Forecasting Energy Availability from Renewable Sources Using Weather Data

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Abstract

The goal of this study is to use weather data to predict the availability of excess energy from renewable sources, particularly solar energy. Machine learning models were created to forecast the availability of surplus energy at least 24 hours ahead of time by utilizing historical weather data, including temperature, wind speed, humidity, and solar radiation. To find patterns and associations, extensive data preprocessing, exploratory data analysis, and machine learning methods like Random Forest and Gradient Boosting were applied. Important findings emphasize the importance of solar radiation and wind speed in forecasts, providing practical advice for managing and integrating renewable energy.

1 Introduction

To reduce reliance on fossil fuels, renewable energy sources like wind and solar are essential for decreasing the negative effects of climate change. However, energy management systems face considerable hurdles due to the intermittent and variable nature of renewable energy output caused by changing weather conditions. To improve resource planning, minimize dependency on non-renewable energy sources, and maximize grid performance, accurate energy availability forecasting is crucial.

By using a machine learning model that uses meteorological data to predict solar energy generation, this study seeks to address these issues. To create prediction models like Random Forest and Gradient Boosting, important climatic parameters including temperature, solar radiation, and dew point are examined. The models let energy suppliers make well-informed decisions about energy distribution and storage by predicting solar energy output at least 24 hours ahead of time.

By highlighting the relationship between meteorological characteristics and energy output and incorporating cutting-edge machine learning techniques for increased prediction accuracy, our work adds to the body of previous literature. With an emphasis on preprocessing, feature engineering, and model validation, the project makes use of a comprehensive weather dataset from Visual Crossing that covers Seattle from 2010 to 2024.

The initial findings demonstrate that Random Forest models are more effective than other methods, such as Gradient Boosting, with Mean Absolute Error (MAE) of 3.85°C, Mean Absolute Percentage Error (MAPE) of 9.83%, and an R-squared value of 0.83. These results show promise for improved grid dependability and energy forecasting accuracy.

2 Problem Definition

The project's goal is to forecast the availability of excess energy from renewable sources, particularly solar energy, by framing the problem as a time-series prediction assignment. Because renewable energy sources depend on changing environmental circumstances, they are by nature intermittent, therefore precise forecasting is essential for sustainable practices and efficient energy management.

Surplus energy availability, or the excess energy produced above and beyond immediate consumption needs, is the task's aim variable. To minimize reliance on non-renewable energy backups, maximize grid performance, and guarantee efficient energy storage utilization, accurate forecasting of this excess is essential. Key meteorological factors that have a substantial impact on the dynamics of energy generation, including wind speed, solar radiation, temperature, and humidity, make up the input features.

The primary goals of this task are:

- To clean the dataset that can be used for the data analysis and model building.
- To identify patterns, correlation between existing features using Exploratory Data Analysis and other means.
- In order to gain a better understanding of the relationship between meteorological elements and renewable energy production, it is necessary to identify and quantify the important weather characteristics that have the biggest impact on energy generation.
- To accurately forecast the availability of surplus energy at least 24 hours ahead of time, allowing for improved planning and resource allocation.

- The objective is to improve energy planning procedures by providing dependable and actionable forecasts that can help energy providers make data-driven choices about grid stability, distribution, and storage.

The growing reliance on renewable energy to fight climate change and lower carbon emissions makes this issue both fascinating and significant. The difficulties presented by renewable energy's unpredictability are immediately addressed by accurate forecasting, which guarantees that these sources can be smoothly incorporated into electricity systems. Furthermore, the knowledge gathered from this effort can spur advancements in sustainable practices, grid management systems, and renewable energy technology, opening the door to a more robust and effective energy infrastructure.

