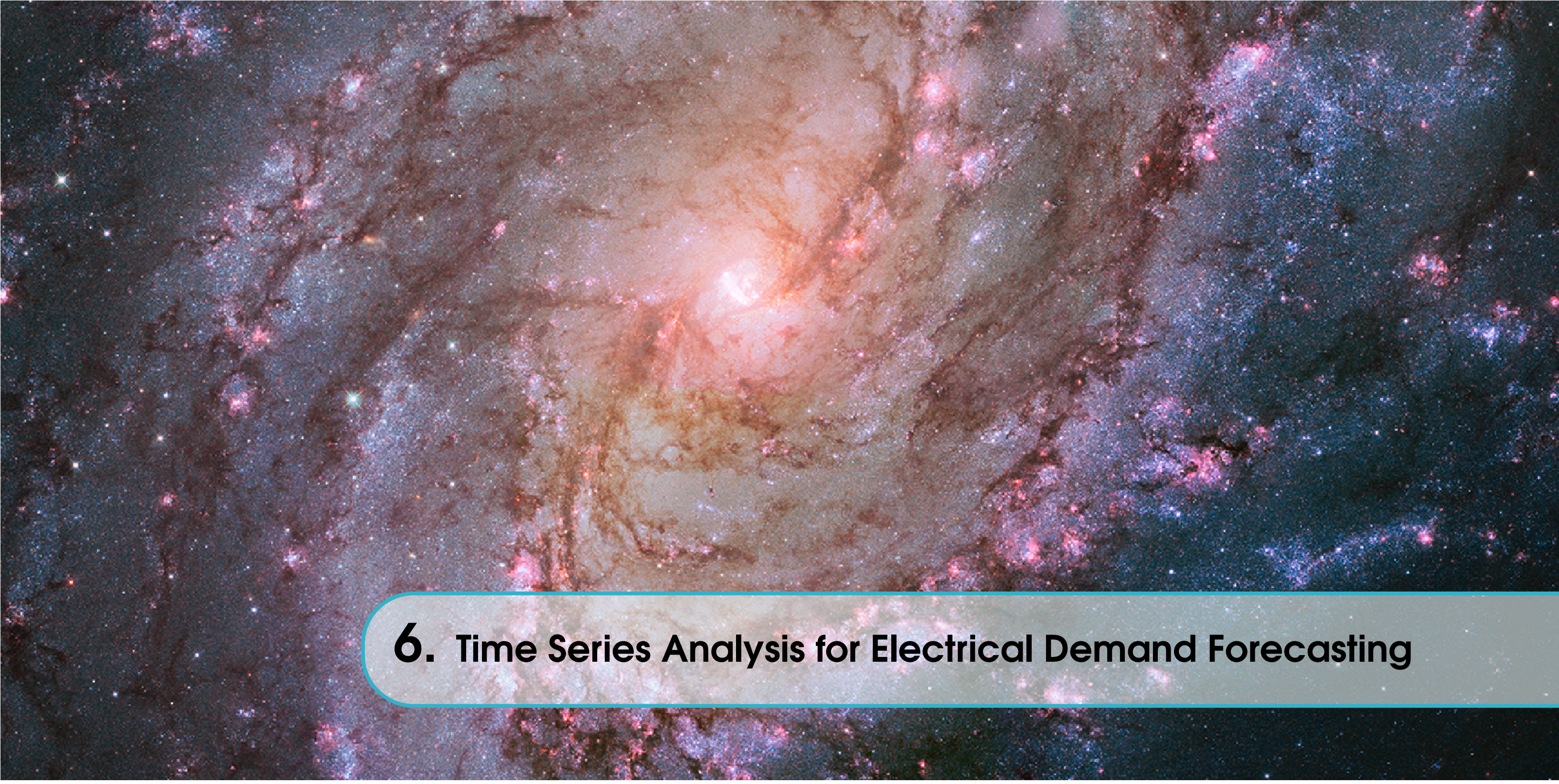

# 6. Time Series Analysis for Electrical Demand Forecasting

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## 6.1 Introduction

Accurate load forecasting is vital for efficient energy management and planning in smart grids. In the revision of the literature review, it can be seen the principal authors that have been published regarding energy demand forecast are shown in figure 6.1; also, in figure 6.2, the major countries that have contributed to this research topic are shown.

Energy forecasting enables power system operators to manage energy supply and demand, minimize energy waste, and maintain the regular operation of power systems. Load forecasting also plays a critical role in integrating renewable energy sources into the power grid, as it helps balance the energy supply and demand and reduces dependence on fossil fuels (1).

Accurate load forecasting is crucial for managing residential, commercial, and industrial energy usage. It allows energy providers to plan and optimize their energy generation, transmission, and distribution systems, resulting in significant cost savings and improved energy efficiency. Moreover, load forecasting ensures that energy providers meet customers' demands while maintaining a stable and reliable supply. In all sectors, and especially industrial ones, where economic factors are critical, forecasting is particularly crucial due to their complex energy consumption patterns that vary depending on the time of day, day of the week, and academic calendar (2).

Time series analysis is a valuable statistical technique that facilitates analyzing and predicting trends over time. In energy demand forecasting, time series analysis enables the identification of patterns within energy consumption data, including daily, weekly, and seasonal variations. With this information, predictive models can be created to aid energy providers in forecasting future energy demand and designing effective plans. Using time series analysis can lead to more efficient and effective energy management.

