Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 5, No.9, May : 2024

EVALUATING SOLAR IRRADIANCE EFFICIENCYMETRICS AND METHODS FOR IMPROVEMENT

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Abstract
Monitoring and safeguarding the solar irradiance based on various features like temperature, pressure, humidity etc. Accurate prediction of solar irradiance for steady supply of electrical energy has always been a difficult task both in the field of physical simulation Solar irradiancehas long been crucial in producing renewable energy. Solar irradiance is the power per unit area (surface power density) received from the Sun in the form of electromagnetic radiation inthe wavelength range of the measuring instrument. Solar irradiance is measured in watts per square metre (W/m2) in SI units. Predictions of solar irradiance positively impact a nation's economic progress with regard to solar power generation.ML techniques can be used to makeprediction in various ways. It can either involve identifying data (classification challenge) or predicting a result (regression algorithms). Regression models anticipate a continuous output, whereas classification models identify an object's category. This literature review reviews different classification and regression models to predict solar irradiance, considering various meteorological factors affecting it.

Keywords: Solar Irradiance, Machine Learning, Gradient Boosting.

I.INTRODUCTION
The escalating demand for renewable energy sources to combat climate change and ensure sustainable development has intensified the exploration of solar power as a viable solution. Solar energy, abundant and environmentally friendly, holds immense potential for meeting global energy needs. However, harnessing this resource efficiently requires overcoming the inherent variability of solar irradiance, the primary determinant of solar power generation.
Solar irradiance, the flux of solar energy per unit area, fluctuates dynamically due to atmospheric conditions, geographical location, and diurnal and seasonal variations. Accurate prediction of solar irradiance is therefore indispensable for optimizing the performance of solar photovoltaic (PV) systems, enhancing grid stability, and maximizing energy yield. Moreover,reliable forecasts enable informed decision-making in various sectors, including agriculture, urban planning, and disaster management. In this paper, we propose an innovative approach for solar irradiance prediction that integrates advanced machine learning algorithms with physical models to enhance prediction accuracy and reliability. We demonstrate the efficiency of our approach through comprehensive validation experiments using real-world datasets, highlighting its potential for practical applications in solar energy management and beyond.

II. LITERATURE SURVEY
Random Forest
Random forest (RF) is commonly used in classification and regression problems. It generates decision trees utilizing random samples, employing their average for categorization and majority

vote for regression. In [33] estimates of surface solar irradiance from the Cloud, Albedo Radiation data collection and ECMWF Reanalysis 5 Edition served as the input for a random forest regression model. The sky-stratification experiment shows that the given model produces improved results in all-sky conditions, with significant gains in the intermediate cloud.

XGBoosting

XGB stands for "eXtreme Gradient Boosting". Boosting is a sequential technique which workson the principle of ensemble. The authors in Ref. [31], proposed an approach for determining the best models, feature selection techniques, and permutations for forecasting short-term solar output. In order to support and indicate that the ensemble of the XGBoost model and the PCA approach has the best performance, extreme gradient boosting (XGBoost) was investigated and tested using actual solar data. This results in the highest r2 score of 99% and the lowest root mean square error of 2.49082.

III. EXISTING SYSTEM

Solar irradiance prediction for steady supply of electrical energy has always been a difficult task both in the field of physical and artificial intelligence. In the existing system results obtained showed that Support Vector Regression (SVR) with normalized Root Mean Square Error (nRMSE) of 7.2% gave the best overall performance. This was followed by Artificial Neural Network (ANN) and Random Forest respectively

Disadvantages

- **Computationally Intensive:** Training an SVM model can be computationally expensive, especially for large datasets. The training time complexity is typically between O(n^2) and O(n^3), where n is the number of samples. This makes SVMs lesssuitable for very large datasets.
- **Limited Flexibility for Handling Noisy Data:** SVMs are sensitive to noise in the data, as outliers and mislabelled instances can significantly affect the decision boundary. While techniques like feature scaling and outlier removal can mitigate this issue to some extent, SVMs may struggle with noisy datasets compared to other algorithms like decision trees.