3 Models, Algorithms, and Measures

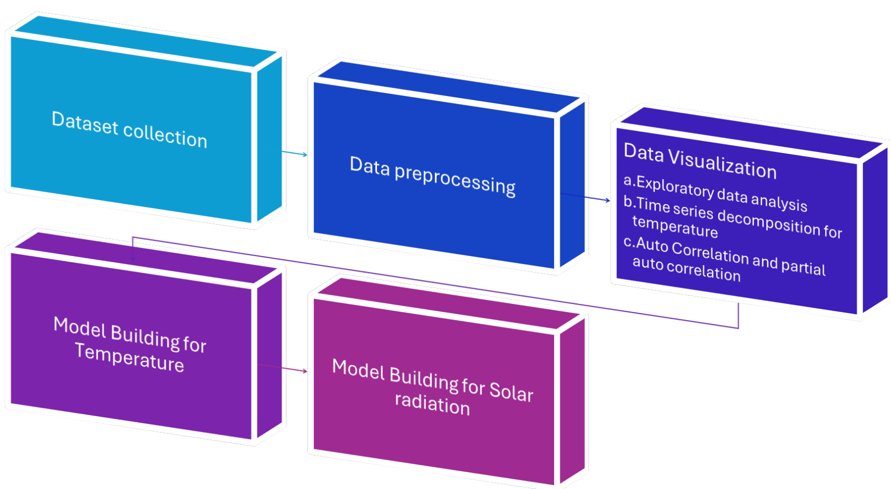


Figure 1: Working flowchart

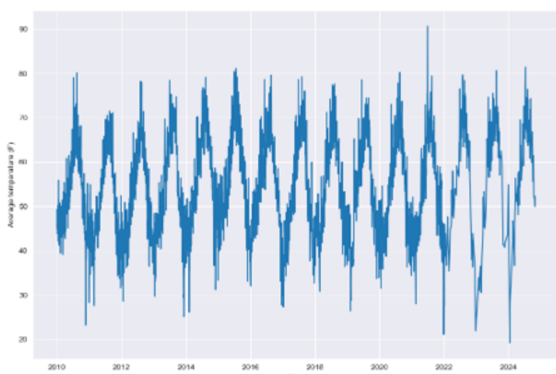
The stages involved in completing the project are described in Figure 1. In order to guarantee the precision and resilience of the forecasts, a number of data preparation methods, models, algorithms, and assessment metrics were used to tackle the issue of forecasting the availability of excess energy from renewable sources. A thorough description of the process may be found below:

3.1 Data Preprocessing

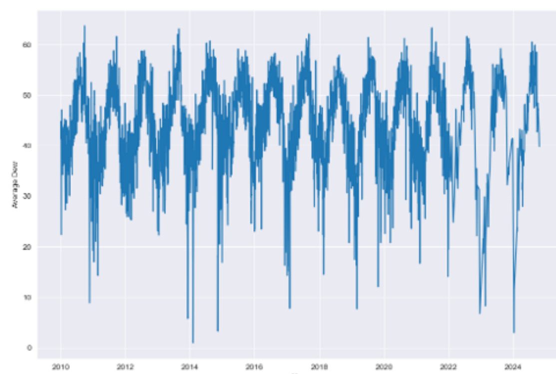
Visual Crossing provided the weather dataset, which was heavily preprocessed. Date data were converted into distinct day, month, and year columns, and missing or NA values were substituted using the proper imputation procedures. To improve model performance, features were normalized and scaled. Lagged variables and other significant qualities were obtained by using feature engineering techniques.

3.2 Visualization and Exploratory Data Analysis (EDA)

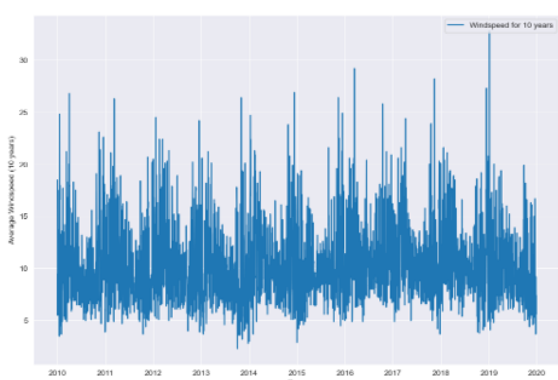
In order to find patterns and connections with energy generation, EDA required graphing important meteorological characteristics such as temperature, humidity, and sun radiation. The selection of features was guided by insights into the relationships between variables that were supplied by time series plots and correlation heatmaps. To find patterns or visual relationships in the charts, additional feature visualizations were carried out. Attached below are a few of the visualizations that were completed.



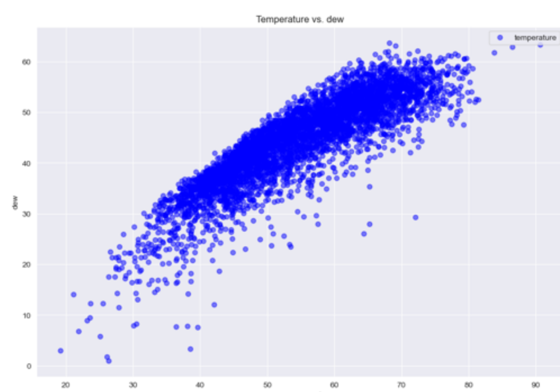
(a) Average Daily Temperature vs Time.



(b) Average Daily Dew vs Time.



