**TIME SERIES ANALYSIS FOR ENERGY DEMAND FORECASTING**

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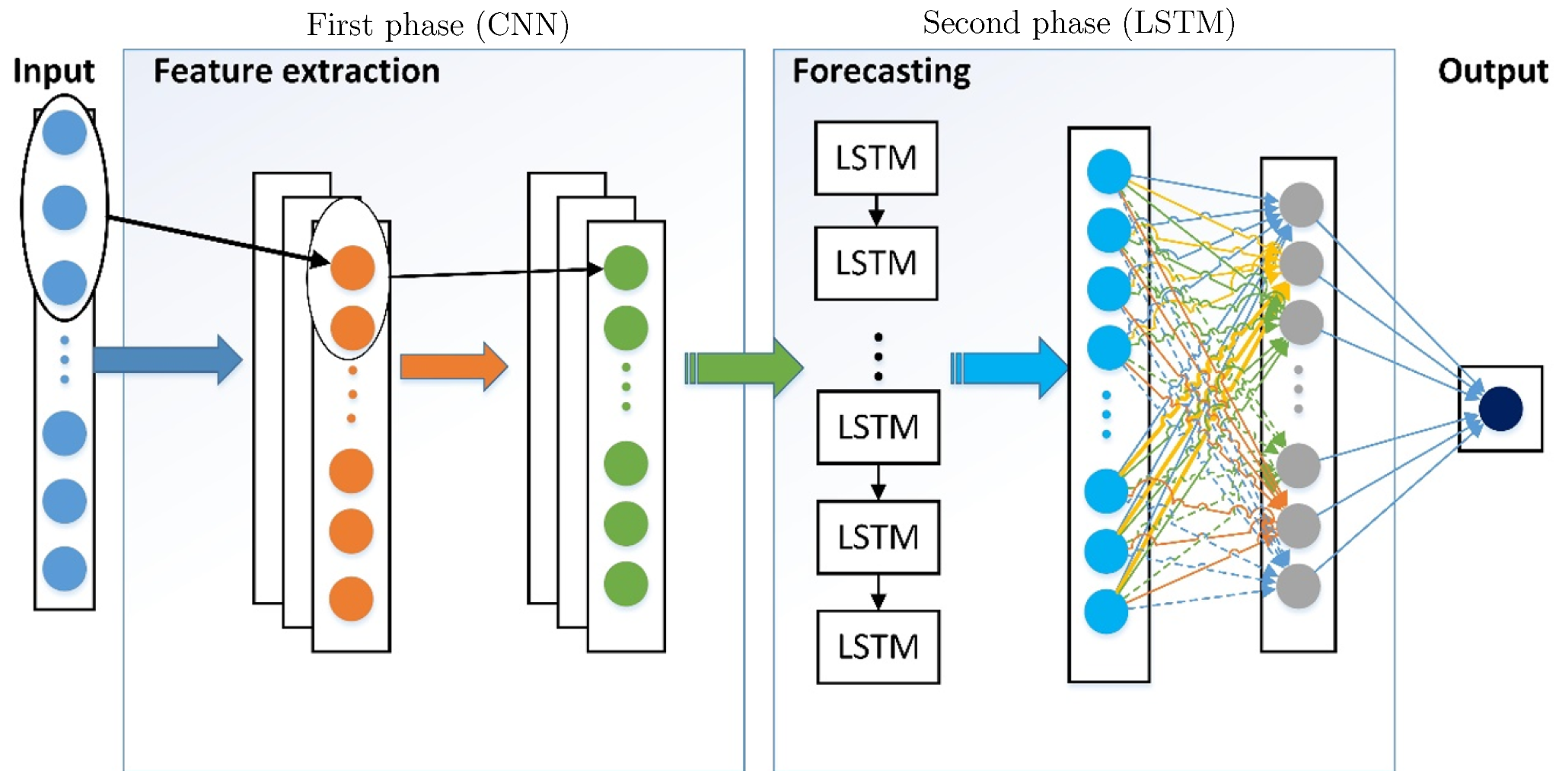
# Chapter 2: Literature Review

## Introduction

Time series analysis forecasting is one of the methods by which the analysis of the various past observations can be done in the system. The various underlying features can be evaluated for the construction of the regressive models that help to forecast the energy demands in the various locations. Thus the time series analysis has been done with the demonstration of the energy demands that occur due to various scientific predictive models. Here by building the various models the historical analysis and the future strategic decision-making approach have been applied to the required observations. For achieving the proper analysis of the applied time series here several steps are followed. Thus the model building for the series representation, the validation checking of the proposed model, and the forecasting or the predictive analysis for the future imputed missing values. Hence in this context, the total time series analysis will be done in the Python platform applying the various machine learning approaches.

## Empirical study

According to Kim *et al*.2019, In this paper, the author has described the predictive residential energy assumptions for the implementation of the CNN and LSTM models in neural networking. Such that here in this context the author has tried to amplify the development of sharply increased power consumption that will help to manage the demand for energy consumption with the rapid increase in human population.

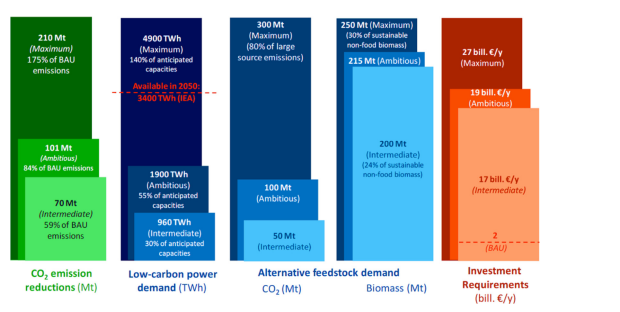


**Figure 1: The proposed Hybrid DNN power forecasting framework**

(Source: https://www.mdpi.com/1996-1073/11/11/3089)

Thus here the generation of electricity consumption from the various energy power plant has been predicted accurately with the advancement of the stable power supplier. Hence here by implementing the CNN and the LSTM model, it helps to extract and to analyze the temporal features with the housing energy consumption prediction. By combining the layers of the convolutional neural networking here the CNN and LSTM method has been applied for the extraction of energy consumption that is proposed to measure the performance of the electric energy consumption for the conventional energy forecasting process, for individual household power consumptions.