IV. PROPOSED SYSTEM

In the proposed system result obtained showed that Gradient Boosting with Root Mean SquareError (nRMSE) give best accuracy than the Support Vector Machine. This is followed by XGBoost, (GHI) Global Horizontal Irradiance, Random Forest and SelectKBest Method. Utilize a gradient boosting algorithm such as XGBoost, LightGBM, or CatBoost to train a predictive model on the preprocessed data. Tune hyper parameters of the gradient boosting algorithm using techniques like grid search or Bayesian optimization to optimize model performance.

Advantages

- **Handles Missing Data:** Gradient boosting algorithms naturally handle missing data by constructing trees based on available features. They do not require imputation techniques for dealing with missing values, making them suitable for datasets with missing observations, which can be common in environmental data.
- **Flexible Loss Functions:** Gradient boosting allows for the use of various loss functions tailored to the specific prediction task. For solar irradiance prediction, loss functions can be customized to prioritize accuracy or account for asymmetric errors, depending on the application requirements.

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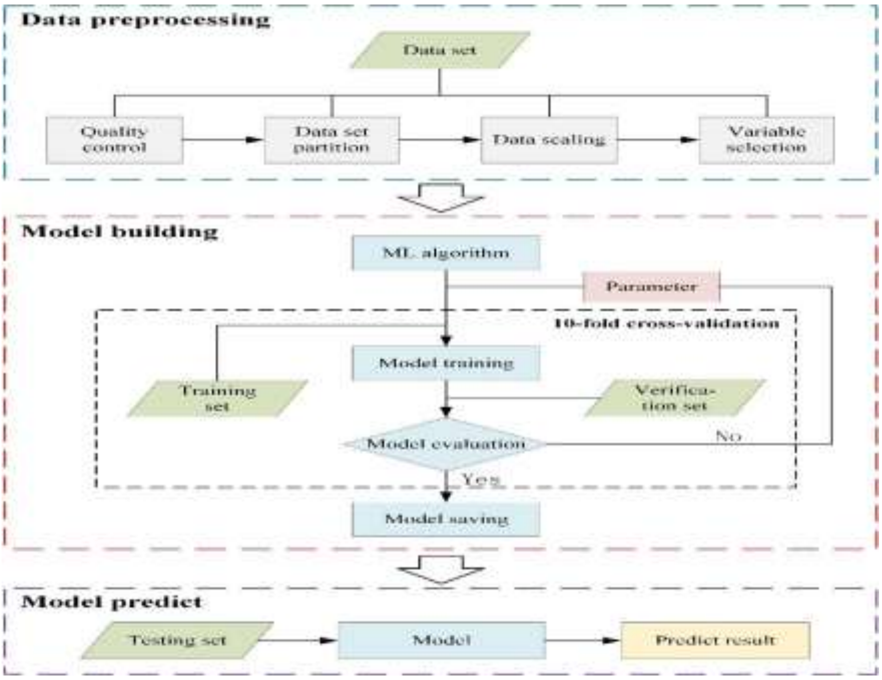
System Architecture



V. RESULT AND DISCUSSION

The result and discussion section encapsulates the culmination of our efforts, showcasing the solar irradiance prediction on various features like temperature, pressure, humidity and so on.

Accuracy: The primary performance requirement is typically high prediction accuracy. Solar irradiance prediction systems should aim to minimize prediction errors and provide reliable estimates of solar irradiance levels. Accuracy can be quantified using metrics such as mean absolute error (MAE), mean squared error (MSE), or root mean squared error (RMSE).

Scalability: The system should be scalable to handle large volumes of data and increasing prediction demands. This includes both training and inference phases of the prediction model. As the dataset grows or the frequency of predictions increases, the system should remain responsive and capable of processing tasks efficiently.

Scatter plots showing the distribution of the values of the various features as a function of the value of the target parameter (solar irradiance). This allows to identify potential non-linear trends present.