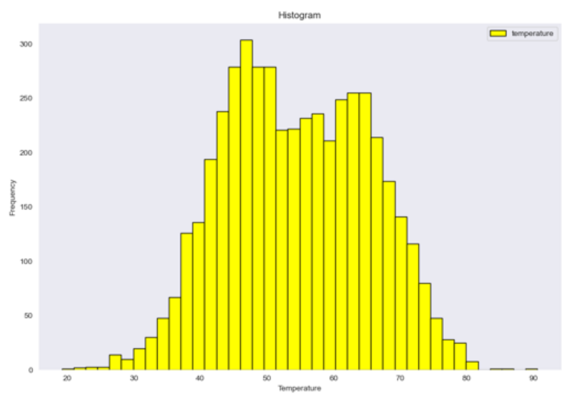
(c) Average Daily Wind Speed vs Time.



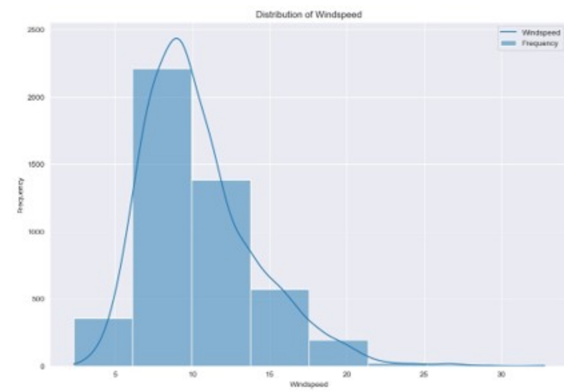
(d) Dew vs Average Daily Temperature Relationship.

Figure 2: Various visualizations of weather data relationships.

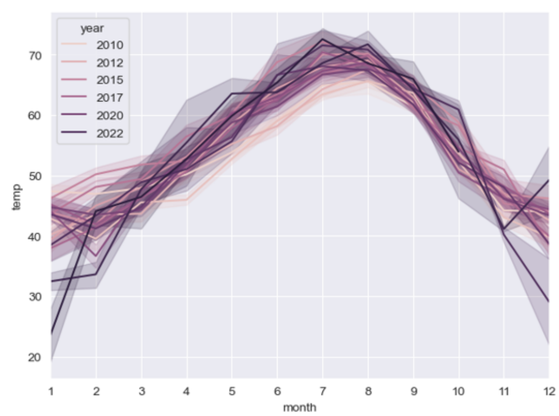
Based on Figure 2, we realized that all weather features have similar patterns every year and came to look at the temperature pattern in Figure 3 (c). They show a similar trend for each year although there are some anomalies during the December and January parts. This also gives us the idea to explore any motifs in the data since it is a time period data.



(a) Frequency Distribution of Average Daily Temperature.



(b) Frequency Distribution of Average Daily Wind Speed.



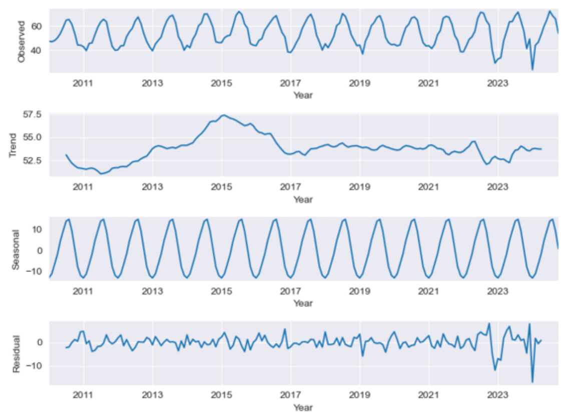
(c) Average Daily Temperature Patterns Across Years.

Figure 3: Frequency distributions and temperature patterns over time.

To determine which values occur most frequently over the full dataset, the frequency distribution of both wind speeds and temperatures is displayed. This study offers insights into the regular weather conditions by assisting in the comprehension of the major tendencies and variances within the data. This visualization helps identify patterns, anomalies, or seasonal trends that may affect energy generation and forecasting accuracy by emphasizing the range and frequency of important variables, such as average daily temperatures and wind speeds.

3.3 Time Series Decomposition for Temperature

To examine its underlying patterns, the temperature data was broken down into trend, seasonal, and residual components. The occurrence of seasonal oscillations was brought to light by this decomposition, which is essential for creating models that can accurately depict temporal dynamics.

