Forecasting of climatic influence on energy generation from renewable resources in Spain using Neural Network Models

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Forecasting of climatic influence on energy generation from renewable resources in Spain using Neural Network Models

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Abstract

The technological advancement and population growth has brought significant impact in the need for electricity throughout the world. The soar in energy demand brought significant impact on environment due to the over usage of conventional methods such as fossil fuels. The combustion of natural gases, coal and oil is releasing considerable amount of CO2 into the atmosphere which highly dangerous to our planet. This can be solved by switching from this traditional method to renewable resources such as solar, wind, biomass etc. which are naturally available in nature in sufficient amount. But their dependency on the weather is a challenging factor. This study is addressing this issue by forecasting the energy generation from renewable resources under the influence of weather. For conducting this, the study employs the advanced neural network models such as LSTM, Stacked LSTM, LSTM-CNN and LSTNet to forecast the impact of weather on renewable energy production. The comparison of results shows, LSTNet's superior performance with 98.99% accuracy over the other models, which is evaluated based on the evaluation metrics such as mean squared error, means absolute error, root mean squared error and r- squared value. The outcomes emphasize the importance of the selection of appropriate predicting models and also showcase LSTNet as a valuable tool for future energy predictions.

Keywords: Weather, Renewable Resources, Neural network models, LSTNet

1 Introduction

In this phase of rapid technological progress and urbanization in the current world, there arise the hike of energy consumption globally, which necessitate the need for assessing the energy consumption method throughout the world. There are conventional methods which are following from the past times which will produce the energy from the combustion of coal, oil, natural gases which will generally call the fossil fuels. But these traditional methods are several severe drawbacks, the first reason is that, these are only present in a finite amount in nature, by the excess use of these resources, it can cause the complete perish of those natural gases and will take millions of decades to reform again. As these gases are limited in the surroundings, it also results in high prices for the energy generation from fossil fuels. The fossil fuel combustion is also posing severe threat to the environment. Combustion of non-renewable resources is causing harm to the whole living beings as it is releasing excess amount of carbon dioxide and nitrous oxide into the atmosphere which cause the rise and accumulation of greenhouse gases and ultimately causing global warming (Opeyemi, B.M et al.; 2021). This has a substantial impact on diverse eco-system and has wide-ranging impacts. Because of these reasons, there emerge the need for thinking about alternate methods for dealing with this situation. For this, the nature is demanding for a sustainable source of energy, which can be obtained by implementing a transition from non-renewable resources to renewable resources. By depending on the natural resources like wind, hydro, tidal, solar, biomass etc. energies, which are available plenty in nature and replenish naturally, helps us to overcome the limitations of fossil fuels. By using these natural resources, we can reduce the emission of greenhouse gases in a significant amount and can avoid the global warming adversities. Nowadays, throughout the world, most of the countries are rethinking of non-renewable resources and take deviation to natural resources.

Every method has its own strengths and weaknesses, the one thing which has a greater impact on the renewable sources is the weather, because of the unpredictable climatic changes the production of energy from natural resources has negative impacts. For instance, the solar energy is depended only on sunlight, in a rainy day, the production of energy is not possible because there won't be any sunlight, likewise wind energy is highly depended on the strength of the wind (Acuzar, A.M.A et al.;2017). Because of these constraints, it is necessary to govern the effect of weather in energy generation and how much it can impact the production of energy.

Spain, as a representative case, has brought impactful measures to raising its renewable energy capacity. This research is addressing the forecasting of energy production from various natural resources in Spain, which is one of the leading top countries which generate adequate amount of energy from renewable resources. Based on the facts, Spain will generate 50% of energy from renewable resources this year, in which 20% is using the wind power. Precise and accurate forecasting is necessary for grabbing essential results which can help in effective energy management and for stability of grid. For this thorough analysis of weather impact on renewable resources in Spain, the energy and weather information over four years from 2015 to 2018 is taken from Kaggle which contain the energy produced from various renewable and non-renewable resources and also different weather factors in which only the case of renewable resources is being considered. The effect of climatic factors on production of energy is being analyzed using different neural network models such as LSTM, LSTM-CNN, Stacked LSTM and LSTNet. A comparison is done here by analyzing the results from each model using the evaluation metrics such as mean squared error, mean absolute error, root mean squared error and r-squared value. Through the analysis it is obtained that the LSTNet method outperforms all other neural network models in terms of the accuracy. A better result is obtained for LSTNet for each of the evaluation metrics. From these findings, LSTNet can be showcased as a valuable tool for future energy predictions for policy makers and stakeholders.

Most of the existing studies concentrated on the forecasting of renewable energy generation without considering the climatic impact on the generation. Some of them may mostly rely on the traditional statistical techniques which may not be able to capture the intricate patterns between weather and energy production (Haddad, M et al.;2019). By considering the neural network models it is possible to address this limitation and to deal with complex patterns.

The limitation of this research is that, it only forecasting the weather influence on energy generation in Spain, so that it can't be applied to other regions with different weather conditions and also the reliability of this work entirely lying on the available dataset, if there is only finite amount of data, it can affect the accuracy of the result. The previous research works in this area are done by concentrating mainly on the energy forecasting, without considering the impact of weather on the energy production and done the forecasting using the traditional forecasting methods. Hence this knowledge gap has been the motivation for this study. This study trying to answer this existing research gap by answering the following research question.

1.1 Research Questions

How well does the LSTNet and other state-of-the-art forecasting neural network models perform when accounting for the influence of weather on renewable energy production?

1.2 Aim

The study is conducted by mainly focusing on improving the accuracy of energy generation from renewable resources under the influence of weather in Spain by exploring and comparing various forecasting approaches. The study focuses on the exploring the applications of different models such as LSTM, Stacked LSTM, LSTM-CNN and LSTNet and it emphasize more on determining the performance difference among these models.