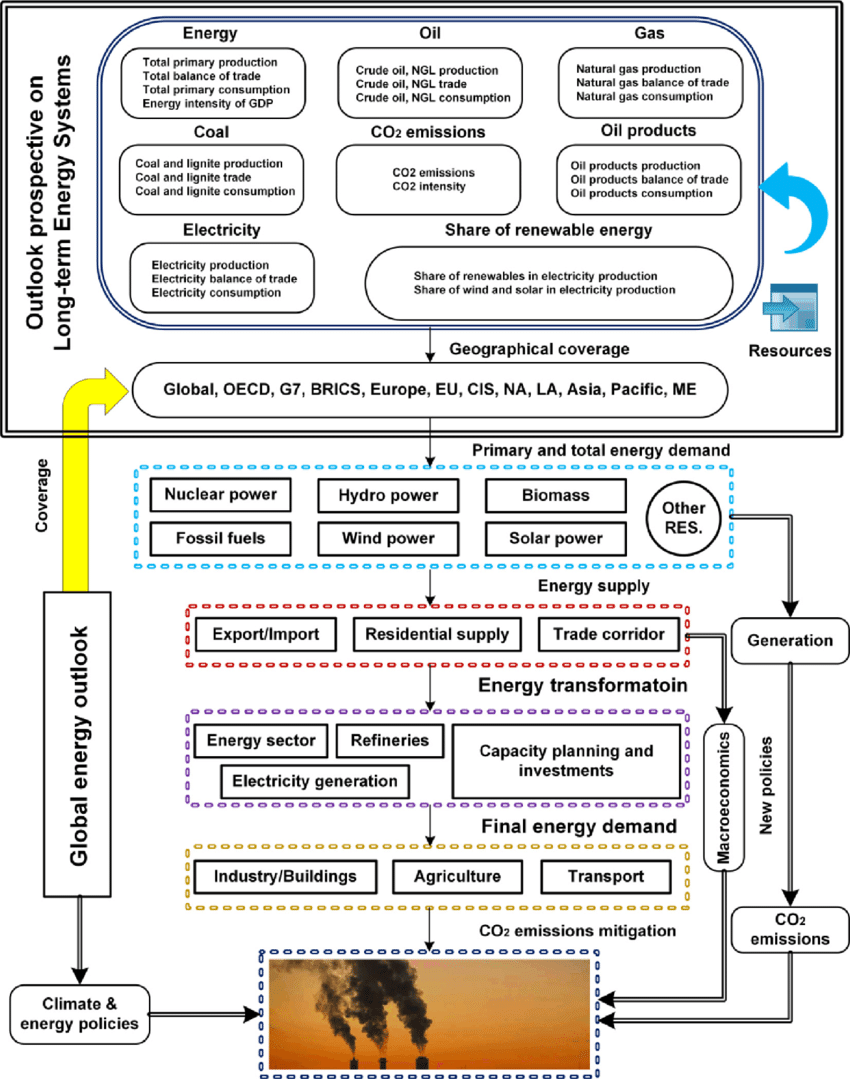
According to Ahmad *et al.2020,* In this paper, the author has clearly focused on discussing the Critical overview of the energy assumptions and also has analysed the future demands of the energy assumptions from the comparative global historical data analysis process in the time series analysis process.



**Figure 2: The Challenges and opportunities of non-fuel applications**

**(**Source:https://www.researchgate.net/figure/Challenges-and-opportunities-for-a-number-of-non-fuel-application-scenarios-by-2050\_fig1\_343380608**)**

Actually presents the critical description of the energy analysis demands developed by the various business sectors and also analyses the energy supply, the overall trading of the gasses , the time series, and also the adaptation of the renewable energy in contrast to the fuel energy assumptions. Thus it is very helpful to track the demand forecasting processes between 1990 to 2040. It has covered the geographic coverage of the global energy demands in various developed countries, like Brazil, India, China, Russia, South Africa etc.

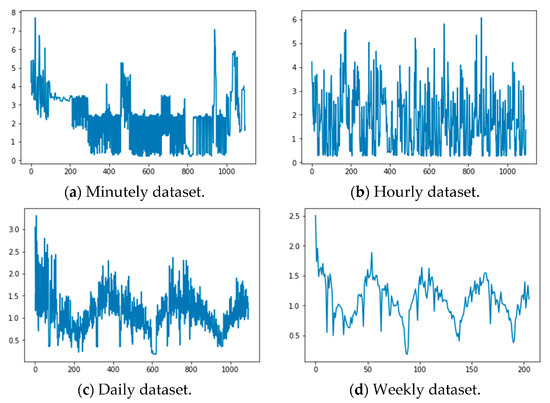


**Figure 3: Methods of over-global energy reviewing**

(Source: https://www.researchgate.net/figure/Methods-of-review-for-the-global-energy-outlook\_fig3\_343380608)

Analysing the various market strategies with the cooperative policymakers helps by creating an impact on the economic and climatic changes, and also reviews the economic and social development based on the energy trading process.

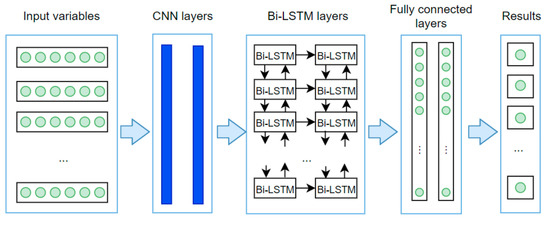
According to Le *et al*.2019, Here in this paper, the author has discussed the various concepts regarding the electric energy consumption for the power management system that would control the development policies for the implementation of the convolutional neural network and the Bi-directional long-term and short-term memory-biased method for the EECP-CBL model.



**Figure 4: The electric energy consumption dataset**

(Source:https://www.mdpi.com/2076-3417/9/20/4237 )

That will be helpful for the prediction of the electrical energy consumption that extracts the various electric power consumptions dataset. Thus it also helps to evaluate the trends of the different time series and also evaluate the several layers of the information by predicting the electric energy consumption.

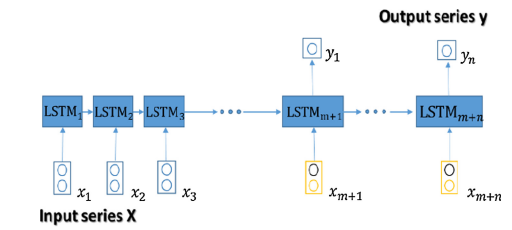


**Figure 5: The EECP-CBL model architecture**

(Source: https://www.mdpi.com/2076-3417/9/20/4237)

So here from this EECP-CBL model framework, the various performance analysis for the metric solutions can be analysed through real-time, long-term, short-term and also medium-term timespans.

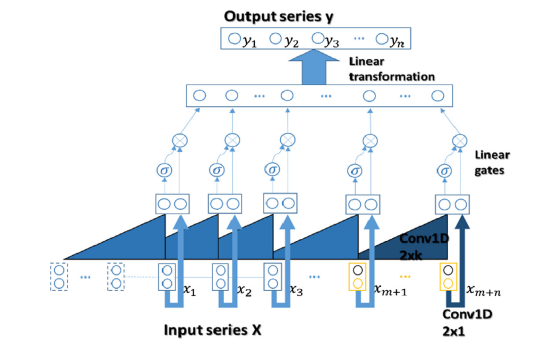
According to Cai *et al*.2019, Here in this paper the Building level load forecasting method by applying deep learning technology in the traditional time series analysis process has been analysed. Here to meet the objective of the author the traditional load forecasting method has been applied by utilizing the various statistical approaches in terms of autoregressive analysis for the integration of the moving averages from the exogenous imputed data i.e, ARIMAX, that gained the attraction for the classical method time-series analysis process.



