



Machine Learning Based Solar and Wind Energy Forecasting

Ch. Sudheer Kumar¹, Mr. A. Ravi Kishore²

¹ UG Student (21341a1230), ²Asst. Professor

Department of Information Technology, GMR Institute of Technology, G.M.R. Nagar, Rajam-532127, A.P 2023-2024

1. INTRODUCTION

Machine learning-based forecasting for solar and wind energy has become integral to the seamless integration of renewable energy sources into the modern power grid. As the world endeavors to reduce its reliance on fossil fuels and combat climate change, harnessing the potential of sunlight and wind has gained paramount importance.

However, the inherently fluctuating nature of solar and wind power generation, contingent on unpredictable weather patterns, presents substantial challenges for grid operators and energy stakeholders striving to maintain a stable and dependable energy supply.

In response to these challenges, machine learning methodologies have emerged as potent tools for predicting solar and wind energy production. These techniques utilize historical and real-time data, including meteorological inputs, to generate precise forecasts of energy generation.

In doing so, they empower grid operators to make well-informed decisions regarding energy generation and distribution, optimize resource allocation, and bolster grid reliability. This introduction lays the foundation for a deeper exploration of the fundamental principles, methodologies, and practical applications of machine learning in the context of solar and wind energy forecasting.

2. LITERATURE SURVEY

Following research papers are studied in details to understand the proposed Solar and wind forecasting technique and experimental result for predicting the output.

2.1. Galahad Alkhatat, Rashid Meh mood publisher platform or journal where the paper is published is IEEE in the provided sources.

1. The primary objective of this paper is to predict the solar and wind energy generation
2. In this paper, the RNN (Recurrent Neural Networks) models were used, a high accuracy rate, with a validation accuracy of 88% and a test accuracy of 82%, surpassing the performance of the CNN and Hybrid forecasting models.
3. The trade off between model computation time needs to be considered when using hybrid models.
4. RNN's can effectively model the time series nature of energy data, making them suitable for forecasting tasks.
5. CNN-based forecasting models in the paper rely on convolutional layers to extract features from the data, while the regression task is performed in the last fully connected layer.

2.2. Mariam AlKandari and Imtiaz Ahmad Department of Computer Engineering, Kuwait University, Kuwait

1. The paper focuses The machine learning models used in the hybrid model include long short-term memory (LSTM), gate recurrent unit (GRU), Auto Encoder LSTM (Auto-LSTM), and a newly proposed Auto-GRU
2. The GRU (Gated Recurrent Unit) model is reported to be the most accurate machine learning model in the research paper. It is followed by the Auto-GRU, LSTM, and Auto-LSTM models.
3. The GRU is a part of RNN (Recurrent Neural Network) and LSTM and Auto GRU
4. LSTM has a more complex architecture compared to GRU, with three gating mechanisms: input gate, forget gate, and output gate. These gates control the flow of information and help in capturing long-term dependencies in sequential data
5. GRU, on the other hand, has a simpler architecture with only two gating mechanisms: reset gate and update gate.