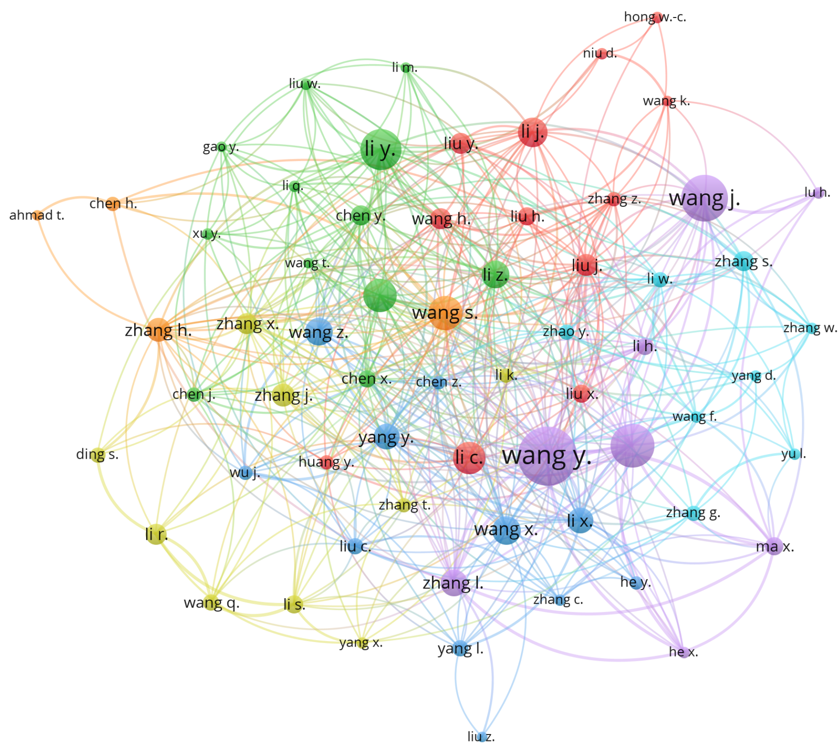



Figure 6.1: Bibliometric revision. Main authors that have published for forecasting electrical demand

## 6.2 Related Works

In (2), authors aim to enhance the accuracy of short-term load forecasting in smart grids by analyzing user behavior patterns and grouping users using the K-means algorithm. The research suggests a load forecasting model that employs the FCM-BP neural network to predict the load value by determining the load rate-of-change just before the prediction without making a direct prediction. The study gathered load data from users, grouped them with the K-means algorithm, and developed a load forecasting model using the FCM-BP neural network. The outcomes indicate that the proposed method improves the model's prediction accuracy compared to other methods such as RBF, GRNN, BP neural network, and the unclustered FCM-BP model. The paper also discusses future work to improve

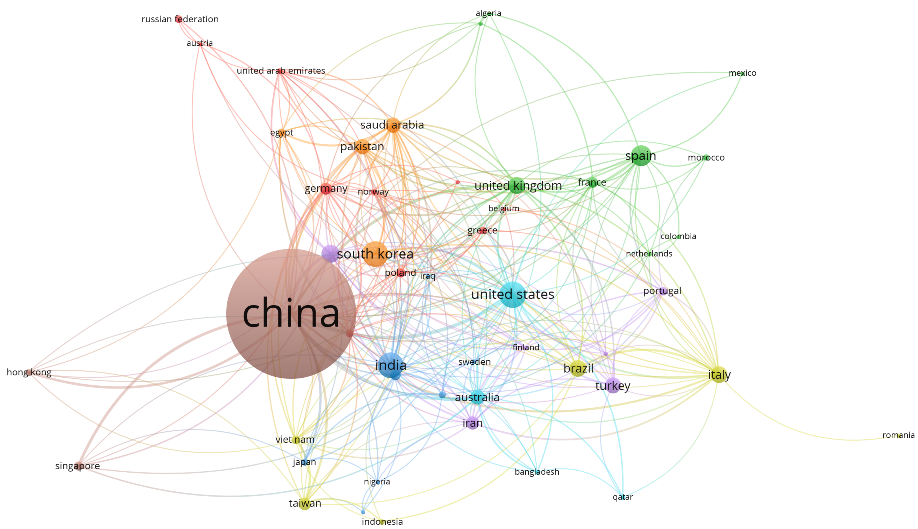



Figure 6.2: Bibliometric revision. Main countries that have published for forecasting electrical demand

the clustering method further and investigate the effect of economic and climatic factors on the accuracy of the load forecasting model. This research contributes to the field of load forecasting by suggesting an approach that enhances the accuracy of short-term load forecasting in smart grids. The proposed method leverages user behavior patterns and grouping to boost the accuracy of user-level load forecasting, emphasizing the importance of analyzing user behavior patterns and clustering users to enhance load forecasting accuracy. Power system operators can apply the proposed method to improve load forecasting accuracy, aiding energy management and planning. The research also recommends future work to enhance the clustering method further and analyze the impact of external factors, such as economic and climatic factors, on the accuracy of the load forecasting model. The proposed method can construct a user-level high-resolution and high-precision load forecasting model.