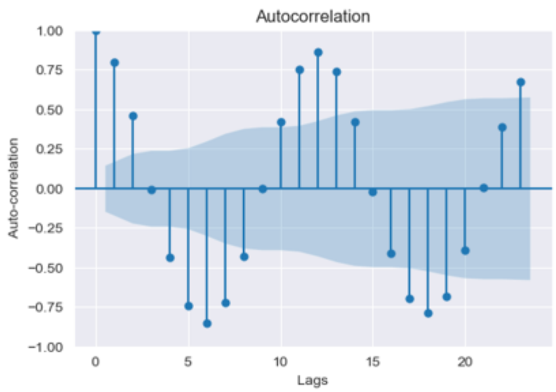


(a) Time series Decomposition for temperature .

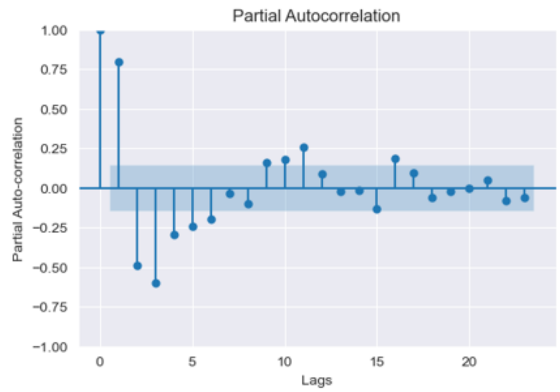
An ADF statistic of -2.15 and a p-value of 0.2262, which is greater than the conventional significance level (e.g., 0.05), indicate that the time series is not stationary. This suggests that the unit root null hypothesis cannot be refuted, suggesting that seasonality or other patterns in the series are likely present and should be taken into account before modeling.

3.4 Autocorrelation and Partial Autocorrelation

To find dependencies in the time series data, autocorrelation and partial autocorrelation plots were created. A crucial realization for creating ARIMA models was that current temperature values had a significant impact on future values, as demonstrated by significant autocorrelation at lag=1.



(b) Autocorrelation.



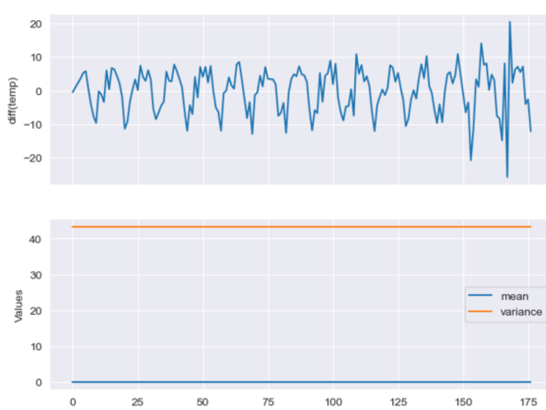
(c) partial Autocorrelation.

Figure 4: Autocorrelation and partial Autocorrelation for temperature data

3.5 Metrics and Parametric Evaluation

Several metrics were used to evaluate model performance:

- Mean Absolute Error (MAE): Measures the average absolute difference between predicted and actual values.
- Mean Absolute Percentage Error (MAPE): Provides a percentage-based error measure for interpretability.
- Root Mean Squared Error (RMSE): Quantifies the average magnitude of error.
- R-squared (R^2): Assesses the proportion of variance explained by the model.



(a) ADF for temperature difference .

As part of the parametric examination, the Augmented Dickey-Fuller (ADF) test was used to determine whether the time series was stationary. The stationarity of the temperature data difference was validated by a p-value of 0.000 and an ADF statistic of -5.93, which is a requirement for ARIMA modeling. Because the temperature data collected here differs from the actual temperature data, the data is rendered stagnant.

3.6 ARIMA Model for Temperature Prediction

To account for the temporal relationships in temperature data, the ARIMA (2,0,1) model was created. An RMSE of 12.69°F and an AIC of 1031.851 were among the measures used to evaluate the model. Short-term dependencies were well-modeled by the ARIMA model, but long-term accuracy required alternative techniques.

Because of how well it captures the temporal relationships and trends present in time-series data, the ARIMA (AutoRegressive Integrated Moving Average) model is selected. Because it uses both historical values (autoregression) and the relationship between the differenced values (moving average) to generate forecasts, it is especially well-suited for forecasting jobs where the data shows autocorrelation. Furthermore, by differencing non-stationary data to attain stationarity—a critical prerequisite for precise time-series modeling—the integration component enables ARIMA to handle non-stationary data. This model is a dependable option for predicting the availability of renewable energy, when temporal patterns are important, due to its adaptability in modifying parameters to fit various time-series patterns. In summary, ARIMA is chosen because of its effectiveness in modeling and predicting complicated, time-dependent data.