**Figure 6: The Gated RNN model for building-level load forecasting**

(Source:https://ari.vt.edu/content/ari\_vt\_edu/en/publications\_archive/day-ahead-building-level-load-forecasts-using-deep-learning-vs--/jcr%3Acontent/content/download/file.res/128.pdf )

So here by the application of the exceptional capabilities over the development of the deep learning processes, the conventional data-driven networks have been analysed for the time series framework with the load-driven single-step building forecasting process evaluation technique. [***Refer to Appendix 1***]



**Figure 7: Gated CNN model for building-level load forecasting**

(Source: https://ari.vt.edu/content/ari\_vt\_edu/en/publications\_archive/day-ahead-building-level-load-forecasts-using-deep-learning-vs--/jcr%3Acontent/content/download/file.res/128.pdf)

Thus it emphasizes the relationship and the commercial environmental process upon which the recurrent neural networking processes have been accumulated for the accuracy, generalizability, robustness and computational efficiency analysis. Hence here with the building of the ARIMAX seasonal model, the performance has been analysed to direct multi-step manners having the best performance forecasting accuracy assumption compared with the ARIMAX model. [***Refer to Appendix 2***]

## Theories and Models

Here the application of the time forecasting model over the various energy demand processes has been analysed.

ARIMA model:’The Autoregressive moving average integration process is the method applying which the time forecasting is generally done (Cai *et al.2019*). Here by combining autoregression, differentiation, and taking the average of the moving the trends and the patterns are analysed. Thus it involves the ARIMA model for the energy demand forecasting for the different time intervals and differs in yearly to hourly methods.

SARIMA model: It is the modified version of the ARIMA model. Thus in this method, the seasonal autoregressive integrated average movement can be measured (Bourdeau *et al.2019*). Thus it helps in the capturing process of the RNN in energy trend data analysis, for the seasonal and non-seasonal component forecasting accuracy process.

Exponential smoothing technique: Here in this process it implies the exponential smoothing process on Holt’s linear model and the triplet model on Holt-Winter’s exponential model. This process helps to observe the historical data by decreasing the weightage of the data and also provides importance to the current data points (Büyükşahin *et al.2019*). It is also known for the simplified and capturing adaptability of the short-term trends for seasonal patterns.

STL: In the seasonal decomposition process, the time series have been analysed for the evaluation of the residual components, the trends of the applied data and the seasonal modelling of the applied data for fulfilling the energy demand exhibitions. Thus here it is also helpful for pattern recognition by measuring the irregularities with the time series decomposition process (Wu *et al.2021*). Thus the STL technique is also helpful for time series energy demand forecasting and modelling process for each of the analysis of the components.

Neural Network: The Artificial neural network is one of the trending processes for gaining popularity in the energy demand forecasting process evaluation (Alhussein *et al.2020*). With the completion of this process, it helps to get the proper capture of complexity accuracy variations with the application of the non-linearity relational data variations and their ability and accuracy assumption. Here these models are also helpful in the long-term memorised data evaluation process and help in the multilayer perceptron model evaluation process that is based on the temporal model and helps to get the energy demand dependability measurement from that time series.

SVR: Another important process of time series analysis is the support vector m, machine analysis technique. Here in this process, the best-fitted data is assumed by the regression analysis process. Thus in this method by minimizing the data variants or by reducing the errors of the applied data the hyperplane is applied to the specific data model (Hewage *et al.2020*). Thus in this process, the energy demand is generated through a time series model by the seasonal factors, the other relevant data predictive components and the lagging of the variables are assumed.

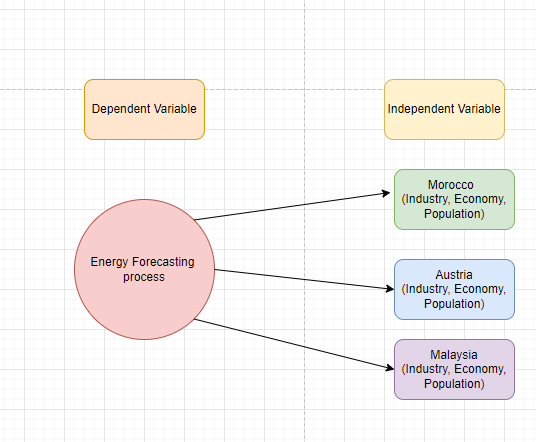
Gaussian Process: The predictive model analysis for the long-term and short-term trend analysis, GP is also a very important method (Li *et al.2019*). Thus in this method, the variations are assumed by incorporating the different components in the time series analysis process. Thus here the flexibility of the frameworks helps to analyze the seasonality, trends and noise involved in the forecasting process. Thus this process is beneficial in the non-linear uncertain data analysis method.

Thus here are various types of methods are available for the evaluation of the time series analysis over the assumptions of the pattern recognition technique in the time series model. The models by selecting, which the dependent factors are analysed are also helpful for the data characteristics evaluation, the specific requirement basis process that is dependent on the availability of the resource assumptions (Alsharif *et al.2019*). Also, it is beneficial for the flexibility assumptions beyond the frameworks that help to calculate the performance accuracy measurement with the identification of the easiest and most suitable process for the specific application.

## Literature Gap

Here from the above descriptions though it is very helpful for accommodating the Time series forecasting model over the Energy demand distribution over various countries, but it follows some problems regarding the implementation of those techniques in a real-time manner. Thus here problems arose in the implementation of the expected observations for the time series data analysis process (Zhong *te al.2019*). Thus it does not accommodate the same observatory series further away, moreover, it does not analyse the accountability over the assumptions of the seasonality for the non-stationary means. Also, the measurement of several statistical approaches has been applied here for the evaluation of the performance accuracy but the exact characteristics can’t be defined here due to the changes in the time sequencing and also the challenges faced in the establishment of the forecasting methods. Thus as that is totally dependable on the stationary data points it suffers due to the limited historical data evaluation process that lacks the new data production and creates so much human error in data accuracy measurement and seasonality measurement process.

## Conceptual Framework



**Figure 8: The Conceptual Framework**

(Source: Self-created in Draw.io)

## Conclusion

Here from taking the idea about various perceptions over the implementation process of the time series evaluation for the measurement of the predictive analysis over the historical data-based inputs. It helps to amplify the knowledge over the assumptions for the accumulation of the time-stamped data that involves the various building models. It also helps by making the observations by the data-driven methods for the decision-making strategy. Thus by applying convolutional data modelling for the application of several machine learning techniques in the time series analysis over the applied historical data can be evaluated. That helps to meet the objectives of the proposed model and also helps to get the proper knowledge about the time series model.

# Chapter 3: Methodology

## Introduction

Time series analysis is the specified method of analysis by which the data points sequencing is analysed from the collected dataset. Thus it can be said by the help of the time series analysis the data points can be implemented through the collection over real-time intervals. Thus here the time series analysis has been done through Python in the Google Collab platform using Exploratory data analysis over the historical data. Thus with the help of the proper time series analysis h, ere the energy demand forecasting has been done for the understanding of the patterns through the selection of the appropriate forecasting model. Before doing the time series analysis here the data required the training and testing for the performance evaluation. That process has been done on the basis of the three locations for the accurate predictive model for the future energy demand based on the historical data.

## Method Outline

For doing the proper time series analysis it follows some of the process. Thus before applying the time series analysis, the data has to be collected. This data again comprised of the various ordered sequencing of the historical data, that are equally specified for equal intervals. Rather than understanding the time series analysis here, it helps into the randomly specified data for the different trends that best-fit for the different applied filter values and do the analytical process to emphasize the data into a new time series predictive model with the evaluation of the data points indeed in the order of time (Lara-Benítez *et al.2020*). Again these time series data is divided into two parts one is for the frequency domain analysis and the other is measured for the time domain methods. After doing the training process the data is sent for the classification process, after which the curve has been fitted for making the relationship with that data. Then this process is further followed by the descriptive and explorative analysis of the applied dataset.