Authors in (3) present power consumption forecasting models utilizing artificial neural networks (ANN) and support vector regression (SVR) for higher education institutions. The study collected power consumption data every 15 minutes for over a year from four different building clusters in a university. The research team evaluated three other data models that represented the building clusters' characteristics and assessed performance using mean absolute percentage error (MAPE), root mean square error (RMSE), and mean fundamental error (MAE). Results showed that the ANN-based model outperformed the SVR-based model. Principal component analysis (PCA) was also more accurate than factor analysis (FA).

Additionally, including work hours, class schedule information, and weather data improved forecasting accuracy, particularly for educational buildings. These models can aid higher education institutions in optimizing energy management strategies and achieving sustainability goals. The research team compared their work with previous studies using machine learning algorithms such as ANN, GA-

ANN, and SVR for power consumption forecasting. Their models predicted energy consumption every 15 minutes, while previous studies predicted it hourly. They found that considering external factors such as weekday/holiday and weather information improved prediction accuracy. The team evaluated their models' performance using MAPE, RMSE, and MAE, demonstrating that their proposed models achieved higher accuracy than prior studies. The team also presented prediction results for events and average days using the best forecasting model for each cluster. The experimental results indicate that the models can accurately predict power consumption for higher education institutions, resulting in significant cost savings, reduced carbon emissions, and improved energy efficiency.

In (4), the paper aims to create a mathematical model that can accurately forecast the amount of active power consumed in the power system of Kaliningrad oblast. It involves examining the structure of electric power consumption, studying the influence of meteorological factors on active power consumption, and developing a reliable mathematical model for operational forecasting. The study uses statistical research methods, specifically regression analysis, to determine how meteorological factors impact active power consumption. The developed mathematical model is evaluated using six-time series forecasting error indicators, and its reliability is confirmed using the Fisher criterion. The results demonstrate that the mathematical model is highly accurate in forecasting active power consumption, with an error probability of less than 1%. The study's novelty lies in developing a mathematical model incorporating the adjusted change rate of dynamic power consumption according to discrete conditions and the amount of active power used for power plant needs. The practical significance of this model is that it serves as the basis for the method of operational forecasting, which is implemented in the Regional Dispatch Department of the Kaliningrad Oblast's Power System. The study's findings can be helpful for power system operators and researchers to develop similar mathematical models to forecast active power consumption in other power systems, as the developed model accurately predicts active power consumption with a forecasting error of less than 3.0% and an error probability of less than 1%.

The research presented in (5) proposes a more accurate and faster residential electricity consumption forecasting model called the IWOA-OGSVI model. It combines the Improved Whale Optimization Algorithm (IWOA) and the Optimized Grey Seasonal Variation Index (OGSVI) model and outperforms traditional models in accuracy and speed. The paper includes an empirical study on residential electricity consumption in four Chinese cities and suggests future research directions. Overall, the article provides valuable insights into developing accurate and prompt forecasting models for electricity consumption.

In (6), the author explores the potential of forecasting electricity consumption for a large healthcare facility. The forecasting technique used is SARIMA modeling, which analyzes past data to predict future values. The study employs the Box-Jenkins procedure to create possible models and compares the performance of SARIMA and ARIMA models. The findings indicate that the SARIMA model outperforms the ARIMA model. The analysis of hospital data spanning 11 years reveals that these dynamic models can accurately forecast electricity consumption.

Research in (7) aims to determine the most reliable short-term load forecasting method for residential consumers during unusual consumption, such as the COVID-19 pandemic. The study evaluates three forecasting methods: linear regression (LR), autoregressive integrated moving average (ARIMA), and artificial neural network (ANN). The authors used multiyear hourly residential consumption data to estimate and validate the accuracy of the forecasts. The main findings indicate that the forecasting methods retained their hierarchy and accuracy in forecasting errors during unusual consumer behavior, similar to normal conditions if a trigger or alarm mechanism existed and there was sufficient time to adapt and deploy the forecasting algorithm. The ANN method generated the best results, followed by ARIMA and LR. The paper's original contribution is the ability to forecast loads that have no historical reference data. The results can be used as best practices during power load uncertainty and unusual consumption behavior.

Authors in (8) focus on accurately forecasting India's reliance on foreign oil using different methods. The authors utilized linear Auto-Regressive Integrated Moving Average (ARIMA) and nonlinear Back Propagation (BP) to correct the nonlinear metabolic grey model (NMGM) forecasting residuals in three steps. They integrated the metabolic idea with a nonlinear grey model to create NMGM, which they combined with ARIMA to develop NMGM-ARIMA and BP to develop NMGM-BP. The proposed models analyzed India's dependence on foreign oil from 1995 to 2017 and forecasted the data from 2018 to 2030. The mean relative error of the proposed forecasting models was approximately 1.5%, which produced reliable results. The forecasts demonstrate that India's dependence on foreign oil is expected to increase to 90% around 2025, which poses a significant challenge to India's oil security and global oil market.

Research in (9) explores how well ARIMA models can predict electrical load time series despite noise interference. They conducted a simulation-based experiment using an ARIMA model based on actual load data from the Polish power system. They introduced varying levels of noise to test its forecast accuracy. The model was then re-identified, its parameters estimated, and new forecasts made to determine the threshold at which the model's forecasting ability broke down. These findings underscore the significance of data preprocessing in data mining and learning and have possible implications for energy policy and power system reliability.