3. METHODOLOGY

3.1 The Solar and Wind energy forecasting ML and DL :

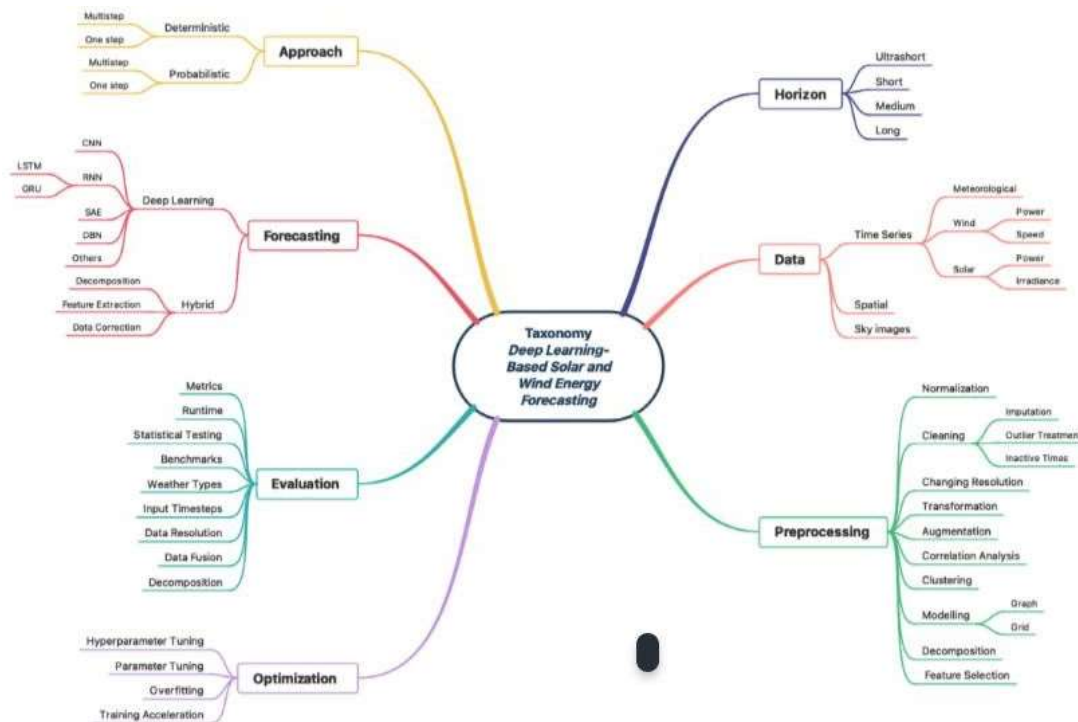


Fig-1: Architecture for solar and wind energy forecasting

Data Sets :

The research paper mentions that most works in wind and solar energy forecasting have used datasets from locations in China, USA, and Australia

The paper also discusses the use of different datasets in the context of specific forecasting models.that summarizes important information about CNN-based forecasting models, including the datasets used

Additionally, the paper mentions the use of data clustering algorithms for preprocessing renewable energy data, such as clustering solar irradiance data into different sky conditions

Data Preprocessing :

Cleaning: This includes the many steps some are handling the missing values, Feature selection, outliers,, removing the in active Time lines

Correlation analysis: This includes to calculate the correlation of all the variables and how they are correlated by each other

There are few many techniques are used in precessioning parts like Transformation , clustering , Train test split

For CNN we have preprocess the images. there we have to adjust the Resolution and Argumentation

Model Selection :

This paper consists of both the Machine learning as well as Deep learning algorithms .The ML algorithms are SVR, RF, DT. The Deep learning algorithms are used are CNN(conventional neural networks) , RNN(recurrent neural network) .The RNN also contains of the algorithms of LSTM(long short- term memory networks) and GRU(Gated Recurrent Unit)

Time series data are sequential data recorded at a specific time interval, which usually ranges from few seconds to an hour in forecasting data. Processing sequential data usually is done using RNN based model and its advanced variations LSTM and GRU.

In stacked LSTM, each LSTM layer output is the input to the next LSTM layer. This deep architecture enables a more complex representation of sequential data over time. Stacked LSTM based models are for wind speed prediction.

The spatio-temporal information is modeled as a graph whose nodes are data-generating entities and its edges represent the interaction between these nodes.

This approach allows information from neighboring stations to improve the forecasts of a target station. The proposed model provides forecasts of wind speed of all nodes in the graph at the same time. In meteorological inputs are used to train the stacked LSTM based model, which reflected on more accurate forecasting than a single LSTM.

In LSTM model with two hidden layers is used for PV power forecasting. Forecast and historical weather variables in addition to historical PV power data were used to train and test the model, which achieves higher accuracy than RNN, Extreme Learning Machine (ELM), and the generalized regression neural network.

LSTM-based forecasting models performance was compared with several machine learning models, such as Support Vector Machine Regression (SVR), Bagged Regression Trees (BRT), Feed Forward Neural Network (FFNN), the Linear Least Squares Regression (LLSR) method, Back Propagation Neural Network (BPNN), and Multi-layer Perceptron network (MLP).

3.2 Solar and Wind energy forecasting using LSTM, RNN and GBM:

The methodology of the research paper involves comparing three neural network-based models, namely RNN, GBM, and LSTM, for short-term wind power forecasting.