## Research Philosophy

Here in this perception, the time series analysis has been applied for the evaluation of the fundamental features of the energy demand distribution that creates the correlation with the various observatory data (Le *et al.2019*). Thus with the application of the stained statistical methods, the time series is analyzed that contains a large amount of data, for the insurance of the consistency and the reality of the applied data with the measurement of various attributes for a certain period and the information generated about those applied attributes (Ahmad *et al.2020*). In this process based on the temporal data, this method has been analyzed on a specific parametric that extracts the statistical information and also analyses the time domain and the frequency applied to that data.

## Research Approach

For doing the time series analysis here the quantitative methods have followed. Thus by the primary data analysis of the applied dataset here the forecasting of the energy demands with the implementation of the historical data has been evaluated. Thus by the identification of the various patterns in the applied data, here the future demand prediction has been done with the pattern recognition process and it is also analysed by the exploratory data analysis process (Moon *et al.2019*). There are several types of methods are present like the ARIMA, MA and the ARIMAX method for the autoregressive analysis process distribution with the integration of the moving average for the statistical evaluation of the proposed model data.

## Research Design

The time series analysis is done by the visualization of the applied data. It is very essential to emphasize and recognize the trends of the time grids that priority to the modulation process or the building method time series from applied historical data (Runge *et al.2019*). After that, the visualised data is sent for the evaluation process where the time series data is observed or rationalized for the applied dataset. In the next step, the data optimization has been done on the basis of the various parametric approach for the application of the ARIMA model in the following process of evaluation. Thus it finally helps to get the proper predictive model of the applied dataset (Kim *et al.2019*). Here in this co, next though the descriptive or the exploratory data analysis has been done also for the distribution of the energy demands in the various areas, it also follows the correlational analysis that demonstrates the diagnostic evaluation from the experimental dataset.

## Research Strategy

For the specialized way of data sequencing and to do the proper time series analysis of the applied dataset at first the data is collected and after that, the data points are analysed through intervals of time. Also, the time series analysis is recorded through the various data points for the consistency of the intervals of the time analysis (Tan *et al.2019*). Also here this method follows the random method of data other ptimization process.

## Data Collection Method

For doing the proper analysis of the time series data here the various historical data are collected from the industrial dataset in this proposed model. Thus here based on the industries like retailing, finance and other economical states, the data is evaluated for the energy assumptions in three different countries (Zhou *et al.2021*). Also al this statistical modelling approach is applied for the decision-making and predictive analysis of the applied time series data model. Thus on the basis of this series of data, the meaningful characteristics and the data extraction is done for the future value predictions, which is observed by loading the data models for their forecasting the energy demands for their pricing and also involved the renewable energy sources for the expected pricing values and adaptive probability assumptions.

## Data Analysis

Here the data analysis is done by taking the classification, of the applied data and after identification of those data it is assigned for categorization (Wan *et al.2019*). Here the curve is fitted for the representation of the relational plots along with the applied deliberate variables within the data model. Thus by the evaluation of the exploratory data analysis process, the patterns are recognized and it is also implemented in the time series data for the proper seasonal variations.

## Research Limitations

In the building process of the time series analysis model, where the data points suffer from weaknesses and also suffer from the generalization of the single-step duty analysis, where the difficulties are obtained for the measurement of the appropriate performance analysis measurement (Wang *et al.2019*). Also, it lags in the identification process of the accurate model evaluation by which the model data can be represented.

## Conclusion

The energy demand forecasting process by the implementation of the time series method is helpful for the analysis of the statistical and economic data evaluation. Thus on the basis of the predictive model, the future assumption has been observed by analysing these data points. Here by analysing the seasonality, randomness and various attributes, the sales have been analysed for the three different countries.

# Chapter 4: Findings and Analysis

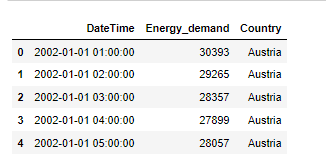
## Introduction

The project is about time series analysis for energy demand using Python. The main aim of the project is to find the comparison of the demand for energy in various countries such as Austria, Malaysia, and Morocco and also predict the future trend for the energy demand. By using the data analysis field, useful insights and patterns can find out from the dataset. From this data analysis, it would be understood the demand for the energy year-wise, month-wise, week-wise, quarter-wise, hourly-wise, day-wise. By understanding this, the energy-producing organization can strategies their plan for producing the energy in a sufficient amount and supplying energy in those countries. The whole project has been done with the help of the Python programming language and the Jupyter Notebook software is used to implement this.

## Result and Analysis

In the data analysis section, the data set is loaded first and the structure of the data is evaluated after loading the data (Chou *et al.* 2019). Also lastly by the visualization techniques, various chart has been plotted for finding the pattern of the demand for energy.

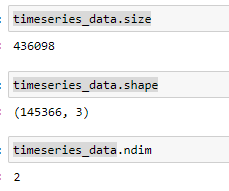
**Data Preprocessing**

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**Figure 10: Loading of the dataset**

(Source: Self-created using Jupyter Notebook)

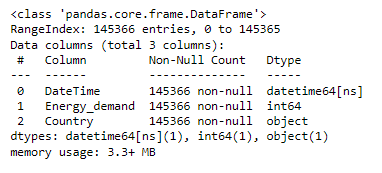
The dataset has been collected in a CSV file. The CSV file has been loaded into the Jupyter Notebook. The dataset is loaded in tabular form (Hu and Chen. 2022). The dataset has only 3 columns such as DateTime, enery\_demand, and the country. The country has the 3 levels such as Austria, Malaysia, and Morocco.



**Figure 11: Structure of the dataset**

(Source: Self-created using Jupyter Notebook)

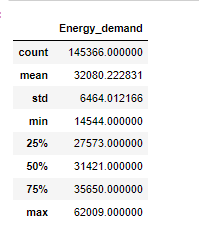
Now, the structure of the dataset has been evaluated. The data frame consists of the 3 columns and 145366 records (Kim *et al.* 2022). The energy demand dataset’s size is 436098. The dataset is 2 dimensional.

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**Figure 11: Information of the dataset**

(Source: Self-created using Jupyter Notebook)

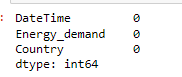
Here the step is to analyze information from the energy demand dataset. In this dataset, the DateTime column is datetime type, energy\_demand is the numeric type and the country column is the object type. The storage of the dataset is 3.3+ MB.

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**Figure 12: Summarization of the dataset**

(Source: Self-created using Jupyter Notebook)

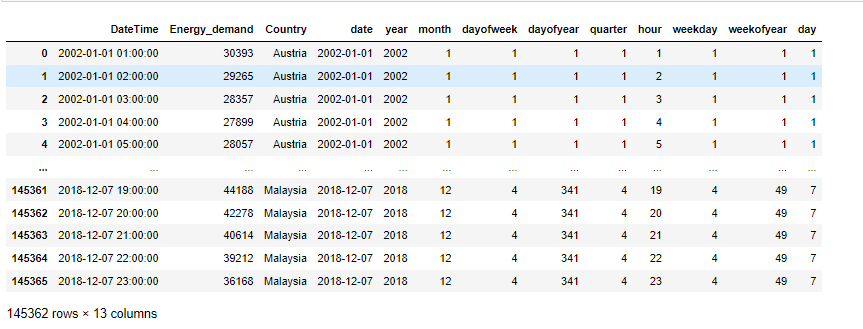
Now, the task has been to implement the summarization of the data with the help of the describe method (Li and Wang. 2022). The summarization of the numeric column such as energy demand is evaluated by the mean, standard deviation, maximum value, min value, 75% quartile, 25% quartile, and first quartile.