1.3 Objectives

The primary objectives of this research are as follows:

- To investigate the effectiveness of LSTM models, stacked LSTM, and LSTM-CNN architectures in capturing temporal dependencies and improving forecasting precision.
- To implement the LSTNet model and evaluate its performance in comparison to forecasting models.

The integration of weather and energy generation will help in getting deeper insights into the energy generation. The neural network models will help in faster run and determining the long-term dependencies present in the data. The findings obtained from this study has the potential to dramatically alter the usage of renewable resources which can offer sake for the humankind globally. The ultimate aim is to determine the best tool which helps in effectively managing the imperishable resources and sustainable energy which will helps in contributing to the good maintenance of our planet. Through this research it will help in analyzing the best model which has best accuracy among the neural network models.

The structure of the work follows: Section 2 explain the related works in this field, Section 3 gives the methodology followed in this research project in detail. The data preprocessing and cleaning of the data, all are explained here. In Section 4, the design specification is explained. It describes the methods using. Section 5 gives the implementation of the methods. In section 6, the results are evaluated. The final Section 7, gives the conclusion and future work.

2 Related Work

(Roshan Karthika, 2021) conducted a research which shows the importance of renewable energy in the current world, which helps in reducing the emission of carbon dioxide in to the atmosphere. The renewable resources like solar, wind, hydro, geothermal etc are considered here to forecasting the energy produced from these sources. The forecasting is done using the neural network models such as LSTM, LSTM-CNN, Stacked LSTM and time series model ARIMA. The objective of the study was to identify whether the historical energy data can accurately predict the energy generation from imperishable resources using neural network model and time series model. LSTM observed a better performance and for the biomass variable LSTM-CNN got good result. Comparing for all model, the ARIMA method got the best result. The forecasting for six month span of time help the policy makers and stake holders for making appropriate decision regarding the energy generation in the future. The study lack in considering the impact of weather on renewable energy generation so it suggests the inclusion of weather into the energy generation as it has a great impact on the energy generation which gives the motivation for doing this project.

In (Paul, S et al.;2021) reviewed the renewable energy generation in different countries by analyzing the developments and trends. A global experiment is conducted in this study for highlighting the importance of renewable energy and result in showing the reduced greenhouse gas emission.

The study highlights the challenges posing by fossil fuels and how the climate change mitigation affects the transitioning to renewable energy resources. The traditional way of energy generation and stages of exploration of climate change influence on renewable energy generation is the discussed here. The strength here is the thorough examination of contributions of natural resources to sustainable development and climate change, the exploration of market failures adds more insights into the study. The study suggests to conduct more research into the energy generation forecasting to get more information and to get practical insights (Owusu, P.A et al.;2016).

(Sharma, N et al.;2011) proposed the site-specific prediction models for solar power generation using National Weather Service forecasts and machine learning techniques. This approach is critical in analyzing the generation from renewables. The paper introduces the NWS forecast to overcome lack of ability in predicting the weather pattern possessed by previous models used. The study mainly aims to contributing in enhancing the efficiency and adoption of distributed generation from renewables. The study lack from the real-world challenges as it is not addressed properly. But this work lacks from limited discussion on model interpretability and also the study specifically concentrate on solar power generation not extended to other renewable energy resources.

(Andrade, J.R et al.;2017) introduces a forecasting framework that gather details from a spatial grid of numerical weather predictions (NWP) for solar and wind energy which also uses Gradient Boosting Trees (GBT) and feature engineering. It emphasizes on the importance of spatial-temporal information for enhancing the accuracy, but it lacks on focusing on specific sites and preferring short-term predictions. The paper discussion in to the interpretability of the models is very limited and also the study focuses on specific sources, so that extending the proposed methods in to other renewable resources is limited.

2.1 Studies Based on Neural Network Models

2.1.1 LSTM

The application of deep learning algorithms which includes the Deep Belief networks, Autoencoder and LSTM for the renewable energy power forecasting which mainly focusing on 21 solar power plants is proposed here. The study demonstrates the significance of accurate forecasting and compares the performance of deep learning models with the neural network models. The obtained results show the Auto-LSTM has the good performance by combining the Autoencoder with the LSTM's forecasting ability gives good performance. The paper suggests to combine the performance of DBN and LSTM for improving the forecasting error and also suggests the combination of Convolutional Neural Networks with LSTMs so that it can learn the filter functions (Gensler, A et al.;2016). This paper lack from limited generalization, as it is only focusing on solar power generation, so it cannot be applied to other renewable resources.

(Harrou, F et al.;2020) proposed a short short-term forecasting of photo voltaic solar energy generation using LSTM, identifying the PV system generation volatility by various weather condition was a big challenge. The practical applicability of the LSTM model is discussed here. The evaluation of the performance using metrics gives a good R squared value and low MAPE value shows better performance of LSTM in forecasting the energy generation. The study suggests to include other recurrent neural network and to add climatic variables to enhance the forecasting quality. This work only focusing on the LSTM model, it's performance is not compared with other forecasting models which gives more comprehensive analysis also external factors are not considered.

For addressing the solar irradiance prediction challenges for distributed PV generation, especially for those who lacks access to historical irradiance data, an approach is introduced. By using weather data, it follows a structured output prediction framework, LSTM networks to catch temporal dependencies and result in the better performance than traditional models. The work suggests to analyze the impact of forecast errors on irradiance predictions (Qing, X et al.;2018).