Other techniques for forecasting are also widely used, as shown in (10), where researchers present a model for predicting power consumption that uses wavelet transform and multi-layer LSTM. The goal is to create an effective power generation and transmission plan while avoiding the waste of electricity resources. The sample data is first processed to eliminate any volatility in the electricity consumption data using wavelet transform to achieve this. Then, the multi-layer LSTM model is used for training using the pre-processed samples. The model is tested by predicting daily power consumption in an area controlled by a US electric power company. Experimental results show that this model has better prediction performance than traditional LSTM and bidirectional LSTM, with a mean square error of 0.019 and a coefficient of determination R2 as high as 0.997. Additionally, wavelet denoising can further improve the prediction performance of the model.

In (11), the paper presents a new way of predicting monthly electricity usage using a hybrid forecasting model. The model combines the HolteWinters exponential smoothing method with the fruit fly optimization algorithm to accurately forecast occasional series, even with limited training data. The fruit fly optimization algorithm is used to identify the best smoothing parameters for the Holt-Winters exponential smoothing. The model was tested using electricity consumption data from a city in China and was found to improve prediction accuracy, even with limited training samples significantly. Additionally, the proposed model is faster than other hybrid benchmark algorithms.

## 6.3 Problem Formulation and Methodology

Accurate energy forecasting is crucial for power system expansion and reliability, as it enables utilities to plan for future energy demands and ensure enough capacity to meet those demands. It is especially significant for renewable energy sources, which can be more variable than traditional fossil fuels. Utilities can better manage their energy supply and avoid blackouts or brownouts through precise energy forecasting of wind turbines or solar panels.

Also, energy forecasting is vital for preparing for future energy needs and ensuring the reliability of the power system. Utilities can use energy supply and demand predictions to identify potential weaknesses in the design and take steps to prevent them. For instance, if a utility expects high energy demand during a specific time, it may activate additional generators or introduce demand response programs to lessen energy usage during peak hours. This proactive approach guarantees that the power system remains dependable and robust, despite changing energy demands and potential disturbances (12).

Load increments uncertainties can significantly impact the stability and reliability of electrical power systems (13). Accurate load forecasting is essential for energy companies to efficiently plan their production and distribution of energy, which can help to avoid wastage or shortages. Techniques for load forecasting are essential to mitigate these uncertainties, as they can help energy companies to make more accurate predictions of future energy demand. This can lead to better resource allocation, reduced operational costs, and improved customer satisfaction. Additionally, load forecasting techniques can help energy companies to identify opportunities for energy conservation and efficiency improvements, which can further reduce the impact of load increments uncertainties on the power system.

Therefore, this work proposes using ARIMA time series for electricity consumption modeling and prediction through Matlab.

### 6.3.1 Study case

Therefore, to conduct a forecasting analysis using time series analysis, actual data on electricity consumption has been collected. Specifically, this work uses monthly electricity consumption data from Quito, Ecuador, from 2004 to 2018, resulting in 180 data records. This information is publicly accessible online through the official Electricity regulator entity of the Ecuadorian government. Figure 6.3 shows the electricity consumption during the period previously stated; in other words, it offers

180 monthly data; additionally, for a better understanding, Figure 6.4 shows only a year (2010) for a better understanding of the electricity consumption behavior.

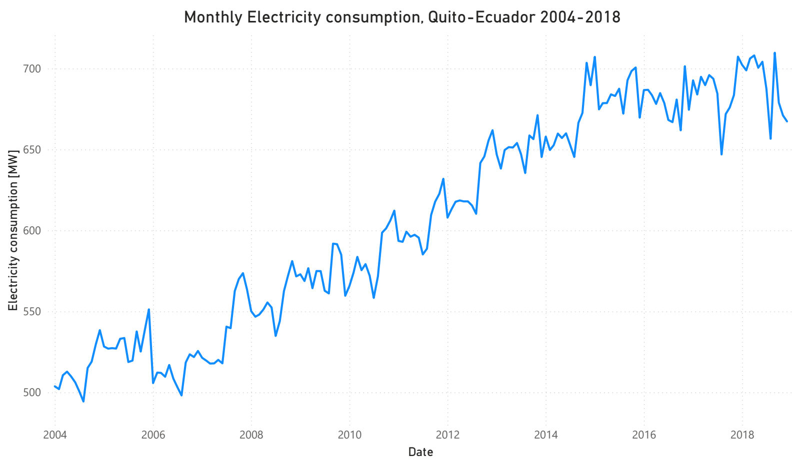



Figure 6.3: Electricity consumption for Quito-Ecuador from 2004 to 2018

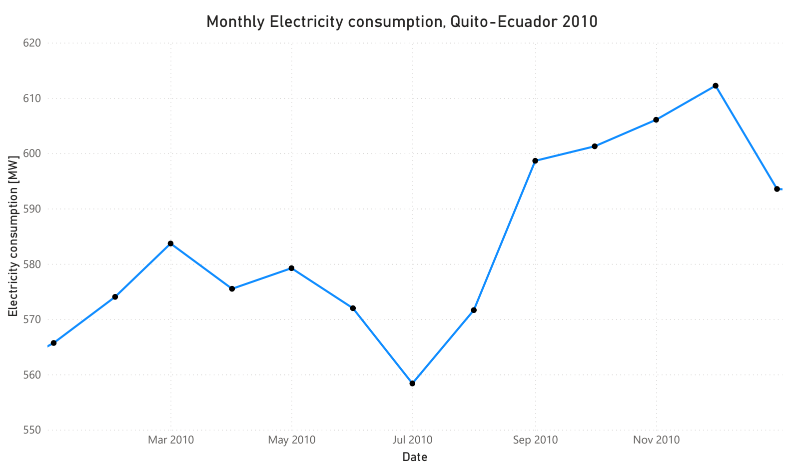



Figure 6.4: Electricity consumption for Quito-Ecuador, for the year 2010

### 6.3.2 Time series analysis: Seasonal Auto-Regressive Integrated Moving Average (SARIMA)

To analyze the seasonal patterns in electricity consumption, this model employs auto-regressive AR and moving average MA models. These patterns tend to repeat themselves periodically, and for this particular study, the period is 12 months based on monthly data. As a result, a SARIMA time series model would be the most appropriate for analyzing the data.