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**Figure 13: Checking the missing values**

(Source: Self-created using Jupyter Notebook)

Now the task is to check the missing value in the columns of the dataset. Missing value lead to biases during the data analysis(Xing *et al.* 2019). After checking the missing value, it has been understood that there is no missing value.

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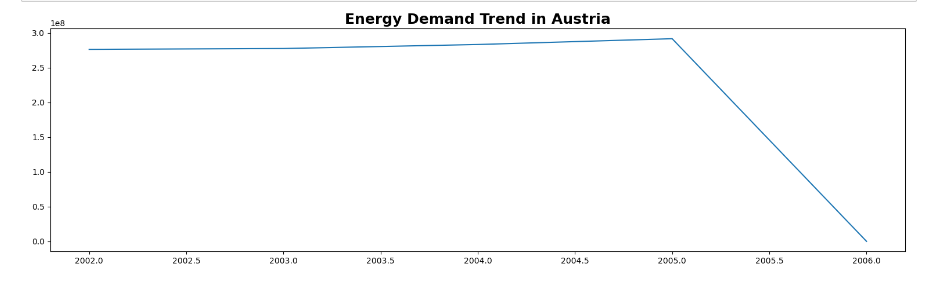
**Figure 14: Create required columns**

(Source: Self-created using Jupyter Notebook)

Some new columns have been created for analyzing the trend. A few additional columns such as date, month, year, day of the week, day of year, quarter, hour, weekday, week of the year, and day columns are created in this data frame.

**Data visualization**

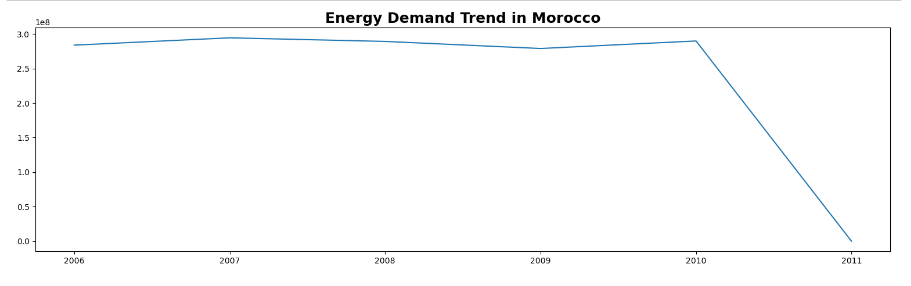
Data visualization is done using the line chart to understand the trend of the demand for energy. The matplotlib library is used for plotting the line chart.

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**Figure 15: Yearly Energy demand Trend in Austria**

(Source: Self-created using Jupyter Notebook)

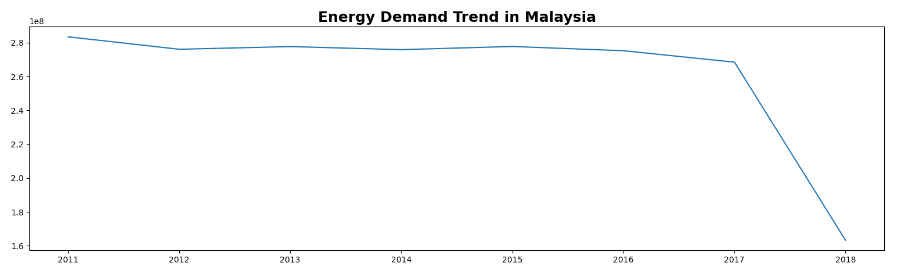
This line chart is plotted for visualizing the trend line to understand the energy demand yearly in Austria. From the visualization, it has been analyzed that, from 2002 to 2006, the deemed for energy is slightly increase yearly in Austria.

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**Figure 16: Yearly Energy demand Trend in Morocco**

(Source: Self-created using Jupyter Notebook)

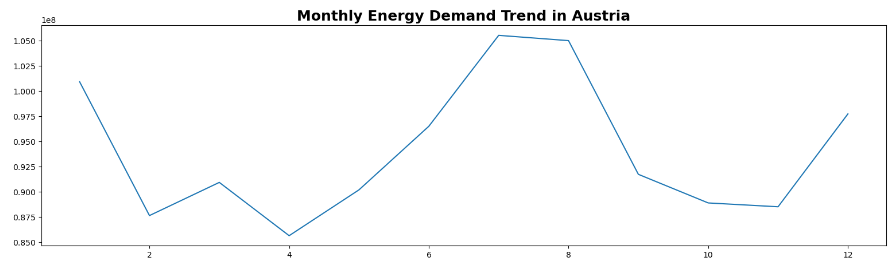
This line chart is plotted for visualizing the trend line to understand the energy demand yearly in Morocco. From the visualization, it has been analyzed that, from 2006 to 2007, the deemed for energy slightly increased, and after that, till 2009, demand is slightly decreasing.

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**Figure 17: Yearly Energy demand Trend in Malaysia**

(Source: Self-created using Jupyter Notebook)

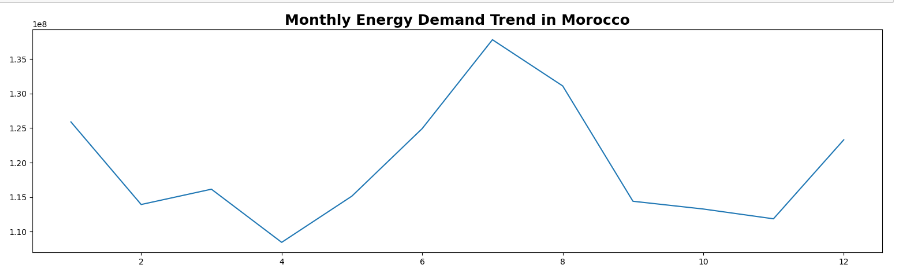
This line chart is plotted for visualizing the trend line to understand the energy demand yearly in Malaysia. From the visualization, it has been analyzed that, from 2011 to 2017, the demand for energy slightly decreased.

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**Figure 18: Monthly Energy demand Trend in Austria**

(Source: Self-created using Jupyter Notebook)

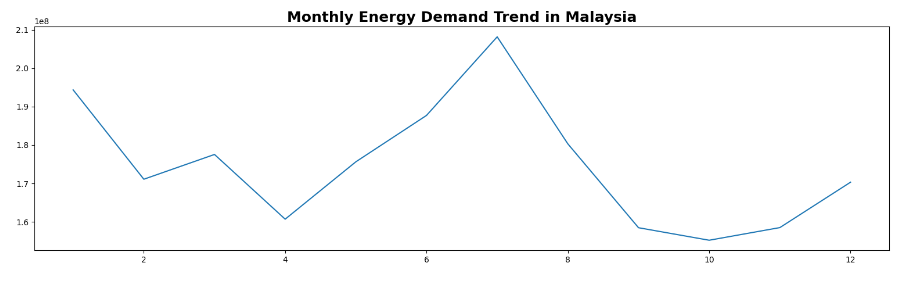
In July month, the monthly energy demand is more in Austria.