2.1.2 LSTM -CNN

In this study, time series analysis is carried out by Grey Wolf Optimizer (GWO)-optimized Convolutional Neural network- Long Short-Term Memory (CNN-LSTM). The hybrid model LSTM-CNN will help the model by enhancing its capacity in capturing the complex patterns and dependencies in the data. By using GWO, it helps in optimizing the network configuration. F-score, precision, recall and accuracy are considered for evaluating the results. The result shows that the GWO-optimized CNN-LSTM outperforms all the other baseline models with an accuracy of 92.3%, also GWO networks had high number of filters in convolutional layers, which helps in catching the important features in the data. Wilcoxon rank test is conducted to confirm the performance of GWO than other baseline models in determining the optimal CNN-LSTM configurations (Xie, H et al.;2020). (Kumari, P et al.;2021) discusses the difficulties of integrating the solar energy with the existing grid system by proposing a hybrid method, LSTM-CNN for predicting global horizontal irradiance (GHI). 23 locations in California, USA is studied and trained the model with meteorological data and LSTM is used for capturing temporal features and CNN to spatial features. Paper highlights the importance of accurate prediction of GHI and the importance of LSTM-CNN for predicting the GHI under diverse climatic conditions. The challenges in the photo voltaic (PV) power generation is reviewed here. The unpredictable environmental challenges is impacting the power generation so there arise the need for accurate forecasting for optimizing the PV power plant operations. The LSTM -CNN which has the capability of extracting meaningful observations from complex data. The review suggests the comparison analysis of existing methods which give more detailed information (Lim, S.C et al.;2022).

2.1.3 Stacked LSTM

Increasing demand for renewable energy like solar Photo Voltaic (SPV) over the fossil fuel energy generation emerges the need for accurate forecasting of energy generation under the unpredictable environmental changes. The paper identifies the limitations of traditional statistical methods, so various deep learning methods like Stacked LSTM, CNN etc. are employed. The limitations of existing CNN pave the way for Stacked LSTM to enhance the effectiveness. The paper suggests to address the challenges of current model to improve the forecasting accuracy (Elizabeth Michael, N et al.;2022). But this work lack from including the meteorological factors into the analysis. (Sowmya, C et al.; 2021) proposes the significance of wind energy in various applications. The study lies upon forecasting the wind speed using the Machine Learning (ML) and LSTM. The study highlights the need using the layering LSTM method for getting better accuracy and so explores the Stacked LSTM method. The paper proposes the comparative analysis of different method and shows the importance of three-layered Stacked LSTM.

2.2 Studies Based on LSTNet

The study concentrates on the attention-based models for wind power forecasting. The paper discusses the limitations in finding the temporal and spatial patterns and thereby perform and compare three models such as Recurrent neural network (RNN), LSTNet, temporal pattern attention-based long-short term memory (TPA-LSTM) and dual-stage attention-based recurrent neural network (DA-RNN). These are evaluated based on the experiment conducted in a wind farm of southeast Australia. The results show better results but it lacks in comparing additional evaluation metrics other than MAE and RMSE. The model does not compare the performances with other existing models (Huang, B et al.;2021).

Table 1: Related Works

Approach	Strength	Weakness	Reference
LSTM, Stacked LSTM, LSTM-CNN and ARIMA	Multiple renewable resources is considered and compared with different forecasting models	Impact of climate on renewable sources is not discussed.	(Roshan Karthika, 2021)

Numerical weather predictions is used for feature engineering combining gradient boosting trees algorithm and spatial temporal data	Exploration of spatial-temporal information. Significant improvements in point forecasting accuracy.	Generalization of proposed method to other renewable energy sources is limited. Discussion on model interpretability is limited.	(Andrade, J.R et al.;2017).
Deep Belief networks, Autoencoder and LSTM	Thorough experimentation using DL, ANN architecture, MLP, LSTM, DBN and Auto-LSTM. Incorporation of clear-sky filter.	Generalization is limited. Lack of discussion of robustness of the given model under various weather conditions.	(Gensler, A et al.;2016).
Analysis using GWO-optimized CNN-LSTM hybrid model	Optimized CNN-LSTM outperforms other models. Hybrid CNN-LSTM architecture helps fo	The complexities in the implementation of hybrid model is not discussed.	(Xie, H et al.;2020).
LSTM method is used	Practical applicability of proposed model is given. Thorough data analysis.	Incorporation of external factors. Comparison of given model with other model is limited which lack from comprehensive understanding.	(Harrou, F et al.;2020)
Stacked LSTM and CNN	Comparative analysis with the state-of-the-art machine learning techniques. A hybrid approach which combines the strength of CNN and LSTM.	External factors influencing solar irradiance is not considered. Generalization is limited.	(Elizabeth Michael, N et al.;2022).
Machine learning techniques SVM, linear least squares	Incorporate the effect of local characteristics on power generation.	Focus only on solar power, not considering other renewable resources.	(Sharma, N et al.;2011)

	Compare multiple regression techniques for generating prediction models.		

The related works gives an insight into the need for forecasting the renewable energy and how the weather impacts the generation of the energy. These works shows the importance of neural network models and their applications. The works shows that the need of comparative analysis among the proposed models which gives a comprehensive analysis and findings. It also showcase the need for more generalized works which means to take into consider different renewable resources and different weather condition which will more accurate and precise instead of focusing on any of the one.

3 Research Methodology

In this section, the entire flow of the research work is explained thoroughly. The process of gathering data from the open sources, cleaning and preprocessing it for making the final on and the implementation of different neural network models are explained here.

3.1 Data Collection

The process of creating a forecasting model starts with gathering pertinent data. For this research, the dataset is obtained from a public opensource platform, Kaggle through ENTSOE and REE. The datasets consist of both hourly energy demand generation and weather which is historical information on Spain's use of renewable energy sources for energy generation and weather. The information should include pertinent variables like date and time, weather, and energy generation figures, and it should span a sizable amount of time. The Energy dataset consists of 28 columns with 35065 rows in total and weather dataset contains 17 columns and 178397 rows.

