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Intelligent Forecasting of Hybrid Solar–Wind Renewable Energy Systems Using Machine Learning Techniques in Python

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Abstract: Hybrid renewable energy forecasting has emerged as a critical research area due to the intermittent and location-dependent nature of individual energy resources. Solar power generation is highly dependent on sunlight availability and is significantly affected by cloudy and rainy conditions. Similarly, wind energy generation requires sustained wind speeds, which vary geographically. In India, wind resources are concentrated in specific regions such as Gujarat, Rajasthan, and Tamil Nadu. Considering the variability and limitations of standalone renewable sources, this study proposes a hybrid energy forecasting model that integrates both solar and wind energy systems to improve prediction accuracy and reliability. The objective is to forecast total power generation by leveraging complementary characteristics of solar and wind resources.A Linear Regression-based machine learning approach is employed to model the relationship between power output (measured in kW or MW) as the dependent variable and multiple environmental and meteorological parameters as independent variables. The selected features include solar irradiance, temperature, humidity, cloud cover, Air Quality Index (AQI), wind speed (m/s), wind direction, and air density. The model is implemented using Python in a VS Code development environment. By combining diverse environmental factors into a unified predictive framework, the proposed hybrid forecasting model aims to enhance energy estimation accuracy and support more efficient renewable energy management. This approach contributes to improved planning, grid stability, and optimal utilization of renewable resources in the transition toward sustainable energy systems.

Keywords- Solar, Wind, Machine learning, VS code, Air Quality Index etc

2.INTRODUCTION

In earlier days when technology was not there so much then the seasons which were fixed for particular work, work was done in that particular seasons and people were adapted to that situation Nowadays technology has advanced and the population rises from earlier days, so seasons are not fixed that in the particular season that thing will not happen. For instance you will find rain in the summer season, you will find summer in the rainy season etc.

Today's busy and tragetic population that no one has time to see their own and they want that their work shouldn't be stopped and the government also wants that work shouldn't be stopped. So for them we have installed solar forecasting app using python

Imagine if we could predict tomorrow's weather with absolute accuracy—how much easier would life be? From planning outdoor events to optimizing energy usage, forecasting plays a crucial role in our daily lives.

We live in an era where technology is advancing rapidly, pushing us toward a future driven by data and smart solutions. One such breakthrough is weather forecasting, a field that has evolved with the power of artificial intelligence and programming.

Back in 2016, the Prime Minister introduced the vision of Digital India, and today, technology has become deeply rooted in every aspect of our lives. Whether it's a school day, a sports match, or a public event, we rely on accurate weather predictions to make informed decisions.

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This brings us to solar forecasting—a game-changer in renewable energy. By predicting solar radiation and weather patterns, we can harness solar power more efficiently, reducing dependency on non-renewable sources and creating a sustainable future.

In this project, we explore how Python, a powerful programming language, can be used to enhance solar forecasting. With smart algorithms and data analysis, we can take a step closer to a future where clean energy is maximized to its full potential.

Weather forecasting plays a vital role in our daily lives, influencing everything from travel plans to major events. One of the most relatable examples is cricket matches. We all know how much the outcome of a match depends on weather conditions.

Imagine a high-stakes game where the skies suddenly turn dark, and rain interrupts play. To avoid such uncertainties, meteorologists analyze weather patterns and provide predictions weeks in advance. Not only does this help teams prepare, but it also ensures that fans and organizers can make informed decisions.

Beyond sports, weather forecasting is crucial in disaster-prone regions. Take, for instance, the eastern part of India, where the Bay of Bengal frequently witnesses cyclones and heavy storms. For people living in coastal areas, early weather predictions can mean the difference between safety and catastrophe. Evacuations, disaster management, and preparedness all depend on accurate forecasting.

We are living in a generation where forecasting and combining of two or more energy is becoming very common. Most commonly forecasting involves mixing of solar and wind energy together and many companies are already using forecasting and combining in a very good manner. It’s a very useful method and still over the world people are focusing on these type of technology.