When working with autoregressive models, it is essential to remember that the current value of a given series can be expressed as a linear combination of its preceding values. This relationship holds for up to a maximum of $p$ previous values, where $p$ is a predetermined value dependent on the specific model being used $\{X(t-1), X(t-2), X(t-3), \dots X(t-p)\}$. By understanding this fundamental principle, one can understand the underlying patterns and trends within a given dataset, leading to a more accurate and informative analysis. Similarly, the MA component is derived using a linear combination of $q$ preceding white noise values $\{Z(t-1), Z(t-2), Z(t-3), \dots Z(t-q)\}$. This method helps to smooth out data patterns and identify underlying trends.

By considering the operator $B$ (Backward shift operator), which describes a temporal item that depends on a previous sample $BX_t = X_{t-1}$. This operator allows defining the autoregressive component of a time series as $\left\{(1 - \Phi_1 B^{12} - \Phi_2 B^{24} \dots)X_t\right\}$ and the moving average part $\left\{(1 - \Theta_1 B^{12} - \Theta_2 B^{24} \dots)Z_t\right\}$.

A $SARIMA$ model is made up of coefficients that determine its order. Two coefficients for the autoregressive and moving average components are denoted as $p$ and $q$, respectively. Additionally, two more coefficients, represented as $P$ and $Q$, are considered for the seasonal autoregressive and moving average components. The differential part is typically set to 1 for an electricity model, and the seasonality corresponds to twelve months. A $SARIMA$ model has six coefficients of interest: three for the non-periodic part $(p, d, q)$ and three for the periodic part $(P, D, Q)$. This information can be represented in equation $(6.1)$.

$$\Phi_P(B^S)\phi_p(B)(1 - B^S)^D(1 - B)^d X_t = \Theta_Q(B^S)\beta_q(B)Z_t \tag{6.1}$$

### 6.3.3 Methodology for electricity consumption forecasting

This project aims to create a methodology for predicting electricity consumption data every month. Then, to achieve this, the data must be analyzed to determine if it displays any seasonal patterns, which is necessary for a SARIMA time series model. The range for coefficients (p,q) and (P, Q) will be identified through correlation and autocorrelation analysis. Using Matlab, the values for each coefficient will be calculated to establish the model. The final step involves forecasting the data and evaluating the error. A detailed outline of this process can be found in Figure 6.5

When the $SARIMA$ model is created, it is necessary to validate the model's error by comparing the original data for electricity consumption $EC$ and the values produced by the model. The residual sum of squares will be used as the criteria for model validation, as is shown in equation 6.2.

$$RSS = \sum_{i=1}^{n} (ED_i - SARIMA_i)^2 \tag{6.2}$$

## 6.4 Matlab Coding and Results Analysis

Thus, the primary action is to meticulously clean and validate the data to initiate the suggested approach. It is essential to ascertain whether the data manifests