3.2 Data Preprocessing

Data preprocessing has a significant impact in ensuring the quality of dataset. Starting with the energy dataset, it undergoes several operations such as dropping of some irrelevant columns which is then subjected to outlier removal which is then followed by the filling of null values. Then the variable 'time' is converted into datetime type using pandas function and it was set as index. In the weather dataset also, unnecessary columns are dropped and duplicate rows are removed based on the time and city name and the data undergoes the outlier removal. Then converted the time variable into datetime type and changed it's name. Besides, the integer columns converted into float64 type for conveniency. The flow of data preprocessing is explained in the following figure.

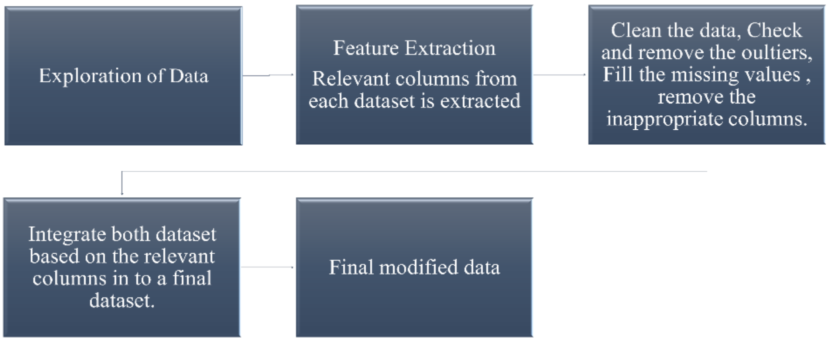

Figure 1: Data Preprocessing Flow

The dataset is checked for null values. Some columns in the energy was completely with no values at all. Those columns are removed at the beginning itself. The outliers is removed then using the z -score. From the energy dataset, 424 is removed and from weather 7843 is removed. Then the data is checked for null values, all rows with missing values was displayed. For the time series data, with the change in time the data points will also change. Filling the empty values with mean, can affect the seasonality of the data also the entire record dropping is not a possible step, because it can affect the time interval entries. Th solution for this to use interpolation. It will estimate the missing values based on the values of the neighboring points. The same is done for both energy and weather dataset to dealing with the null values.

```
In [11]: # Fill null values using interpolation
         energy.interpolate(method='linear', limit_direction='forward', inplace=True, axis=0)
```

Figure 2: Filling Null Values

3.2 Feature Engineering

From the two datasets, relevant columns are extracted. For energy data, the total energy generation can be obtained by summing up the values of all generation variables related to renewable resources. In the energy dataset, there are some columns with no entries, those columns are removed from the dataset and also those variables which are not renewable sources, like fossil fuels, nuclear etc are also removed and only those comes under renewable energy, which are biomass, hydro, solar, waste etc are added together to obtain the total energy generation. After obtaining the total energy, all the generation variables are removed as we only need the total energy generation. In both of the dataset the common variable is the time variables which contain data from 2014 to 2018, it was set as an index. For the weather data, the meteorological features such as temperature, wind, rain, snow and cloud is extracted from the dataset and finally those extracted variables from energy and weather dataset are merged together to obtain the final dataset. A small diagram of selection of variables is provided below.

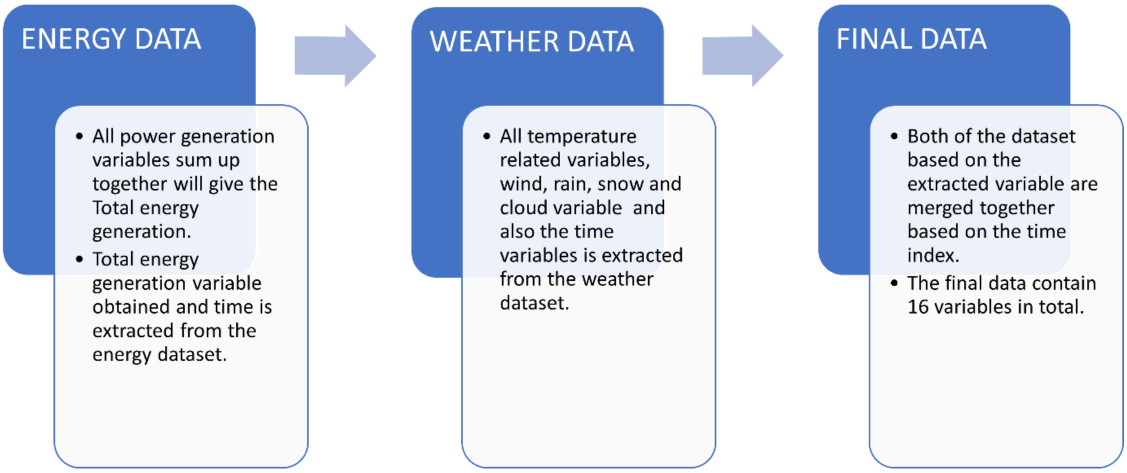

Figure 3: Selection of Variables

3.3 Exploratory Data Analysis (EDA):

Some basic visualizations were done to enhance the understanding of variables. Histograms of weather features were visualized in order understand the distribution of each variables. Correlation matrix is calculated using heatmap, for all weather features with the total energy generation variable. Scatter plot is plotted, to visualize the relationship of weather variables with energy generation.