If we go all over the world then we will found one thing that our natural gas resources are coming to their end. I know you might be surprised by hearing this but yes it’s true. According to the study the data which is being released by Indian government we found that natural resources will only be found for the next 50 to 100 years and after that no chance of resources will be out there. Today everybody is dependent on natural resources and the sad part is that we are using only human period and now there’s been a rapid rate. India, being a country with diverse climatic conditions and a rapidly growing energy demand, holds immense potential for the implementation of hybrid renewable energy systems. The government has already set ambitious goals to increase the share of renewables in the national energy mix. In such a scenario, intelligent forecasting of hybrid systems can play a pivotal role in energy planning, optimizing grid performance, and reducing dependence on fossil fuels. The integration of smart forecasting models with IoT-enabled devices and smart meters can further enhance system automation and decision-making. In all these contexts of innovations, the Government of India launched the Digital India Mission in 2016 under the leadership of Prime Minister Shri Narendra Modi. This mission aims to transform India into a digitally empowered society and knowledge economy. One of the core visions of this mission is to ensure that government services are made available to citizens electronically through improved online infrastructure and increased internet connectivity. Under this initiative, the promotion of smart technologies—including smart grids, digital energy forecasting systems, and AI-powered monitoring tools—has become a national priority. Our project, which leverages intelligence techniques for hybrid renewable energy forecasting, aligns directly with the goals of the Digital India Mission by contributing to smarter, data-driven energy solutions for a sustainable future.

Therefore, our research aims to develop and evaluate an intelligent forecasting model that predicts the energy output of a hybrid renewable energy system combining solar and wind resources. By using intelligence techniques, our goal is to ensure more accurate, efficient, and real-time energy forecasting which will ultimately contribute toward a more sustainable and self-reliant energy infrastructure for the future. In earlier decades, seasonal patterns were relatively stable, and agricultural as well as industrial activities were planned according to predictable climatic conditions. However, with rapid technological advancement, population growth, urbanization, and climate variability, weather patterns have become increasingly unpredictable. Unseasonal rainfall, unexpected heat waves, and irregular monsoon cycles are now common occurrences. Such variability directly affects agriculture, transportation, public events, disaster management, and energy production.

Weather forecasting has therefore become an essential scientific tool for planning and decision-making. Accurate forecasting supports scheduling of outdoor events, transportation systems, and sports activities. For example, in sports such as cricket, weather interruptions can significantly impact match outcomes. Beyond daily convenience, forecasting is critically important in disaster-prone regions such as the eastern coastal areas of India near the Bay of Bengal, where cyclones and severe storms frequently occur. Early prediction enables timely evacuation and disaster preparedness, thereby reducing loss of life and property.

With the increasing global demand for energy and the gradual depletion of fossil fuel reserves, renewable energy sources such as solar and wind have gained significant importance. Studies indicate that natural gas and other fossil fuel reserves are finite and may be exhausted within the next few decades if current consumption rates continue. Consequently, there is a global shift toward sustainable and hybrid renewable energy systems that combine multiple energy sources for improved reliability and efficiency.

Solar forecasting plays a crucial role in optimizing renewable energy generation. Accurate prediction of solar irradiance and power output enables better grid management, improved load balancing, and enhanced energy storage planning. Recent advancements in machine learning and deep learning techniques have significantly improved forecasting accuracy. Various studies have applied algorithms such as K-Nearest Neighbors (KNN) [10], Random Forest and Support Vector Machines [2], Convolutional Neural Networks (CNN) [4], Long Short-Term Memory (LSTM) networks [5][12], and hybrid deep learning models [6] for solar power prediction. Comprehensive reviews highlight the growing role of artificial intelligence in energy forecasting applications [9][13][14].

Hybrid renewable energy systems, particularly the integration of solar and wind energy, are increasingly being adopted worldwide. Intelligent forecasting of such systems enhances grid stability and ensures optimal utilization of renewable resources. Deep learning approaches have demonstrated strong performance in capturing nonlinear dependencies and time-series patterns in solar energy data [3][7][8].