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**Figure 19: Monthly Energy demand Trend in Morocco**

(Source: Self-created using Jupyter Notebook)

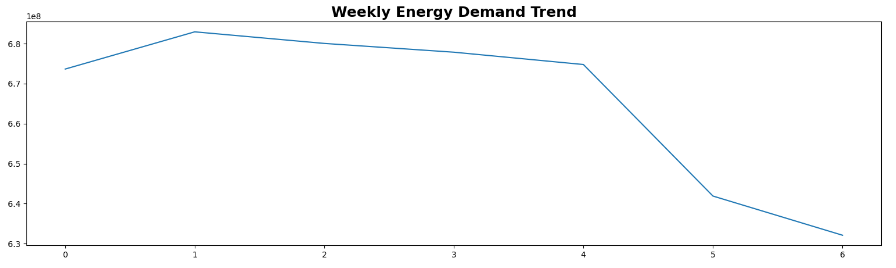
In July month, the monthly energy demand is more in Morocco.

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**Figure 20: Monthly Energy demand Trend in Malaysia**

(Source: Self-created using Jupyter Notebook)

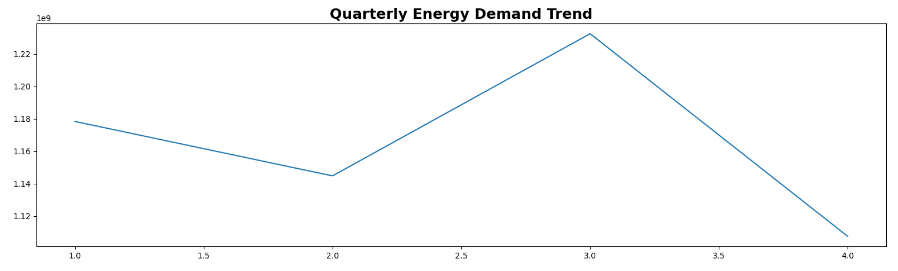
In July month, the monthly energy demand is more in Malaysia.

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**Figure 21: Weekly Energy demand trend**

(Source: Self-created using Jupyter Notebook)

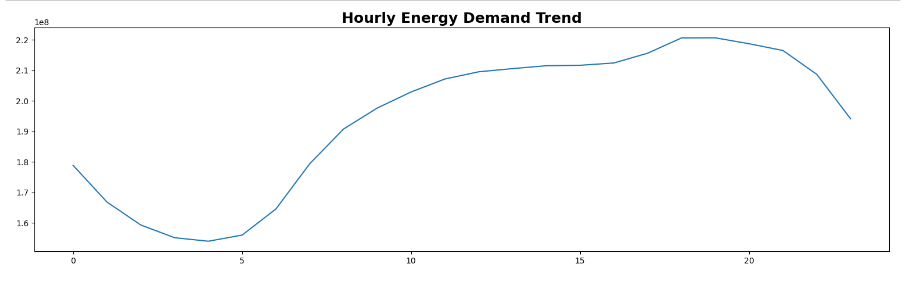
The line chart is plotted to visualize the trend of the energy demand weekly. From the visualization, it has understood that on the 2nd day of the week, the energy demand is more.

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**Figure 22: Quarterly energy demand trend**

(Source: Self-created using Jupyter Notebook)

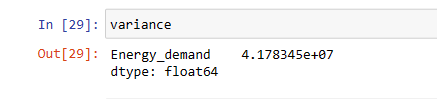
In the 3rd quarter, the energy demand is more than the other quarter. The quarterly energy demand trend is visualized using the line chart. The demand for energy is less in the second quarter.

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**Figure 23: Hourly Energy demand trend**

(Source: Self-created using Jupyter Notebook)

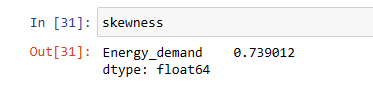
In between 5 to 18 hours, the energy demand is more. The hourly energy demand is increasing from the 5th hour to the 18th hour. The hourly demand is less in the 4th hour. ***[Refer to Appendix 3]***

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**Figure 24:Variance Calculation**

(Source: Self-created using Jupyter Notebook)

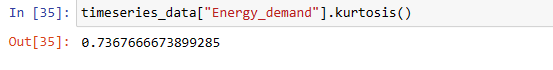
Variance calculations how far every information point spreads from the mean worth in a period series dataset. It evaluates the changeability in the information. To work out fluctuation, first, register the mean of the time series by adding every one of the perceptions and partitioning by the all-out number of data of interest. Then, at that point, for every data of interest, work out the squared contrast between its worth and the mean. Total this multitude of squared contrasts and separation by the quantity of information focuses less one. This gives the fluctuation - a bigger difference esteem demonstrates the information is more fanned out from the mean, while a little change shows it groups intently around the mean. Variance is valuable for contrasting the instability of various time series. It additionally includes in further developed time series ideas like autoregressive models. High unpredictability makes time series more challenging to foresee, so evaluating difference helps measure the intricacy of demonstrating a specific dataset after some time.

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**Figure 25:skewness of moments Calculation**

(Source: Self-created using Jupyter Notebook)

Skewness measures the imbalance of the likelihood dispersion of a period series around its mean. A decidedly slanted dispersion has a long right tail, while an adversely slanted circulation has a long left tail. To ascertain skewness, first track down the mean and standard deviation of the time series. Deduct the mean from every data of interest and separate by the standard deviation, giving the normalized values. Block these normalized values and view as normal - this is the third second about the mean. At long last, partition the third second by the standard deviation raised to the third power. The subsequent worth is the skewness. A skewness of 0 demonstrates a symmetric conveyance. Positive skewness implies more outrageous positive qualities, while negative skewness demonstrates more outrageous negatives. Evaluating skewness decides the state of information conveyance and reasonable anticipating models. Exceptionally slanted time series might require change before the examination. Understanding skewness additionally helps the translation of expectations from time series models.

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**Figure 26: Kurtosis Calculation**

(Source: Self-created using Jupyter Notebook)

Kurtosis calculates the greatness of the tails of a period series dissemination contrasted with a typical circulation. It shows how likely outrageous qualities are to happen. To ascertain kurtosis, first track down the mean and standard deviation of the time series. Deduct the mean from every data of interest and gap by the standard deviation to get normalized values. Take the fourth force of each normalized worth and view it as the normal - this gives the fourth second about the mean. Partition the fourth second by the standard deviation to the fourth power. Take away 3 from this outcome to work out overabundance kurtosis. A positive overabundance of kurtosis shows weighty tails and more outrageous qualities contrasted with typical dissemination. A negative overabundance kurtosis demonstrates lighter tails. Kurtosis decides exceptions, the need for information changes, and the reasonableness of estimating models that expect ordinariness. Higher kurtosis suggests more fluctuation in projections. Evaluating kurtosis gives data on the state of the information dispersion basic for deciphering and precisely demonstrating time series information.