3.4 Data Modelling

Here various time series forecasting methods is implemented to predict the renewable energy generation under the influence of weather. The implementation is done on the merged final dataset. Some four different approaches are employed here by implementing TensorFlow and Keras and the methods are LSTM, Stacked LSTM, LSTM-CNN and LSTNet. For all the model, the total energy generation and selected weather features are scaled for preparing the training data and for the test data the predictions are generated. The MinMaxScaler from the sklearn library is used for scaling the data. LSTNet combines the strength of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). The hybrid architecture helps to capture both the local patterns using CNN and to capture short term dependencies using LSTM. In this weather variables are selected as external covariates and total energy generation as target variable. Hybrid model is created using Keras functional API. In this model, for the LSTM and CNN has separate input branches and the outputs are Combined together before it gets passed through the Dense layer for final prediction. This approach of data modelling allows for the comprehensive assessment of performance of these different models.

3.5 Evaluation

Performance of each model is evaluated using the evaluation metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R-squared value. For the comparison, predicted values and actual values are plotted together.

$$\textbf{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \qquad \textbf{(1)}$$

$$\textbf{RMSErrors} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \qquad \textbf{(2)}$$

$$\textbf{MAE} = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} = \frac{\sum_{i=1}^{n}|e_i|}{n} \qquad \textbf{(3)}$$

4 Design Specification

Preprocessing of data, feature engineering, data modelling are done in the jupyter notebook python. After completing the preprocessing and data cleaning, when the final data is ready, the neural network models are applied on the final data in jupyter notebook. For the implementation of LSTM, Stacked LSTM, LSTM-CNN and LSTNet, TensorFlow with a high-level API named Keras is used. MinMaxScaler from sklearn library is used for scaling purposes and the training set and testing set is derived from the final main dataset.

4.1 LSTM

Long Short-Term memory (LSTM) is a type of Recurrent neural network (RNN) which is a specialized one designed to overcome the limitations possessed by RNN in capturing the long-term dependencies present in the data. The key components of LSTM consists of :
Cell State: indicate the long-term memory
Hidden State: indicate the short-term memory
Gates: Controls the flow of information
In the input gate is the one who decide what all information to be added, the forget gate identifies what to be removed and output gate have impact in the next hidden state. These helps LSTM to remember or fail to recall all the sequential steps, which make it effective for problems which have dependencies such as time series prediction. The ability to maintain the important info over long term made LSTM a crucial model for prediction and in handling complex data.

4.2 Stacked LSTM

This is an advanced architecture which enhance the capability of LSTM by sequentially adding multiple LSTM layers. The process flow here is such a way that, each LSTM layer process the input sequence and it is passed to the output sequence and then it is to be passed to the coming layers. Through these layers of abstraction, it helps in determining the complex patterns and dependencies existing in the input data. From the very beginning bottom layer, it treats the raw data and through layers of process, more complex patterns are identified and in the final stack, refined output sequence is passed which is then used for prediction. As this method has the ability to capture the complex structures and long-term relationships existing in the data, it can be chosen for the forecasting problems.

Figure 4: Stacked LSTM Flow

4.3 LSTM-CNN

LSTM-CNN which is a hybrid architectural model which is employed by concatenating the strength of Convolutional Neural Network (CNN) and Long Short- Term Memory(LSTM) together which helps in capturing the temporal and spatial features present in the data. The process flow is like that, Initially, the input data is passed through the CNN layer, here it diagnose any spatial features presenting in the data and these identified spatial features are then passed to the LSTM layer where it undergoes and determine the temporal features and long-term dependencies present in the data. By combining both of the spatial and temporal patterns together, LSTM-CNN make a comprehensive understanding of the input data. This is useful not only for the text data, which is effective for image and video data, which helps in understanding the spatial and temporal features and in making accurate predictions.

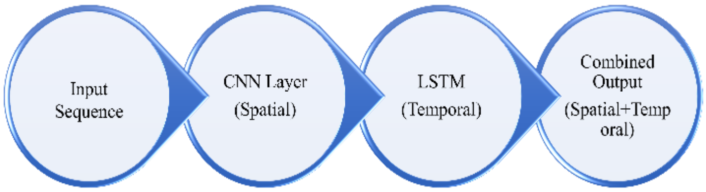

Figure 5: LSTM-CNN Flow

4.4 LSTNet

Long Short-Term Time Series Network, is a neural network architecture which integrates the strength of LSTM and CNN which helps in capturing the long-term dependencies and short -term fluctuations. The skip-connection mechanism in LSTNet, helps for the direct flow of information from the input to output. LSTNet is efficient in incorporating and integrating all the components to create a effective presentation of time-series data, which helps in accurate prediction for the future analysis. It is efficient in handling all kind of time-series data and only take reduced training time comparing with other model architectures. Because of the effective performance of this method, it makes it powerful tool in the forecasting applications such as energy, where the need of determining short term patterns and long-term dependencies is important.

Figure 6: LSTNet Flow

5 Implementation

This section describes the examination of different forecasting models for the production of renewable energy under the influence of weather. The 'energy' and 'weather' datasets both had missing values, so the investigation started with painstaking data cleaning and preprocessing to remove them. The LSTM, Stacked LSTM, LSTM-CNN, Hybrid, and LSTNet models yielded a variety of insights regarding their forecasting abilities.
After preprocessing the merged final data, the correlation matrix is displayed in order to get an insight of relationships between weather variables and energy generation. This analysis shed important light on the connections between different meteorological parameters and the production of energy.