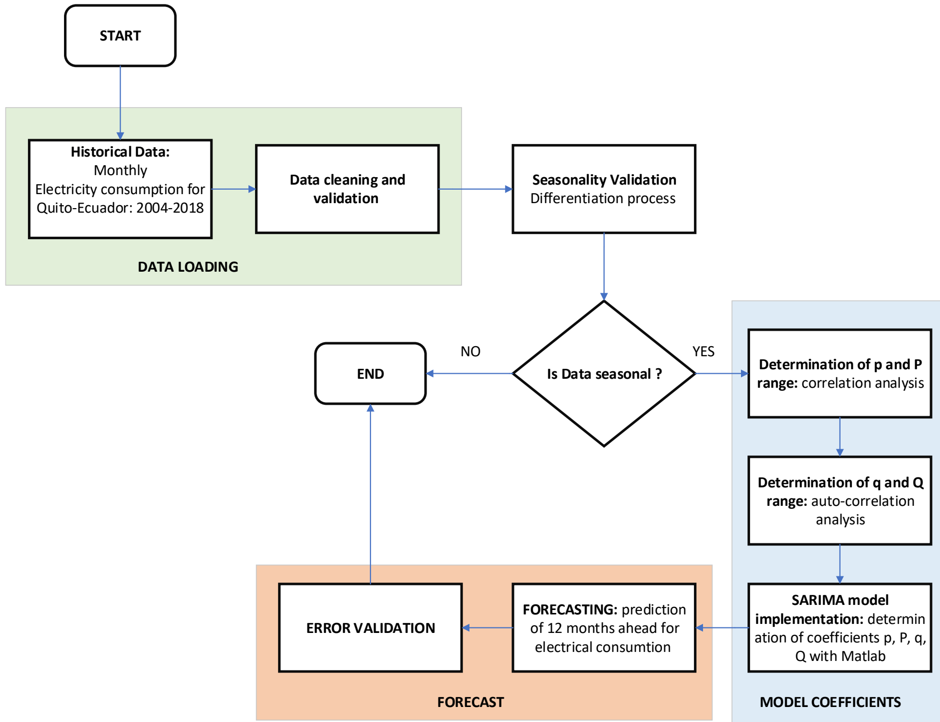


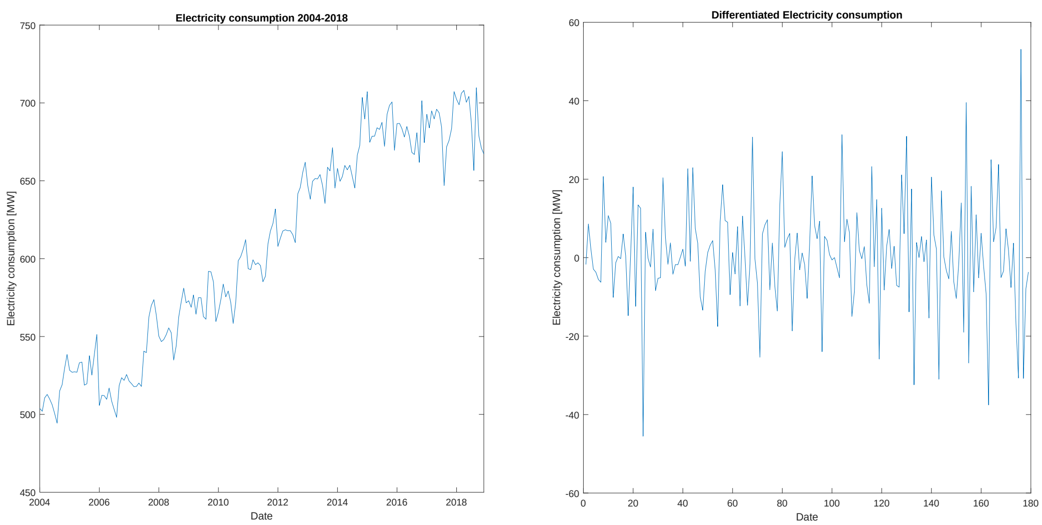

Figure 6.5: Methodology for electricity forecasting

any seasonal trends. If such movements are present, the time series of electricity consumption ought to show no increasing pattern post-differentiation. This entire procedure is conducted on Matlab; the corresponding code is shown below.

```
clc, clear
%% DATA LOADING
opts = detectImportOptions('DATA_MONTHLY_18.csv');
opts = setvaropts(opts,"DATE",'InputFormat','MM/dd/uuuu');
ec = readtable('DATA_MONTHLY_18.csv',opts);

demand=ec{:,"MAXDEMAND_MW_"};
date=ec{:,"DATE"};

%% VISUAL REPRESENTATION
% Original Data
figure()
subplot(2,1,1)
plot(date,demand)
title('Electricity consumption 2004-2018')
xlabel('Date')
ylabel('Electricity consumption [MW]')

%% SEASONALITY VERIFICATION
% Data differentiation
```

```
demand_dif=diff(demand);
subplot(2,1,2)
plot(demand_dif)
title('Differentiated Electricity consumption')
xlabel('Date')
ylabel('Electricity consumption [MW]')

h=gcf;
set(h,'PaperPositionMode','auto');
set(h,'PaperType','A4');
set(h,'PaperOrientation','landscape');
set(h,'Position',[10 0 500 800]);
set(h, 'InvertHardcopy', 'off')
figure = gcf;
figure.Color = 'white';
print -pdf -r800 figure1
```

After applying this analysis to the electricity consumption of Quito-Ecuador from 2004 to 2018, Figure 6.6 shows that this data corresponds to a seasonal time series.



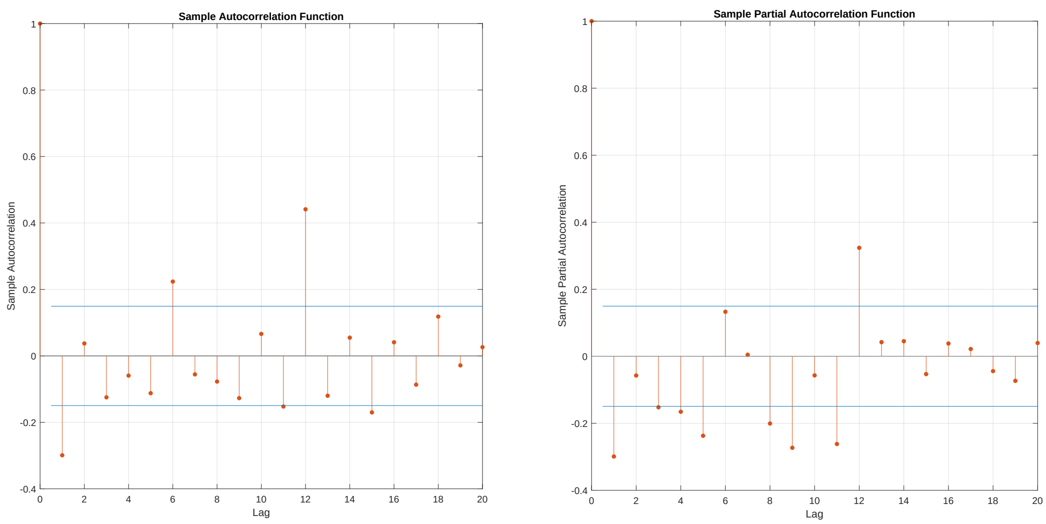

(a) Time series for electricity consumption (b) Differentiated time series

Figure 6.6: analysis for seasonality in electricity consumption for Quito-Ecuador from 2004 to 2018