3.7 Random Forest and Gradient Boosting for Temperature Prediction

Random Forest and Gradient Boosting, two ensemble learning models, were used to predict temperature. With an MAE of 3.85°C, MAPE of 9.83%, and R^2 of 0.83, Random Forest surpassed Gradient Boosting, proving its robustness and appropriateness for non-linear connections in meteorological data.

3.8 Random Forest for Solar Power Prediction

Using characteristics like temperature and solar radiation, Random Forest was also used to predict the production of solar energy. The model's excellent prediction abilities highlighted machine learning's potential for use in renewable energy applications.

These models and algorithms offer actionable forecasts to help energy providers optimize energy management systems, and they are backed by thorough preprocessing and rigorous evaluation. Predictions that are accurate and comprehensible and in line with the project's objectives are guaranteed by the use of sophisticated measures.

4 Implementation and Analysis

4.1 Dataset Description and Acquisition

We fetched the dataset from Visual Crossing for this project, which includes detailed meteorological information for Seattle from 2010 to 2024. Since only a certain number of rows could be accessed daily using Visual Crossing's free version, data had to be manually downloaded every day due to financial limitations. Key meteorological characteristics like temperature, dew point, solar radiation, wind speed, cloud cover, and visibility were represented by the dataset's initial 5,419 samples and 32 features. The most pertinent characteristics, such as temperature, solar radiation, and wind speed, were selected for energy prediction based on their relationship to solar energy generation.

4.2 Data Preprocessing and Cleaning

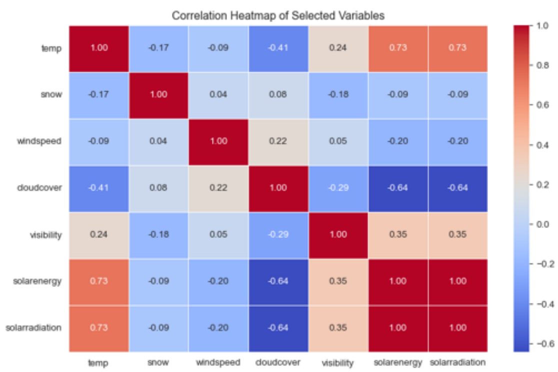
Extensive preprocessing was performed to prepare the dataset for analysis:

- Missing values were addressed by applying appropriate interpolation techniques. Columns such as `precip`, `snowdepth`, `precipprob`, and `snow` were filled with zeros for consistency.
- The `preciptype` column was converted to categorical format with missing values replaced by the placeholder "no precipitation."
- Temporal features, such as day, month, and year, were extracted from the `datetime` column for feature engineering purposes.
- Various interpolation methods, including linear, nearest, spline, and polynomial, were applied to the temperature data to handle gaps in measurements.
- The dataset was sorted chronologically, and scaled using normalization techniques to ensure uniformity across features.

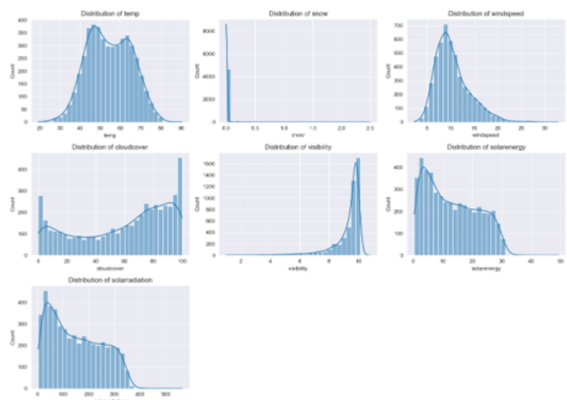
4.3 Exploratory Data Analysis (EDA)

EDA was conducted to uncover patterns and trends in the data:

- **Temperature Trends:** Plots such as average temperature vs. days and yearly temperature patterns (temperature vs. months from 2010–2022) revealed seasonal variations.
- **Meteorological Correlations:** Pairwise relationships like temperature vs. dew point and average wind speed vs. days were visualized to understand dependencies among features.
- **Feature Insights:** Key features like snow, wind speed, cloud cover, visibility, solar radiation, and solar energy were explored to assess their distribution and temporal behavior.



(b) Coorelation Heatmap of selected variables.



(c) Frequency Distribution of each features.

Figure 5: Exploratory Data Analysis (EDA) for handpicked features.

The heatmap shows there's a high correlation between temperature and SolarEnergy/SolarRadiation features with value of 0.73. Similarly cloud cover is inversely proportional to SolarEnergy/SolarRadiation because of high negative value of -0.64. Solar energy and solar radiation are interrelated and the most correlated one with the value of 1 but we needed other features like temperature with solar energy/radiation to build the model.