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**Figure 27:Bar Graph using data frame visualization**

(Source: Self-created using Jupyter Notebook)

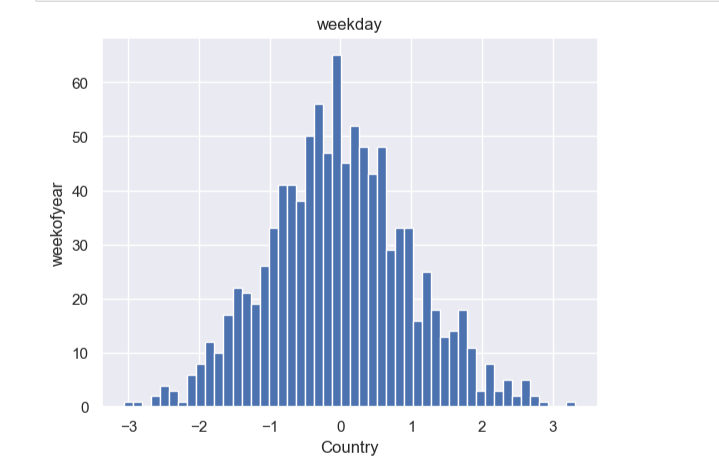
Bar graph using data frame visualization are a typical method for predicting time series information put away in an information outline. With the time variable on the x-pivot and the worth variable on the y-hub, each time span can be addressed by a rectangular bar with level corresponding to the information esteem. Reference charts permit simple correlation of values across various time spans. Variety coding bars by classifications or utilizing assembled bars to address numerous factors gives further bits of knowledge. Choices like mistake bars demonstrate changeability in point gauges. Bar graphs can likewise sum up time series qualities like occasional changes and patterns when plotted for longer time periods. They assist with recognizing designs over the long haul. Customizations like marks and legends explain the full setting. Visual diagrams are restricted by not associating individual data of interest, so need smooth patterns of line plots. Be that as it may, their effortlessness, instinct, and capacity to feature correlations make structured presentations an essential time series representation procedure, particularly for discrete information like month-to-month or week-by-week measurements or model outcomes summed up at set expectation stretches.

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**Figure 28: Bar Graph visualization**

(Source: Self-created using Jupyter Notebook)

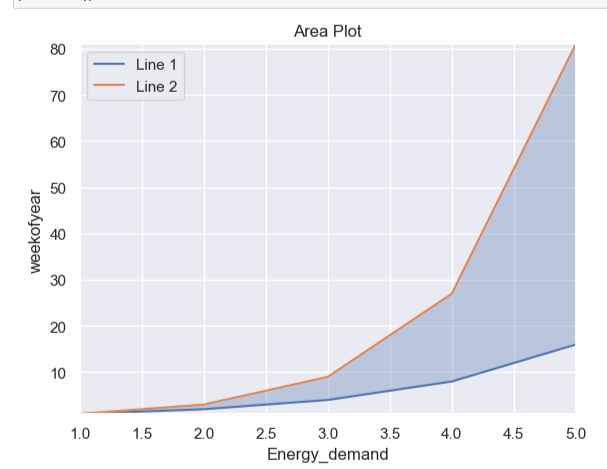
A bar graph is a basic yet powerful method for imagining time series information. It plots rectangular bars with levels relative to the information values for each time span. The bars are separated at equivalent spans on the flat pivot addressing the time aspect, while the upward hub catches the extent of the information. Contrasting bar graphs next to each other permits simple understanding of changes in the information over the long run. Bar diagrams can feature designs like occasional vacillations at customary intermittent stretches. Their effortlessness and instinct makes reference diagrams a central instrument for time series information representation and investigation.



**Figure 29: Histogram Graph visualization**

(Source: Self-created using Jupyter Notebook)

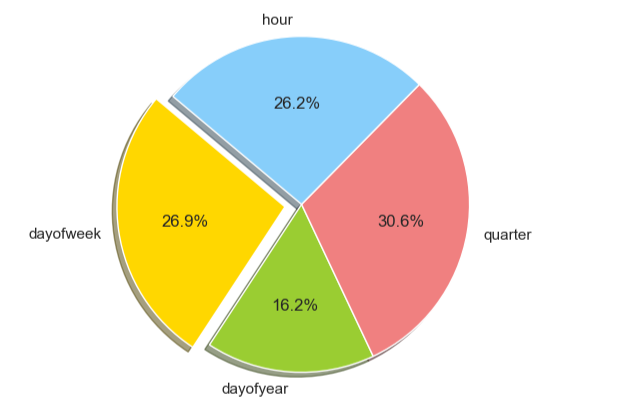
Time series histograms can uncover examples and patterns in information over the long run. Dissimilar to standard histograms which show the dispersion of a solitary dataset, time series histograms imagine the progressions in conveyance of a measurement throughout different time spans. For instance, a histogram for site traffic could show day to day guests for every month more than a year. This permits you to see increments or diminishes in rush hour gridlock over the long haul. Time series histograms make it simple to detect occasional cycles and exceptions initially. The state of the circulation might move from one month to another, demonstrating evolving patterns. Spikes or dunks in specific time spans are apparent as bars that stand apart from the general example. Looking at histograms next to each other makes patterns and oddities more obvious. Changing the receptacle size can feature various parts of the information. Time series histograms give a conservative representation to figuring out circulations, varieties, and examples across fleeting information. They consolidate complex time series data into a straightforward visual organization for fast investigation and examination.



**Figure 30: Area graph plot visualization**

(Source: Self-created using Jupyter Notebook)

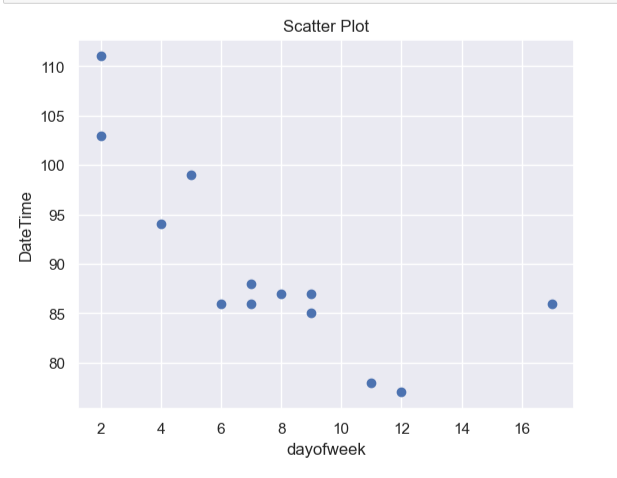
Area diagrams are powerful for envisioning time series information. Dissimilar to line diagrams which just associate pieces of information, Area charts occupy the space under the line to accentuate the extent of progress. The filled Area addresses the aggregate all out of the measurement over the long run. This makes it simple to analyze sums across various time spans. For instance, an Area diagram of site traffic would show a filled locale addressing all out guests each month. Higher Areas show more traffic. Plunges or valleys uncover times of low traffic. The incline of the line shows whether the information is expanding or diminishing. More extreme slants address quicker paces of progress. Area diagrams make it simple to distinguish designs like occasional changes and generally drifts. Contrasting numerous Area diagrams permits you with contrast different time series. Generally speaking, Area charts feature the combined effect of changes over the long haul. The filled Area centers consideration around the absolute worth and how it advances. For time series information, Area diagrams are more powerful than line graphs at conveying size and patterns.