Then, an analysis was performed on electricity time series data to ascertain the order of autoregressive and moving average coefficients for the SARIMA model. The data were scrutinized using correlation and autocorrelation techniques to identify significant lags greater than one. It helped to determine the order of each coefficient accurately and efficiently. The Matlab code for this analysis is shown as follows.

```
%% SERIES CORRELATION
figure()
autocorrect(demand_dif)
h=gcf;
set(h,'PaperPositionMode','auto');
set(h,'PaperType','A4');
set(h,'PaperOrientation','landscape');
set(h,'Position',[10 0 800 800]);
set(h, 'InvertHardcopy', 'off')
figure = gcf;
figure.Color = 'white';
print -pdf -r800 figure3

%% SERIES PARTIAL AUTOCORRELATION
figure()
parcorr(demand_dif)
h=gcf;
set(h,'PaperPositionMode','auto');
set(h,'PaperType','A4');
set(h,'PaperOrientation','landscape');
set(h,'Position',[10 0 800 800]);
set(h, 'InvertHardcopy', 'off')
figure = gcf;
figure.Color = 'white';
print -pdf -r800 figure4
```

Matlab analysis of correlation and partial auto-correlation shown in figure 6.7 reveals four significant lags in the time series correlation; this suggests that the autoregressive component should have an order ranging from 0 to 4. The partial auto-correlation analysis indicates seven significant lags, implying that the moving average order should range from 0 to 7.




(a) Correlation analysis for electricity consumption

(b) Partial auto-Correlation analysis for electricity consumption

Figure 6.7: analysis for autoregressive and moving average indexes order

So far, the analysis for electricity consumption has provided the following criteria:

- Autoregressive component $p$ varies from 0 to 4.
- Moving average component $q$ varies from 0 to 7.
- Considering that the time series has been differentiated once, $d = 1$ and $D = 1$.
- $P$ takes the same values as $p$.
- $Q$ takes the same values as $q$.
- As data was taken by one sample per month, seasonality $S = 12$

Next, it is necessary to build a SARIMA model in Matlab using the already discussed structure and determining the values for the associated coefficients (p, q, P, Q). Once the model is created, the error will be evaluated using equation 6.2.

```
%% SARIMA MODEL CREATION

%% Seasonal ARIMA Model
% Estimate a SARIMA Model of demand1
SARIMA_mdl = arima('Constant',0,'ARLags',1:4,...
    'D',1,'MALags',1:7,'SARLags',[12,24],...
    'Seasonality',0, 'SMALags',[12,24],...
    'Distribution', 'Gaussian');
SARIMA_mdl = estimate(SARIMA_mdl,demand,'Display','off');
```

```

% Sarima Model
residuals = infer(SARIMA_mdl,demand);
model = demand+residuals;

% RSS calculation for error
error_ab=demand - model;
error_p=error_ab./demand;
error_p=abs(error_p*100);
error_mean=mean(error_p)
RSS=sum(error_p)

figure()
plot(demand,'LineWidth',2)
hold on
plot(model,'--', 'LineWidth',2, 'Color', '#D95319')
legend('Original electricity consumption',...
    'Time series created with SARIMA model,' 'Location', northwest')
title('Original time series vs Sarima Model')
xlabel('Sample')
ylabel('Electricity consumption [MW]')

h=gcf;
set(h,'PaperPositionMode','auto');
set(h,'PaperType','A4');
set(h,'PaperOrientation','landscape');
set(h,'Position',[10 0 1000 800]);
set(h, 'InvertHardcopy', 'off')
figure = gcf;
figure.Color = 'white';
print -pdf -r800 figure4
```

The values for each coefficient $(p, q, P, Q)$, the residual sum of squares $RSS$ and average error per sample are shown in table 6.1

Table 6.1: SARIMA model coefficients and results

| Name | Description |
|---|---|
| $p$ coefficients | [0.0848375, -1.12611, 0.128075, -0.931196] at lags [1 2 3 4]] |
| $q$ coefficients | [-0.497183, 1.12716, -0.647343, 1, -0.546107, -0.0214771, -0.0948195] at lags [1 2 3 4 5 6 7] |
| $P$ coefficients | [0.0265442, 0.806656] at lags [12 24] |
| $Q$ coefficients | [0.293264, -0.504022] at lags [12 24] |
| Seasonal coefficient | $S = 12$ |
| Residual sum of squares $RSS$ | 201.7595 |
| Average error per sample | 1.1209% |

