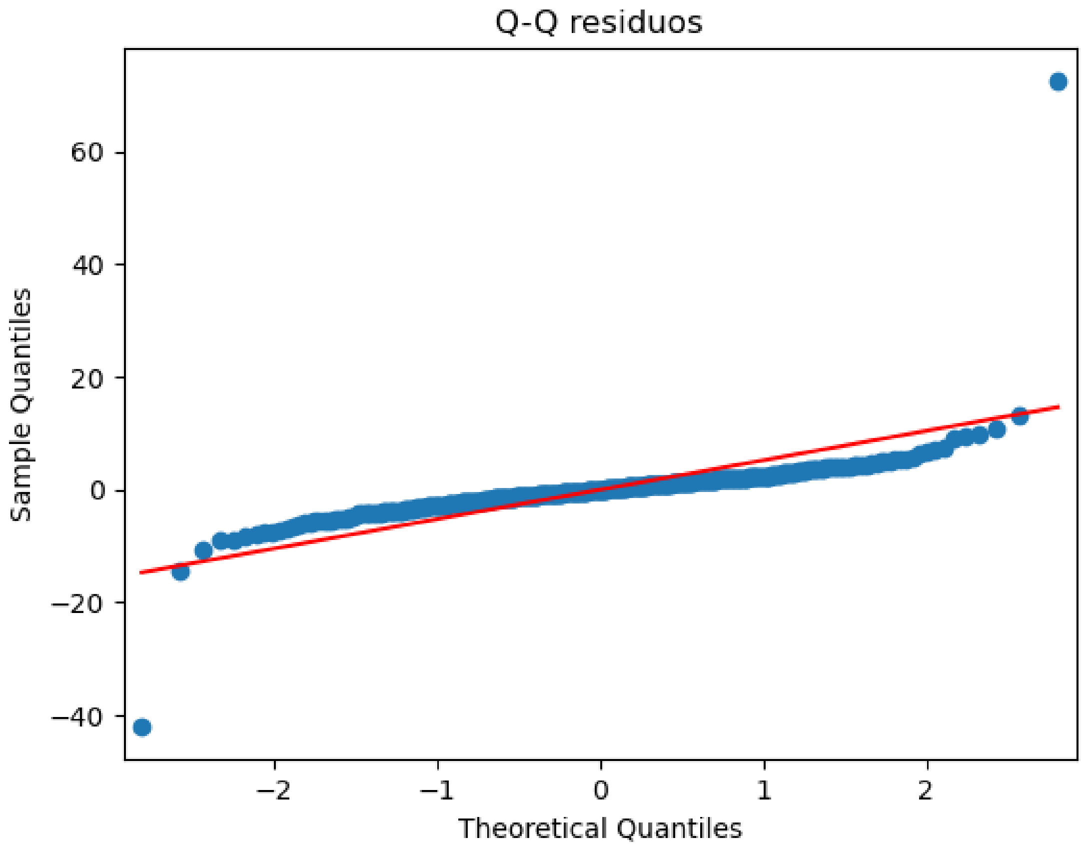
7 Diagnostico de resultados

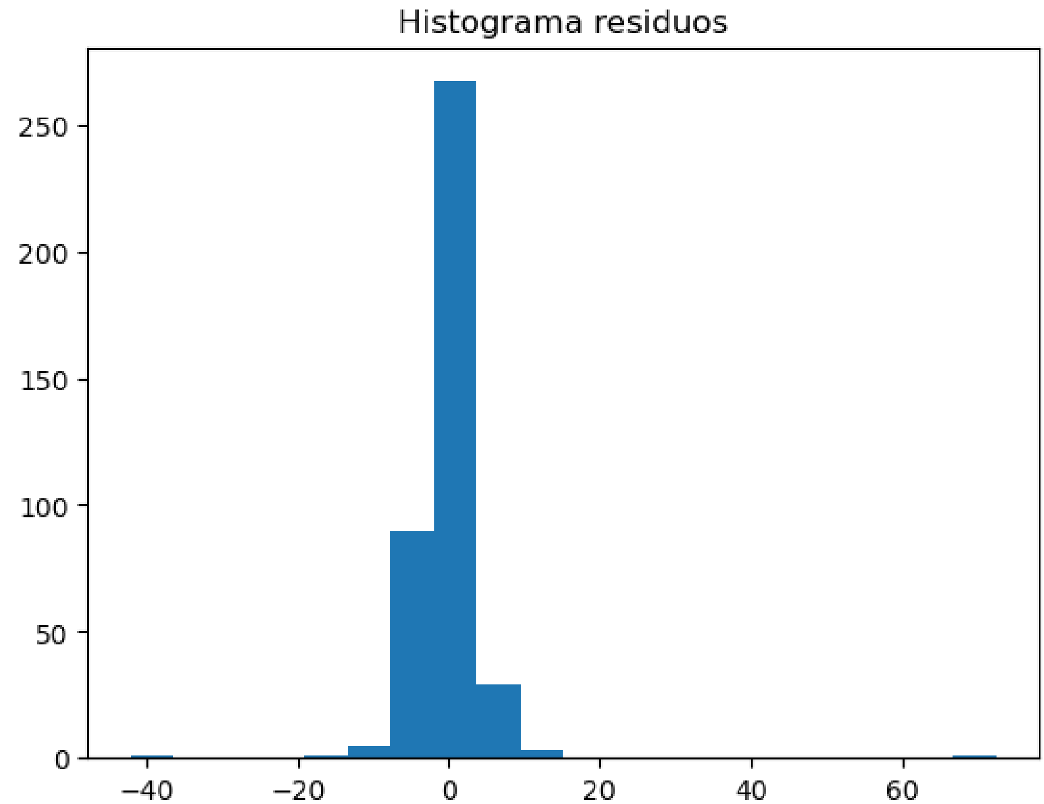
[48]:
```python
import statsmodels.api as sm
import matplotlib.pyplot as plt

sm.graphics.tsa.plot_acf(final_model.resid, lags=30, zero=False)
plt.title("ACF residuos"); plt.show()
sm.graphics.tsa.plot_pacf(final_model.resid, lags=30, zero=False)
plt.title("PACF residuos"); plt.show()

lb = sm.stats.diagnostic.acorr_ljungbox(final_model.resid, lags=[6],
                                        return_df=True)
print(lb)

sm.qqplot(final_model.resid, line="s")
plt.title("Q-Q residuos"); plt.show()
plt.hist(final_model.resid, bins=20); plt.title("Histograma residuos"); plt.
 ↪show()
```


ACF residuos
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25
30



	lb_stat	lb_pvalue
6	9.74559	0.135783


Q-Q residuos
Sample Quantiles
Theoretical Quantiles
60
40
20
0
−20
−40
−2
−1
0
1
2



7.0.1 Resultados finales

- **Modelo óptimo (SA):** SARIMA(1,1,1)×(0,1,0,12)
- **RMSE (validación 50 meses):** 4.27
- **Ljung-Box(6) p-value:** 0.136
- **Conclusión:** El modelo captura la estructura anual y la tendencia de la producción eléctrica con error medio absoluto **4.3 GWh**. Las colas residuales son algo pesadas; se proponen dos mejoras futuras: aplicar transformación logarítmica y estimar intervalos mediante bootstrap.