5.1 LSTM

Initially the final merged data is loaded in to jupyter notebook environment. The splitting of data into training and testing set is the initial phase. The dataset consist of four years of data. Based on this, the data is splitted such that the training set includes first three years of data and the remaining for test data. Then min-max scaling is applied for both energy and weather variables. The structuring of training data into sequential input sequences is the crucial step in which each represents the 24 hours of data with target variable as 25^{th}- hour energy generation, which means the next hour of the day. The LSTM is compiled using the MSE and Adam optimizer, where the LSTM is constructed such a way that it uses a single alyer of 50 units and Rectified Linear Units (ReLU) activation function. The training is done until 10 epochs with batch size of 32.
The same scaling is done for the test set, and a similar input sequences like training data is created for test. Then, the LSTM trained model is the used for predicting the energy generation on test set. The obtained predictions are then converted to the original scale and e then the performance of model is evaluated using the evaluation metrices. Then finally the predicted values are plotted against the actual values for visual representation. The model configuration for LSTM is given below.

Table 2: LSTM Model Configuration

LSTM Parameter	Value
Input Layer	50
Hidden Layer	50
Dense Layer	1

Activation Function	ReLU
Batch Size	32
Epochs	10
Loss Function	MSE

5.2 LSTM-CNN

The same as in the LSTM, the data is first split into training and test sets and them min-max scaling is applied for both energy and weather features. The LSTM- CNN model is build such a way with an LSTM layer featuring of 50 units and ReLU activation function and 1D convolutional layer with 64 filters with a kernel size of 2. For down sampling, the MaxPooling1D is done with that a flatten layer is added for transforming the output into aa 1D array. The dense layer is finalized for prediction. Over 10 epochs the training is done with batch size of 32. The evaluation metrics such as MSE, RMSE , MAE and R- squared are analyzed for finalizing the model's performance. LSTM-CNN combines the spatial and temporal patterns, which enhances the ability in capturing the patterns in the time series data. The model configuration is given below.

Table 3: LSTM-CNN Model Configuration

LSTM-CNN Parameters	Values
LSTM Layer	Units : 50, Activation : ReLU
Conv1D Layer	Filters: 64, Kernel Size : 2
MaxPooling1D Layer	Pool Size : 2
Dense Layer	1
Optimization	Adam
Loss Function	MSE
Epochs	10
Batch Size	32

5.3 Stacked LSTM:

Similar to the LSTM, the data is splitted in to training and testing and scaling is done on both data. Input sequence for training, which comprise 24 hours of data and 25th hour as target being considered. Th stacked LSTM is configured such that, it has two LSTM layers, in which the first layer has 50 units, ReLU activation, return sequences. Whereas the second layer consists of 50 units and ReLU activation. For final prediction, dense layer with one units is used. The model is compiled here also using Adam optimizer and MSE loss function. Execution of training is done upto10 epochs with batch size of 32. The results are analyzed using the evaluation metrices and the predicted values are plotted against the actual values for the visualization of the result. The stacked structure helps in enhancing the ability of network in learning complex patterns, which leads to improving the forecasting performances.

Table 4: Stacked LSTM Model Configuration

Stacked-LSTM Components	Values
LSTM Layer 1	Units: 50, Activation: ReLU, Return Sequence: True
LSTM Layer 2	Units: 50, Activation: ReLU
Dense Layer	Units: 1
Optimizer	Adam
Loss Function	MSE
Epochs	10
Batch Size	32

5.4 LSTNet:

The Long Short-Term Memory Network (LSTNet) is performed by loading and preprocessing the dataset first with external covariates such as wind speed, wind degree, rain, snow and cloud has been selected and scaled. The data then undergoes training and testing and then a sequence of input-output pairs are created. The LSTNet model is a hybrid architectural model which integrate both LSTM and Convolutional Neural Network (CNN), which helps in analyzing temporal and spatial patterns and long-term dependencies. In this model architecture it consists of three LSTM layers each with 64 units and a 1D CNN layer with 32 filters and kernel size of 3. The external covariates is then merged with the input data and the model is then trained using Adam optimizer and MSE loss function. After completing the training process, on the test set predictions are made. Finally, the performance is evaluated using the evaluation metrices. Ater that, for the visual analysis the plot of predicted versus actual values is plotted.

Table 5: LSTNet Model Configuration

LSTNet Components	Value
LSTM Layers	Number: 3, Units: 64, Activation: ReLU
CNN layers	Filters: 32, Kernel : 3, Activation: ReLU
External Covariates	Wind speed, Wind deg, Rain, Snow, Cloud all
Optimizer	Adam
Loss Function	MSE
Epochs	10
Batch size	32

LSTNet comprises the strength of both LSTM as well as CNN, which helps in capturing the long-term temporal and spatial dependencies existing in the data. By including the external covariates, it helps in enhancing the model’s ability to consider the other factors which are influencing the energy generation.

6 Evaluation

6.1 LSTM:

The LSTM was trained on 10 epochs and the predicted values are plotted against the actual values. The result is as shown below.

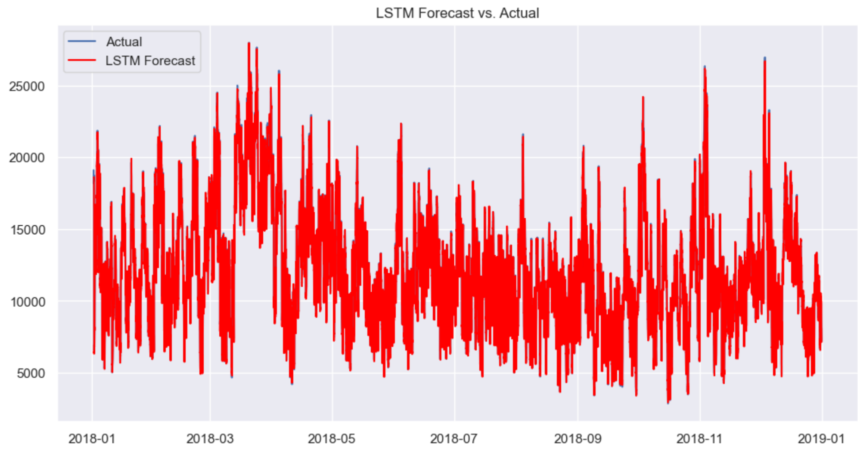

Figure 2: LSTM Predicted Vs Actual

The obtained evaluation metrics for the method is given as:

Table 6: LSTM Evaluation Metrics

R -Squared	0.9893
MSE	182005.25
MAE	210.32
RMSE	426.62

From the figure, it is crystal clear that, the predicted value and actual value are lying closely, the close alignment tells the capability of LSTM in capturing the trends and patterns present in the data. In the observed metrics, the R square value shows the better accuracy of the result which indicate the model is accurate in predicting the energy consumption under the influence of weather. The MSE value is relatively high because of the characteristics of the data which may affect the prediction. But the close alignment of predicted values indicate that the LSTM model was successful in determining the patterns and temporal dependencies existing in the data.

6.2 Stacked LSTM:

The Stacked LSTM model is trained for 10 epochs and the obtained visualization is plotted below.

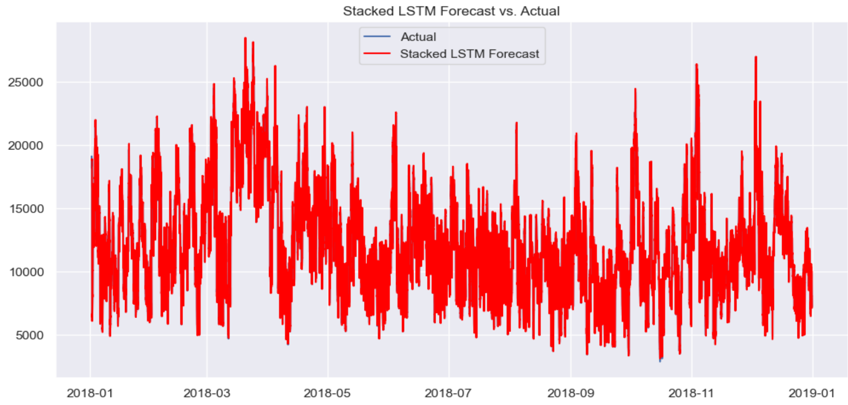

Figure 3: Stacked LSTM Predicted Vs Actual

The Evaluation metrics for Stacked LSTM:

Table 7: Stacked LSTM Evaluation Metrics

R Squared	0.9898
MSE	174317.22
MAE	188.78
RMSE	417.51

The Obtained R square value is nearly close to one, which shows the high accurate predictive capability. The plot given above shows the close alignment of predicted values to the actual values, indicate that the model is successful in capturing the underlying patterns and trends existing in the data. Here also MSE value is relatively high which can affect the prediction. The obtained output shows that the stacked LSTM is an accurate method for predicting the energy consumption under the influence of weather.

6.3 LSTM CNN:

The LSTM-CNN model is also trained using 10 epochs and the results obtained is given below.

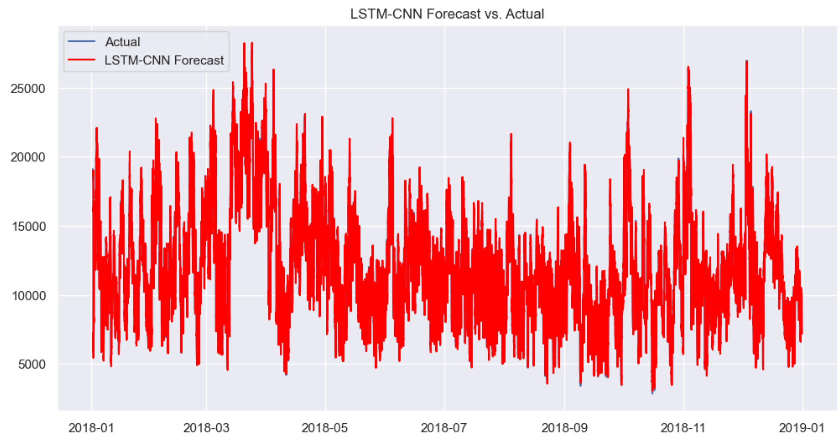

Figure 4: LSTM-CNN Predicted Vs Actual

The evaluation metrics for LSTM-CNN:

Table 8: LSTM-CNN Evaluation metrics

R Squared	0.9806
MSE	330847.85
MAE	297.10
RMSE	575.19

The result shows a reliable and accurate performance of LSTM-CNN model in predicting the energy generation. The close alignment of predicted value with actual value shows the model was able to capture the underlying patterns in the data. By evaluating the evaluation metrics, it is obtained a good R square value shows overall a good fit and better performance but the MSE, MAE and RMSE values are comparatively high here as well.

6.4 LSTNet:

The LSTNet model is also trained for 10 epochs and the obtained results are given below.