4.4 Evaluation Metrics and Results

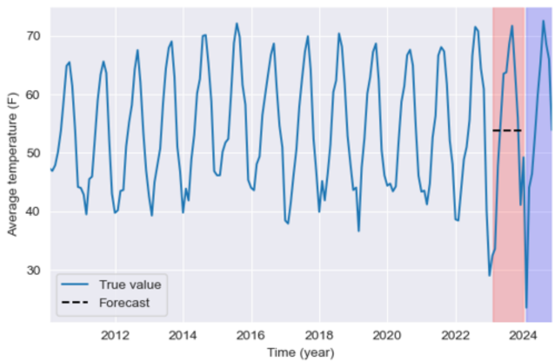
Models were evaluated using the following metrics:

- Mean Absolute Error (MAE): Measures the average error in predictions.
- Mean Absolute Percentage Error (MAPE): Provides a percentage-based error measure.
- Root Mean Squared Error (RMSE): Indicates the average magnitude of error.

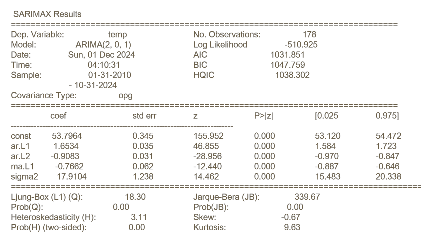
- R^2: Assesses the proportion of variance explained by the model.

In solar energy prediction, the Random Forest model fared better than other models, proving the value of ensemble approaches in renewable energy forecasting.

Machine Learning Models:



(a) Datasplit for training/testing.



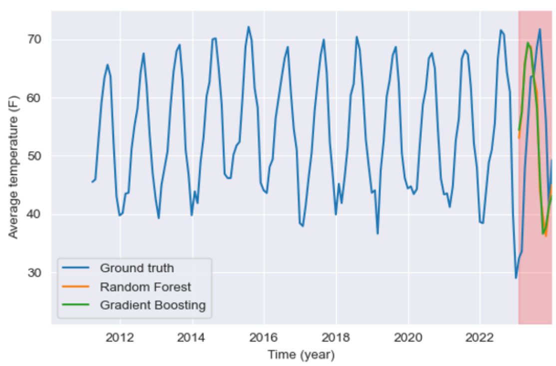
SARIMAX Results

Dep. Variable:	temp	No. Observations:	178
Model:	ARIMA(2, 0, 1)	Log Likelihood	-510.925
Date:	Sun, 01 Dec 2024	AIC	1031.851
Time:	04:10:31	BIC	1047.759
Sample:	01-31-2010 - 10-31-2024	HQIC	1038.302
Covariance Type:	opg		

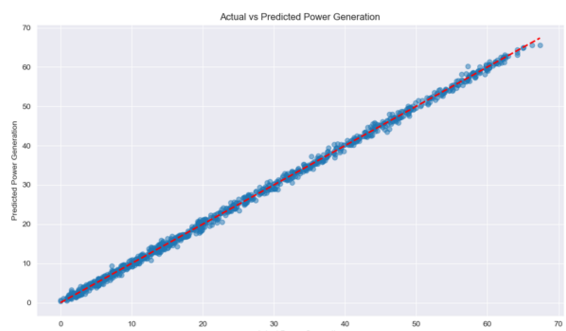
	coef	std err	z	P>|z|	[0.025	0.975]
const	53.7964	0.345	155.952	0.000	53.120	54.472
ar.L1	1.6534	0.035	46.855	0.000	1.584	1.723
ar.L2	-0.9083	0.031	-28.956	0.000	-0.970	-0.847
ma.L1	-0.7662	0.062	-12.440	0.000	-0.887	-0.646
sigma2	17.9104	1.238	14.462	0.000	15.483	20.338

Ljung-Box (L1) (Q):	18.30	Jarque-Bera (JB):	339.67
Prob(Q):	0.00	Prob(JB):	0.00
Heteroskedasticity (H):	3.11	Skew:	-0.67
Prob(H) (two-sided):	0.00	Kurtosis:	9.63

(b) ARIMA model for temperature.



(c) Temperature model predictions using Random forest and gradient boosting.



(d) Solary power model predictions using Random forest.

Figure 6: Models implemented and their predictions

- **SARIMAX:** A seasonal ARIMA(2,0,1) model was built to predict temperature. The model demonstrated limited performance with an RMSE of 12.69°F and AIC of 1031.851.
- **Random Forest:** This ensemble method was employed for both temperature and solar energy prediction. It achieved the best performance for temperature prediction with an MAE of 3.85°C, MAPE of 9.83%, and R^2 of 0.83.
- **Gradient Boosting:** Despite its lower performance compared to Random Forest, Gradient Boosting provided insights into feature importance and contributed to a robust analysis pipeline.