**Figure 31: Pie chart Graph visualization**

(Source: Self-created using Jupyter Notebook)

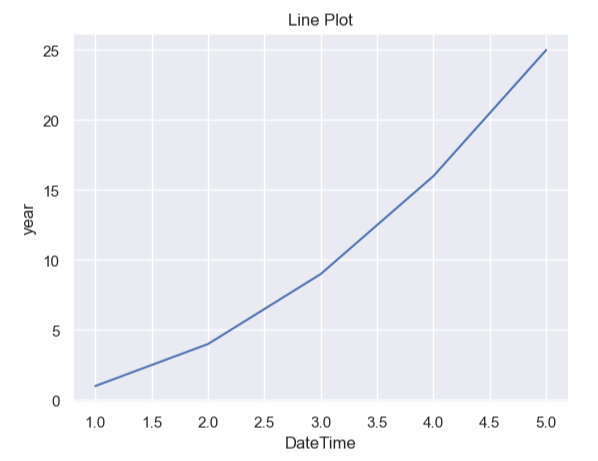
Pie outlines are not extremely successful for imagining time series information. Not at all like histograms or region diagrams, are pie outlines not intended to show changes after some time. Every pie chart regularly addresses a solitary time span, with cuts of the pie addressing classifications or fragments of information. To imagine patterns after some time, numerous pie diagrams for various time spans would should be drawn next to each other. This can consume a great deal of visual space and makes correlations troublesome with continually changing pie sizes and cut points. The portions in a pie chart encode the information utilizing points and region, which doesn't permit the watcher to handily follow how a specific classification or section changes across time. For time series information, it is smarter to utilize a diagram like a line outline where the patterns and direction of the information are outwardly encoded as slants and bends. Pie diagrams are more helpful for showing corresponding correlations or breakdowns across various classifications in a solitary time span. In any case, for imagining designs over the long haul, histograms, region diagrams, bar outlines, and line charts are by and large preferable decisions over pie charts.



**Figure 32: Scatter plot visualization**

(Source: Self-created using Jupyter Notebook)

Scatter plots can be a successful method for picturing time series information. The x-hub addresses time, while the y-hub plots the upsides of the time series. Every information point is plotted as a point on the chart. The dissipate plot shows the connection among time and the measurement being estimated. Patterns become apparent as the thickness and slant of focuses. Up slants demonstrate expanding values over the long haul. Descending slants show diminishing qualities. The steepness of the slants demonstrates the pace of progress. Dissipate plots make it simple to recognize anomalies and instability when focuses are further away from the general pattern. Gathering data of interest into ordinary time spans can uncover repetitive examples. Fitting pattern lines to the information focuses helps feature generally speaking increment or abatement. Vivified dissipate plots can show much more obviously how time series information advances. In general, Scatter plots convey a straightforward yet adaptable perception for dissecting patterns, cycles, and exceptions over the long haul. Line plots make it simple to distinguish repetitive examples that are recurrent over the long haul. Logical data like objective qualities or verifiable midpoints can be added to help examination. Enlivened line plots can represent how time series develop. Basic yet adaptable, line plots permit instinctive investigation of patterns, paces of progress, anomalies, and occasional examples over the long haul. They change crude information into a quick visual rundown of how measurements differ after some time.



**Figure 33:Line Plot visualization**

(Source: Self-created using Jupyter Notebook)

Line plots are one of the most well-known ways of picturing time series information. They show patterns after some time by associating data of interest with line portions. The x-pivot addresses time increases while the y-hub plots the measurement values. A line plot uncovers the direction of the information - whether it is expanding, diminishing, or staying consistent over the long haul. The slant of the line shows the pace of progress - more extreme inclines mean quicker change. Numerous lines can be plotted to think about various time series. Spikes or gets in contact with in feature anomalies or unexpected changes in the information. Holes in information can likewise be addressed.

## Conclusion

It is concluded that the proper data analysis is done on the demand for energy to understand the trend in Austria, Malaysia, and Morocco. The data analysis floors some steps in this project. First, the dataset is collected from the Kaggle dataset. They can likewise show in general patterns by plotting long time periods. Visual components like variety coding bars, adding mistake bars, and including marks/legends give further setting. While visual diagrams don't interface information focuses constantly like line outlines, they succeed at making examinations across discrete time spans. This makes them ideal for imagining routinely divided time series information like month-to-month measurements, model expectations at set spans, or total outcomes like aggregates or midpoints throughout uniform time cans. After that quality of the dataset has been accessed. Here the Line chart has been visualized to visualize the trend. From the visualization, some facts have been found such as the hourly energy demand increasing from the 5th hour to the 18th hour. In the 3rd quarter, the energy demand is more than the other quarter. The whole project is implemented using the Python programming language and the Jupyter Notebook software.

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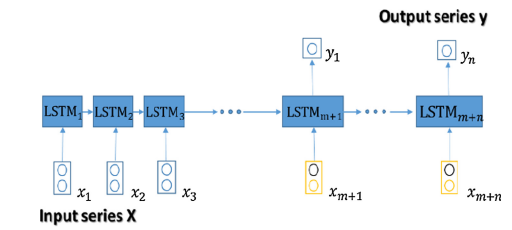
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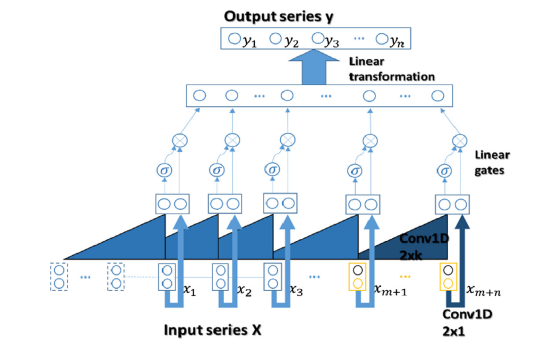
# Appendices

**Appendix 1:** **The Gated RNN model for building-level load forecasting**



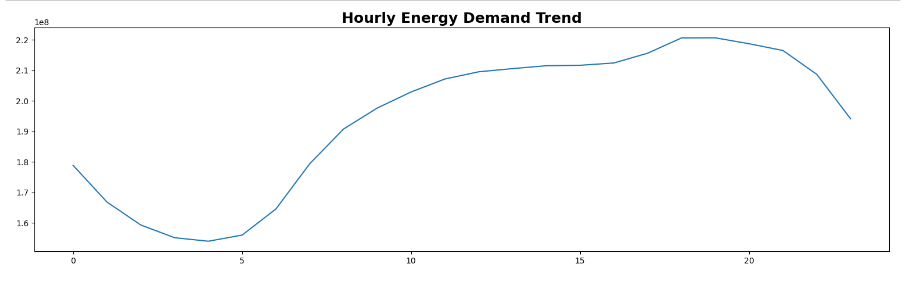
(Source:https://ari.vt.edu/content/ari\_vt\_edu/en/publications\_archive/day-ahead-building-level-load-forecasts-using-deep-learning-vs--/jcr%3Acontent/content/download/file.res/128.pdf )

**Appendix 2: Gated CNN model for building-level load forecasting**



(Source: https://ari.vt.edu/content/ari\_vt\_edu/en/publications\_archive/day-ahead-building-level-load-forecasts-using-deep-learning-vs--/jcr%3Acontent/content/download/file.res/128.pdf)

**Appendix 3: Hourly Energy demand trend**

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(Source: Self-created using Jupyter Notebook)