The dataset used for the study consists of annual hourly data of wind turbine power output and wind velocity in the Kolkata region of India. The first step in the methodology is dataset pre-processing, where the data is cleaned and prepared for analysis.

Next, the three models (RNN, GBM, LSTM) are implemented and trained using the pre-processed dataset. Performance parameters are then calculated to evaluate the accuracy and effectiveness of each model. The models are compared based on these performance parameters to determine the best model for wind power forecasting. Finally, the outcomes of the analysis are discussed, and suggestions for future work to improve the accuracy of the neural network models.

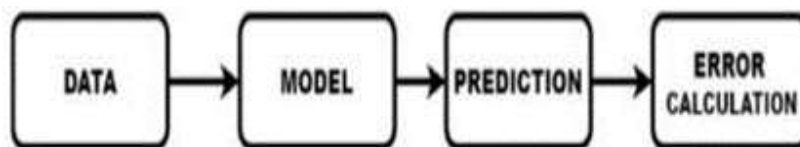


Fig-2: Flow chart of Model Architecture

Model:

RNN, GBM and LSTM algorithms are used in this work as described.

(a) The size of hidden layer for each network is 100.

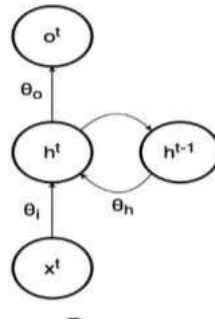
(b) In all the algorithms, Wind velocity (in m/sec) is Input parameter, while the targeted parameter or the output parameter to be predicted is Output Power (in kW)

RNN is a category of neural networks where links flanked by the computational units led to formation of a directed circle. Contrasting to the MLP or feed forward network, BRNN know how to utilize their in-house remembrance or memory to procedure out the random sequences of inputs.

In a RNN, the information or data, cycles in the course of a loop. When it construct a decision, it takes into account the current input as well as what it has well-read from the inputs it received previously. As a result of their inside memory, RNN's can recall vital things about the info they got, which empowers them to be exceptionally exact in anticipating what's coming straightaway

LSTM is an unusual sort of RNN, evolved in 1997 by Hochreiter and Schmidhuber. On observing its architecture, we deduced that the standard hidden layers of BRNN are substituted by LSTM cells. These cells are made up of a variety of gates which can manage the input flow.

Graphical representation of RNN model:



Variable t , output at the instant of time (t) depends upon the situation of hidden layers at time (t), which is quite similar to that of feed forward neural network.

Gradient Boosting Machine:

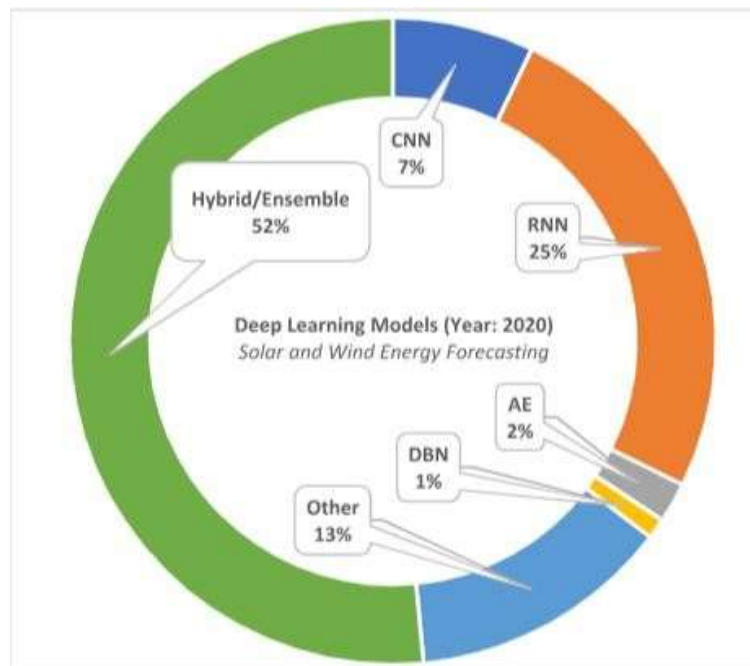
GBM (Gradient Boosting Machine) is a methodology for resolving classification and regression problems, which generates a predictive or forecasting model in the variety of ensemble of weak predictive model, typical example is a decision trees. GBM constructs the model or system in a step- by-step or stage-wise manner, which is very much similar to other alternative boosting methodology do, and thus it generalizes them by permitting the minimization or optimization of an arbitrary differentiable loss function. Boosting is one type of ensemble technique where the forecasters/ predictors are not created alone, rather they are created sequentially