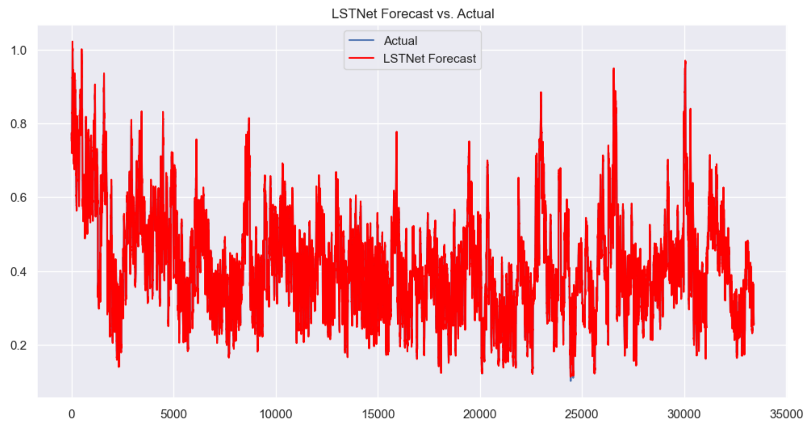

Figure 5: LSTNet Predicted Vs Actual

The evaluation metrics for LSTNet:

Table 9: LSTNet Evaluation metrics

R Squared	0.9899
MSE	0.00020
MAE	0.00598
RMSE	0.0144

From the above results, it is very clear that the actual and predicted values are lying very closely, indicating the accurate prediction performance. Comparing with the above LSTM methods, LSTNet obtained low MSE, MAE and RMSE value and also a high R square value which is higher than all other methods and close to one. All these results further validate the highly accurate performance of the model. High R squared value shows that this model was able in explaining the all the significant variability in the given data. All the result shows that the LSTNet model is very effective in forecasting the energy generation under the influence of weather other than the LSTM neural network models.

6.5 Comparison of Results

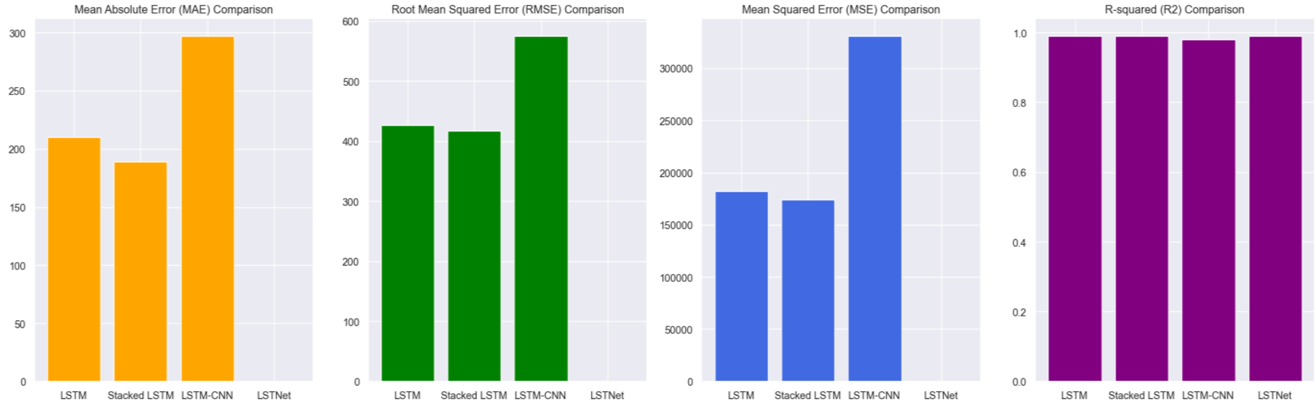

Figure 6: Comparison Plot of Results

In comparison of the results, performance metrics has a crucial role in providing valuables insights. Taking into consideration, both LSTM and Stacked LSTM obtained excellent accuracy in prediction, where stacked LSTM slightly exceed the LSTM which indicate the effect of additional layers. Following these LSTM-CNN also acquired good accuracy value but it got higher error rate in comparison with all other models. All the LSTM models got comparatively high error rate in which LSTM-CNN is relatively very high which shows a complexity of inclusion of convolutional neural network. Exceptionally, the performance of LSTNet is remarkable. LSTNet outperforms all the other LSTM models with low error rate, mean absolute error rate, root mean squared error rate and excellent r squared value. LSTNet is highly proficient in capturing the long-term dependencies and intricate patterns. The comparison of results helps in understanding the strength of each model and also helps in adopting most appropriate method for energy forecasting.

6.6 Discussion

By analysing the results obtained, all the given models performed good in accurately predicting the energy generation under the influence of weather. All those four models acquired good accuracy in prediction in which LSTNet comes to the top. This shows that all these models can be used as a tool for policy makers and stake holders in forecasting weather-based energy forecasting for future plans. All the performed models are good in capturing the long-term dependencies and complex patterns existing in the data. The previous researches based on these methods shows good result in accurately predicting the energy generation. Similarly, these methods capture good result in accurately predicting by incorporating the weather as a new variable. But, except LSTNet all other models have high mean squared error rate value, among these LSTM-CNN has relatively very high value. By going deeper into the reasons behind why those neural network models got higher errors will be beneficial. For obtaining a robust results by overcoming the limitations of individual models, an ensemble modelling technique can be adopted. For this, an ensemble of LSTM, LSTM-CNN, Stacked LSTM and LSTNet can be created, through this approach it will help in attaining more accurate and promising results.

7 Conclusion and Future Work

The study revolves around the performance of neural network models and their effectiveness. The research was successful in accurately predicting the energy generation with better accuracy results. The comparison of results shows that LSTNet method outperforms all other methods by obtaining high accuracy and low error rate. Followed by LSTM and Stacked LSTM got strong accuracy with slight difference. The study highlights the LSTNet as the top performer and provide a substantial contribution to our understanding of the best forecasting techniques in this field. It also emphasize the significance of these meteorological factors such as temperature, wind, precipitation etc. in influencing the production of energy in Spain. The study has a limitation as this work is conducted based on the provided dataset of Spain, when it comes to the case of other particular regions, it can introduce biases. So, generalizing these findings through different countries with different geographical features require cautions. For enhancing the generalizability, for future studies, test developed models on datasets from different sources and different regions. Also, the degree of accuracy in these scenarios can be affected by sudden shifts in weather patterns. It should be acknowledged since they can affect the applicability of the findings.

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