4.5 Key Implementation Steps for Random Forest in Solar Energy Generation

The meteorological dataset was loaded and preprocessed to make sure all necessary features were present before the implementation started. To ensure consistency, missing characteristics like `windspeed` and `cloudcover` were introduced with default values. A weighted mix of important weather parameters, including `solarradiation`, `solarenergy`, and `temp`, was used to create a synthetic goal variable, `power_generation`.

If a synthetic goal variable, ‘powergeneration‘, does not already exist, this code creates one in order to preprocess the data. To replicate real-world variability, random noise is applied to the target, which is determined by weighting important features including ‘solarradiation‘, ‘solarenergy‘, ‘temp‘, and ‘uvindex‘. The target (‘y‘) and features (‘X‘) for model training are returned by the method.

To replicate real-world variability, random noise was introduced. Following an 80-20 split of the data into training and testing sets, features were scaled and normalized to enhance model performance. This processed data was used to train a Random Forest regression model, which produced a high accuracy mean squared error (MSE) of 0.4702 and an R-squared (R^2) score of 0.9985. The model's robustness was further confirmed by cross-validation with five folds, which produced a mean R^2 score of 0.9973 ± 0.0029. Scatter plots comparing actual vs. expected power generation were created in order to assess model predictions, providing visual proof of the model's efficacy.

In order to capture true variability in solar power generation, the methodology relies on strong data preparation techniques, such as handling missing values, scaling features, and creating synthetic target variables. Because it can efficiently handle high-dimensional data and non-linear relationships, a Random Forest regression model was selected. Model performance was evaluated using evaluation metrics including Mean Squared Error (MSE) and R-squared (R^2), and five-fold cross-validation made sure that the model's predictions applied well to data that had not yet been seen. Clear insights into the forecast accuracy and dependability of the model were offered by visualization approaches, such as scatter plots of actual versus anticipated values. Together, these strategies helped create a forecasting model that is both very effective and easy to understand.

5 Final Results and Discussion

The significance of careful data preprocessing and the application of cutting-edge machine learning algorithms were brought to light by the implementation and analysis process. Model development was directly influenced by the knowledge gathered via statistical analysis and EDA, which produced precise and useful energy projections. Future research will involve merging hybrid models for additional performance enhancements and broadening the dataset to encompass a variety of geographical areas.

Random Forest
MAE = 3.85 (degrees Celsius)
MAPE = 9.83 %
RMSE = 5.45 (degrees Celsius)
MSE = 29.66 (degrees Celsius squared)
R2 = 0.83

Gradient Boosting
MAE = 4.71 (degrees Celsius)
MAPE = 11.85 %
RMSE = 6.41 (degrees Celsius)
MSE = 41.13 (degrees Celsius squared)
R2 = 0.76

(a) Temperature prediction model stats

Improved Mean Squared Error (with new features): 0.4702
Improved R-squared Score (with new features): 0.9985
Cross-validated R^2 (with new features): 0.9973 ± 0.0029

(b) Solar power prediction model stats

Figure 7: Final Stats

6 Related Work

With the increasing use of sustainable energy sources, the challenge of predicting the availability of renewable energy has attracted a lot of attention lately. Similar issues have been examined in a number of studies, with a special emphasis on forecasting solar and wind energy. Below, we emphasize the differences in our approach and discuss important related studies.

6.1 Related Studies

- **Time-Series Models for Renewable Energy Forecasting:** Forecasting the availability of renewable energy has made extensive use of conventional time-series models like ARIMA and SARIMA. For example, using past meteorological data, researchers have used SARIMA models to forecast solar energy output. These models are good at capturing seasonality and linear dependencies, but they frequently struggle to handle intricate, non-linear interactions between factors like wind speed, temperature, and sun radiation.

- **Machine Learning Approaches:** Forecasting renewable energy has shown success with machine learning models like Random Forest, Gradient Boosting, and Support Vector Machines. These models are very good at managing feature interactions and non-linear relationships. For instance, by utilizing meteorological factors like wind speed, humidity, and cloud cover, gradient boosting models have been utilized to forecast solar radiation. Nevertheless, a lot of these research are constrained by tiny datasets or have a narrow focus on particular energy sources.