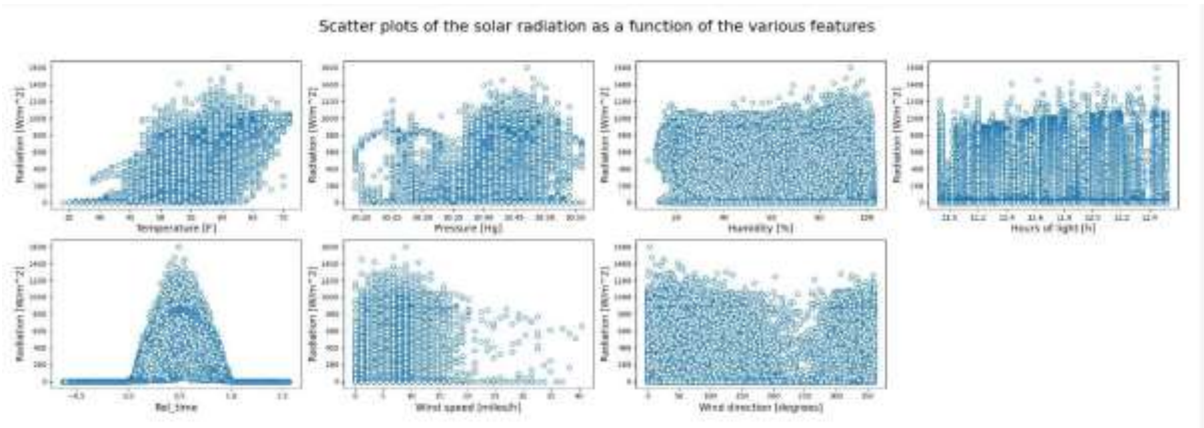


Fig1: SCATTER PLOTS OF THE SOLAR IRRADIANCE AS A FUNCTION OF VARIOUS FEATURES

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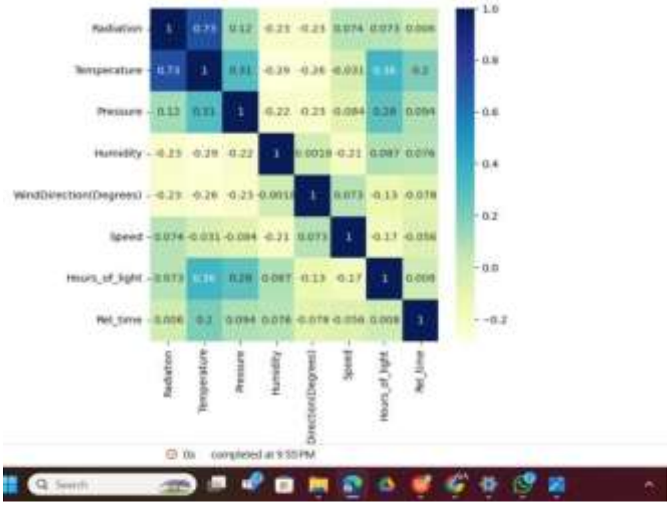

Fig2: Correlation matrix

The correlation matrix indicates a positive linear correlation between the ambient temperature and the solar radiation (coefficient = 0.73). No clear linear correlation appears for the other features, and the second highest correlation value is identified for the humidity(yet it is only of -0.23).

VI. CONCLUSION

Solar power has gained a significant importance as a clean, renewable and an alternative source of energy over the past few years. With the help of this solar irradiance prediction, we can find the quality in power grid operation. By using these techniques XGBoost and Gradient Boosting we are increasing the accuracy and performance for existing system. In future works, we plan to implement ensemble learning method by combining different machine learning algorithms analysed in this paper to achieve greater accuracy. To achieve greater accuracy, we combined Gradient Boosting and Random Forest, based on the root mean square error value we concluded that Gradient Boosting is best prediction method than the Random Forest because it changes the week learners into strong learners i.e flexibility in loss functions and also handles missingdata.

- Root Mean Square Error -> 0.9 for Gradient Boosting
- Root Mean Square Error -> 0.77 for Random Forest

VII. REFERENCES

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