Finally, after creating the $SARIMA$ model and verifying that the RSS and average per sample error are acceptable, the next step consists of creating forecasted values for the next 12 months of electricity consumption. The Matlab code for this analysis is shown as follows.

```
%% FORECASTING DATA
% Plot only 8 last years
demand2=demand(100:end)
T=length(demand2);
```

```
[yF,yMSE] = forecast(SARIMA_mdl,12,demand);
upper = yF + 1.96*sqrt(yMSE);
lower = yF - 1.96*sqrt(yMSE);

aux=demand2(end-1:end);
yF=cat(1,aux,yF);
upper = cat(1,aux,upper);
lower = cat(1,aux,lower);


figure()
plot(demand2,'LineWidth',2)
hold on
h1 = plot(T-1:T+12,yF,' k', 'LineWidth',2, 'Marker', 'diamond');
h2 = plot(T-1:T+12,upper,'r--,' 'LineWidth,' 1.5,'Marker,''*');
plot(T-1:T+12,lower,' r--', 'LineWidth',1.5, 'Marker','*')
grid on
grid minor
xlim([0,T+11])
title('Electricity consumption forecast and 95% Forecast Interval')
xlabel('Sample')
ylabel('Electricity consumption [MW]')
legend([h1,h2], 'Forecast', '95 % Interval', 'Location','NorthWest')
hold off

h=gcf;
set(h,'PaperPositionMode','auto');
set(h,'PaperType','A4');
set(h,'PaperOrientation','landscape');
set(h,'Position',[10 0 1200 800]);
set(h, 'InvertHardcopy', 'off')
figure = gcf;
figure.Color = 'white';
print -pdf -r800 figure5
```

Forecasting values are shown in figure 6.8 in the black colored line. Also, this figure shows confidence intervals of $\pm 5\%$.

## 6.5 Conclusions

Energy forecasting plays a critical role in predicting future energy demand and ensuring the reliability of the power system. It allows utilities to plan for energy needs, manage supply, and identify potential vulnerabilities in the system. Accurate forecasting becomes even more crucial as the shift towards renewable energy sources continues due to their inherent variability. Therefore, investing in reliable and precise energy forecasting methods is imperative for utilities to meet customer demands and maintain a dependable power system.

By utilizing time series analysis, it is possible to accurately model and understand electricity consumption behavior. By creating a precise mathematical model, predictions can be made with a high degree of reliability. Research has shown that

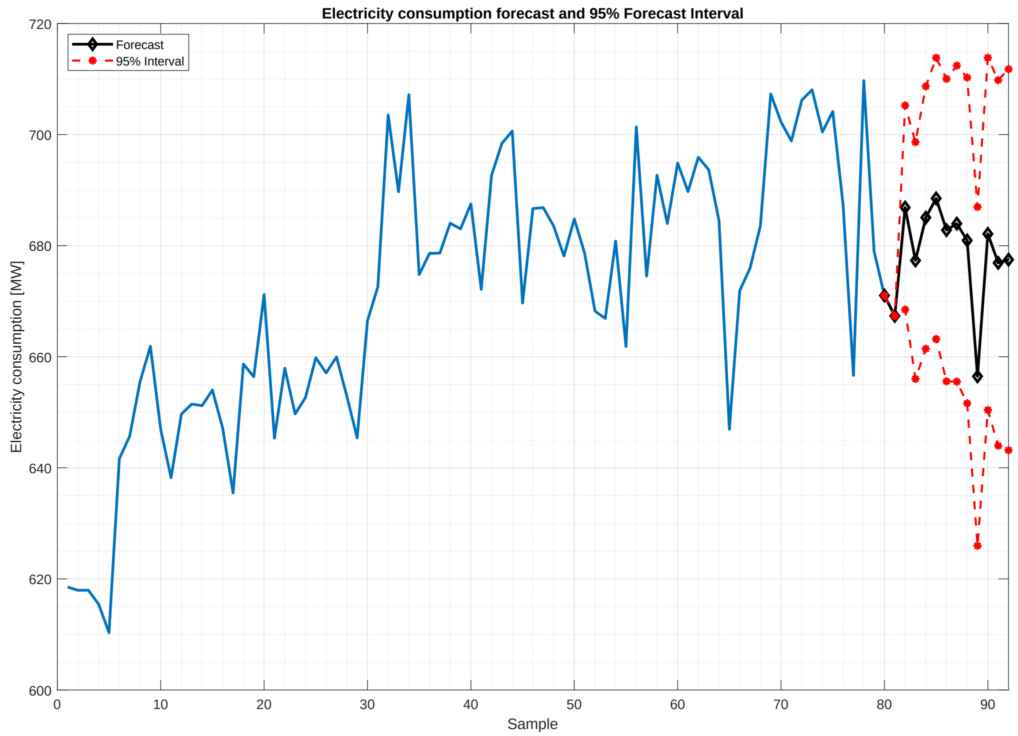



Figure 6.8: Electricity consumption forecast with 95% confidence intervals

such models can produce a small residual sum of squares (RSS) and average error per sample, further bolstering the dependability of predicted values.

In this work, a highly useful tool is presented that enables users to create an effective time series model for energy consumption. It should be noted that this tool is versatile and can be applied to any problem. It is crucial to assess the model's errors in order to determine its alignment with actual data. The residual sum of squares (RSS) is a key metric for this evaluation, as the closer it is to zero, the more accurate the predicted values will be. This tool is an excellent resource for anyone seeking to make reliable forecasts and optimize their energy usage.

Additionally, time series analysis can identify potential risks and opportunities in the energy market, allowing companies to adjust their strategies accordingly. Overall, time series analysis is an essential tool for energy companies looking to stay ahead of the curve and make informed decisions about the future of energy consumption.

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