India, with its diverse climatic conditions and rapidly growing energy demand, holds immense potential for implementing hybrid renewable energy systems. The Government of India has set ambitious renewable energy targets to increase the share of clean energy in the national grid. In 2016, under the leadership of Prime Minister Shri Narendra Modi, the Digital India Mission was launched to transform India into a digitally empowered society. One of its major objectives is to promote smart technologies, digital infrastructure, and data-driven solutions across various sectors, including energy management. Intelligent energy forecasting systems integrated with IoT-enabled devices and smart grids align closely with this national vision.

In this context, the present research aims to develop and evaluate an intelligent forecasting model for predicting the energy output of a hybrid renewable energy system combining solar and wind resources. The proposed approach utilizes machine learning techniques to enhance forecasting accuracy and system efficiency. By improving real-time prediction capabilities, this research contributes toward sustainable energy planning, reduced dependence on fossil fuels, and the development of a self-reliant and environmentally responsible energy infrastructure.

3. METHODOLOGY

This paper employs a machine learning–based approach for hybrid renewable energy forecasting using meteorological and synthetic datasets. The overall methodology consists of data acquisition, preprocessing, feature engineering, model development, and evaluation. The implementation is carried out using Python due to its simplicity, extensive libraries, and suitability for data analysis and machine learning tasks. The development environment includes Jupyter Notebook and Visual Studio Code.

3.1 Programming Environment and Tools

Python is selected as the primary programming language because of its flexibility and strong ecosystem of data science libraries such as NumPy, Pandas, Matplotlib, and Scikit-learn. These libraries facilitate efficient data manipulation, visualization, and implementation of machine learning algorithms.

The forecasting model is developed using the Linear Regression algorithm, a supervised learning technique used to model the relationship between a dependent variable (power output in kW/MW) and multiple independent variables (meteorological parameters). Linear Regression estimates the output using the following mathematical formulation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

Where: Y= Predicted power output

- β_0= Intercept
- $\beta_1, \beta_2, \ldots, \beta_n$= Regression coefficients
- $X_1, X_2, \ldots, X_n$= Independent variables
- ϵ= Error term

The model learns optimal coefficient values by minimizing the Mean Squared Error (MSE) between actual and predicted outputs.

3.2 Data Source

The dataset used in this study is obtained from Kaggle. After comparing publicly available sources such as Open Weather Map and Visual Crossing Weather, Kaggle was selected due to dataset accessibility and suitability for experimental research.

Because high-quality real-world hybrid renewable datasets were limited, synthetic data available on Kaggle was utilized. Synthetic datasets allow controlled experimentation and facilitate model validation under simulated environmental conditions.

3.3 Data Preprocessing

Since the dataset is synthetic and in raw CSV format, several preprocessing steps are performed prior to model training to ensure data quality and reliability.

3.3.1 Synthetic Data Handling

The dataset is imported in CSV format and validated using Python-based error handling mechanisms (try–except blocks). This approach ensures:

- Detection of missing values
- Identification of invalid or corrupted entries
- Prevention of runtime execution errors

Missing or inconsistent values are either removed or appropriately handled to maintain dataset integrity.

3.3.2 Noise Simulation and Smoothing

Noise and outliers can significantly affect model performance by distorting underlying patterns. To address this issue, the following techniques are applied:

a) Z-Score Method

The Z-score measures how many standard deviations a data point is from the mean:

$$Z = \frac{X - \mu}{\sigma}$$

Where:

- X= Data point
- μ= Mean of dataset
- σ= Standard deviation

Data points with excessively high or low Z-scores are treated as outliers and removed or adjusted.

b) Gaussian Noise Handling

Controlled Gaussian noise is introduced during experimentation to simulate real-world environmental variability. This enhances model robustness and improves generalization capability under practical operating conditions.

3.3.3 Feature Transformation

Time-based features exhibit cyclic behavior (e.g., 23:00 is followed by 00:00). To preserve this cyclical nature and avoid discontinuity, sinusoidal transformation is applied using sine and cosine functions:

$$Time_{sin} = \sin\left(\frac{2\pi t}{T}\right)$$

$$Time_{cos} = \cos\left(\frac{2\pi t}{T}\right)$$

Where:

- t= Time value
- T= Total period (e.g., 24 hours for daily cycle)

This transformation maps linear time values onto a circular representation, improving the model's ability to learn periodic patterns in weather and energy generation data.