- **Deep Learning Techniques:** Forecasting for renewable energy has benefited from recent developments in deep learning, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. These techniques are excellent at identifying intricate patterns and temporal correlations in big datasets. Nevertheless, huge labeled datasets and substantial computer resources are frequently needed for deep learning techniques, which can be difficult to acquire.

6.2 How Our Approach Differs

Our approach builds upon the strengths of the aforementioned methods while addressing some of their limitations:

- **Integration of Multiple Features:** Our method incorporates a wide range of meteorological characteristics, such as temperature, solar radiation, dew point, wind speed, and cloud cover, in contrast to many earlier research that concentrate on a small number of aspects. A more comprehensive depiction of the variables impacting the availability of renewable energy is offered by this comprehensive feature set.
- **Focus on Data Preprocessing:** Our research highlights the significance of thorough data preprocessing, which includes feature engineering, normalization, and addressing missing information. We guarantee data quality and consistency using sophisticated interpolation techniques, which are frequently disregarded in previous research.
- **Scalable and Accessible Methods:** Our use of Random Forest and Gradient Boosting achieves a balance between accuracy and efficiency, despite the fact that deep learning techniques demand substantial processing resources. These models can be used in practice since they are interpretable and computationally feasible.
- **Customized Dataset Collection:** Due to financial limitations, our dataset, which covers 14 years (2010–2024), was manually curated. Our approach shows that high prediction accuracy may be achieved even with little resources, in contrast to previous work that relied on extensive private datasets.
- **Comprehensive Evaluation:** To verify the assumptions of our models and increase their robustness, we use statistical testing (such as the Augmented Dickey-Fuller test) and exploratory data analysis (EDA) in addition to common measures like MAE, MAPE, RMSE, and R^2.
- **Focus on Practical Applications:** Our research focuses on practical insights for energy providers in addition to addressing the theoretical aspects of forecasting. Our method helps to improve grid management and lessen dependency on non-renewable backups by forecasting the availability of excess energy 24 hours ahead of time.

Although earlier research has advanced the field of renewable energy forecasting significantly, our method stands out for combining a variety of characteristics, using strong preprocessing methods, and striking a balance between interpretability and model accuracy. We provide a scalable and workable strategy for managing renewable energy by resolving the shortcomings of earlier research and adapting our methodology to real-world limits.

7 Conclusion

In this study, we developed a predictive model based on weather data to address the problem of forecasting the availability of surplus energy from renewable sources. The experiment used a dataset with important meteorological factors, such as temperature, wind speed, dew point, and solar radiation, that covered 14 years (2010–2024). We created a high-quality dataset that allowed for efficient model training by utilizing feature engineering, exploratory data analysis, and comprehensive data pretreatment.

Random Forest outperformed the other machine learning techniques, including Gradient Boosting and Random Forest. The model's Mean Absolute Error (MAE) of 3.85°C, Mean Absolute Percentage Error (MAPE) of 9.83%, and R^2 score of 0.83 showed how accurate it was in predicting temperature and energy. Statistical methods like time-series decomposition and the Augmented Dickey-Fuller test further validated the predictive models' underlying assumptions.

In order to enhance renewable energy forecasting, this work emphasizes the significance of combining a variety of characteristics, reliable preprocessing methods, and scalable machine learning models. The suggested method helps to optimize energy grid management and lessen reliance on non-renewable energy sources by offering actionable 24-hour energy availability projections.

8 Future Works

under order to test the model's resilience under a range of climatic and environmental circumstances, future research will concentrate on enlarging the dataset to include a variety of geographic areas. To improve model performance, more meteorological and environmental factors will be incorporated, including altitude, seasonal adjustments, and the likelihood of precipitation.

We will investigate hybrid and sophisticated time-series models like LSTM and ARIMA to further increase accuracy and scalability. Complex temporal dependencies and non-linear interactions in the data may be captured by these models. Furthermore, by modifying the models to include wind speed and turbine-specific data, the concept can be applied to other renewable energy sources, including wind turbines. The goal of these initiatives is to expand the methodology and advance the field of sustainable energy management techniques.

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A Appendix: Code and Supplementary Material

For reproducibility and further exploration, the following resources are provided:

A.1 Project Code

The complete project code, including data preprocessing, exploratory data analysis, model implementation, and evaluation, is available on GitHub:

- **GitHub Repository:** `https://github.com/peersahab/data-science-project`

A.2 Dataset Information

The weather data used for this project was obtained from Visual Crossing. Details and documentation about the dataset can be found at:

- **Visual Crossing Weather Data:** `https://www.visualcrossing.com/resources/documentation/weather-data/weather-data-documentation/`

For any questions or issues, please reach out to us using the emails present at the top of the report.