4. RESULTS AND DISCUSSION

4.1 The Solar and Wind energy forecasting ML and DL :

The taxonomy of wind and solar energy forecasting is rich with deep learning methods .Hybrid forecasting and recurrent neural networks (RNN) are commonly used models in wind and solar energy forecasting .Convolutional neural networks (CNN) are also frequently used in the field .Probabilistic and multi step ahead forecasting methods are gaining attention in wind and solar energy forecasting. Some studies have analyzed the impact of using meteorological data in addition to power data on model accuracy Researchers often compare the performance of deep learning models with other models such as SVR, RF, DT, MLP, and statistical methods like ARMA, ARIMA, and SARIMA .The provided sources do not explicitly mention additional points to consider. However, the points mentioned above provide key insights into the models and methods used in wind and solar energy forecasting.

Deep learning models performance on test data:



- LSTM-based models, both alone and in hybrid models, have shown superior accuracy in forecast horizons longer than 15 minutes

4.2 Solar and Wind energy forecasting using LSTM ,RNN and GBM:

The study compares the performance of RNN, GBM, and LSTM models for short-term wind power forecasting .The results show that LSTM performs better than RNN and GBM in terms of accuracy and performance parameters The accuracy of the models is assessed using performance parameters such as Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE) .The MAPE value is higher for GBM, while MSE and RMSE values are least for LSTM .The simulation results demonstrate that LSTM, RNN, and GBM are all able to forecast wind power with good accuracy, but LSTM performs better .The paper suggests that future work could involve hybrid models of LSTM, GBM, or RNN, and the inclusion of other parameters such as wind direction and temperature.

Comparative analysis of Basic RNN and LSTM

PARAMETERS	RNN	LSTM	GBM
Mean Absolute Error (MAE)	0.264405	0.176683	0.320215
Mean Absolute Percentage Error(MAPE)	9.867345	6.563425	11.1049
Mean Square Error (MSE)	0.0080	0.0078	0.1623
Root Mean Square Error (RMSE)	0.354985	0.231292	0.402920

- These accuracy methods provide quantitative measures to compare the performance of the RNN, GBM, and LSTM models for wind power forecasting.

5. CONCLUSION

In conclusion, the escalating global demand for sustainable energy has ushered in the widespread adoption of solar and wind power, underscoring the imperative for precise forecasting to ensure grid stability and optimize resource allocation. This review provides a concise overview of recent strides in employing machine learning (ML) techniques to enhance the accuracy of solar and wind energy forecasts, critical for the successful integration of renewable energy into existing grids. Accurate energy predictions hold paramount importance in the context of sustainable energy transitions, particularly as nations worldwide shift toward cleaner energy sources. The ML models examined, including random forest, Gradient Boosting, Support Vector Machines, and Long Short-Term Memory networks, offer promising avenues to tackle the challenges posed by the inherently variable nature of renewable resources. While these ML models exhibit notable strengths in refining prediction accuracy, it is pivotal to acknowledge their reliance on the quality and quantity of available data. The performance of these models hinges on continuous data collection and refinement to mitigate the impact of incomplete or inaccurate data. Looking ahead, this review serves as an invitation for further exploration into the fusion of ML and renewable energy forecasting. The identified trends suggest a dynamic evolution of methodologies, potentially involving the integration of advanced neural network architectures and reinforcement learning techniques. Such advancements are crucial for developing forecasting frameworks that can adapt to the evolving conditions of renewable energy systems. In the quest for a sustainable energy future, the synthesis of machine learning and renewable energy forecasting emerges as a beacon of innovation, promising a cleaner, more resilient global energy landscape.

6. REFERENCES

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