4.RESULT

In this paper the hybrid forecasting system demonstrates high accuracy and reliability in predicting both weather conditions and renewable energy generation for user-specified locations. By integrating machine learning models with comprehensive meteorological datasets, the system effectively captures complex relationships between atmospheric variables and power output.

The analysis incorporates critical meteorological parameters, including temperature, solar irradiance, cloud cover, humidity, pollution index, wind speed (m/s), sunshine duration, air pressure, solar radiation, air temperature, relative air humidity, and time-based features such as Normalized Mean Time (NMT). The inclusion of these variables enables the model to account for temporal variations and environmental interdependencies that directly influence solar and wind power generation.

Results indicate that combining solar and wind forecasting into a hybrid framework significantly improves prediction stability compared to standalone models. Solar energy predictions perform strongly during clear daytime conditions, while wind energy compensates during periods of low solar irradiance, such as cloudy weather or nighttime. This complementary behavior reduces forecasting uncertainty and enhances overall power output estimation.The system successfully provides real-time weather insights and energy generation forecasts, supporting improved grid management, operational planning, and informed decision-making for stakeholders. Furthermore, hybrid forecasting reduces energy curtailment by offering more accurate generation estimates, thereby improving the efficiency and economic feasibility of renewable energy projects.

Fig .1 Solar Energy Production

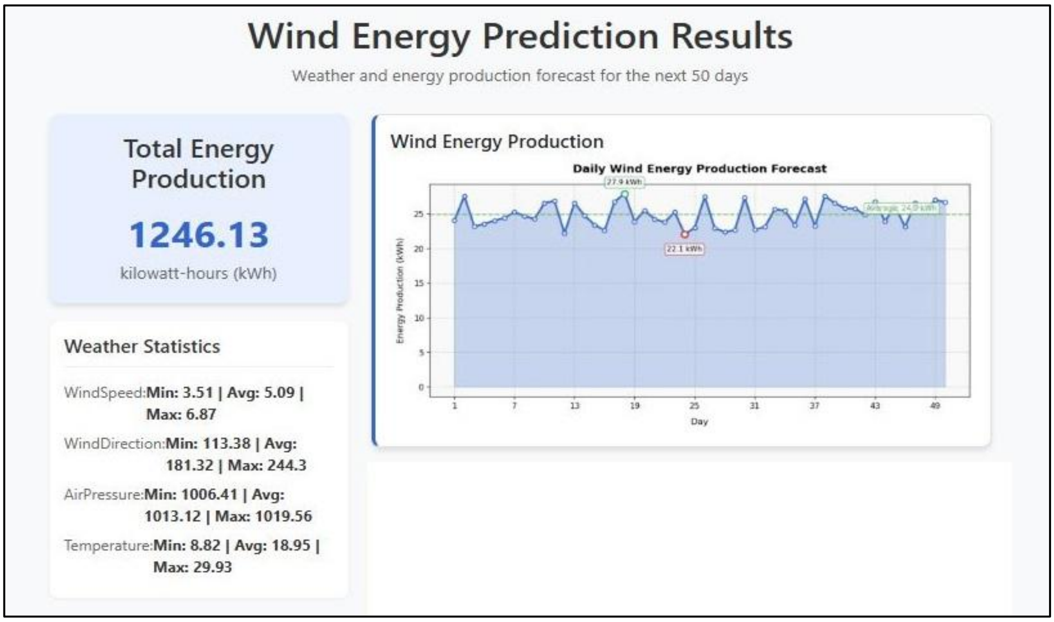

Fig.2 Wind Energy Production forcasting

5. CONCLUSION

This paper presents a machine learning–based hybrid forecasting framework that integrates solar and wind energy prediction with detailed meteorological analysis. By leveraging multiple environmental parameters and temporal data, the proposed system enhances forecasting accuracy and reliability for renewable energy generation.

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