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Satellite–Meteorological Data Fusion for Enhancing Short-Time Solar Irradiance Prediction

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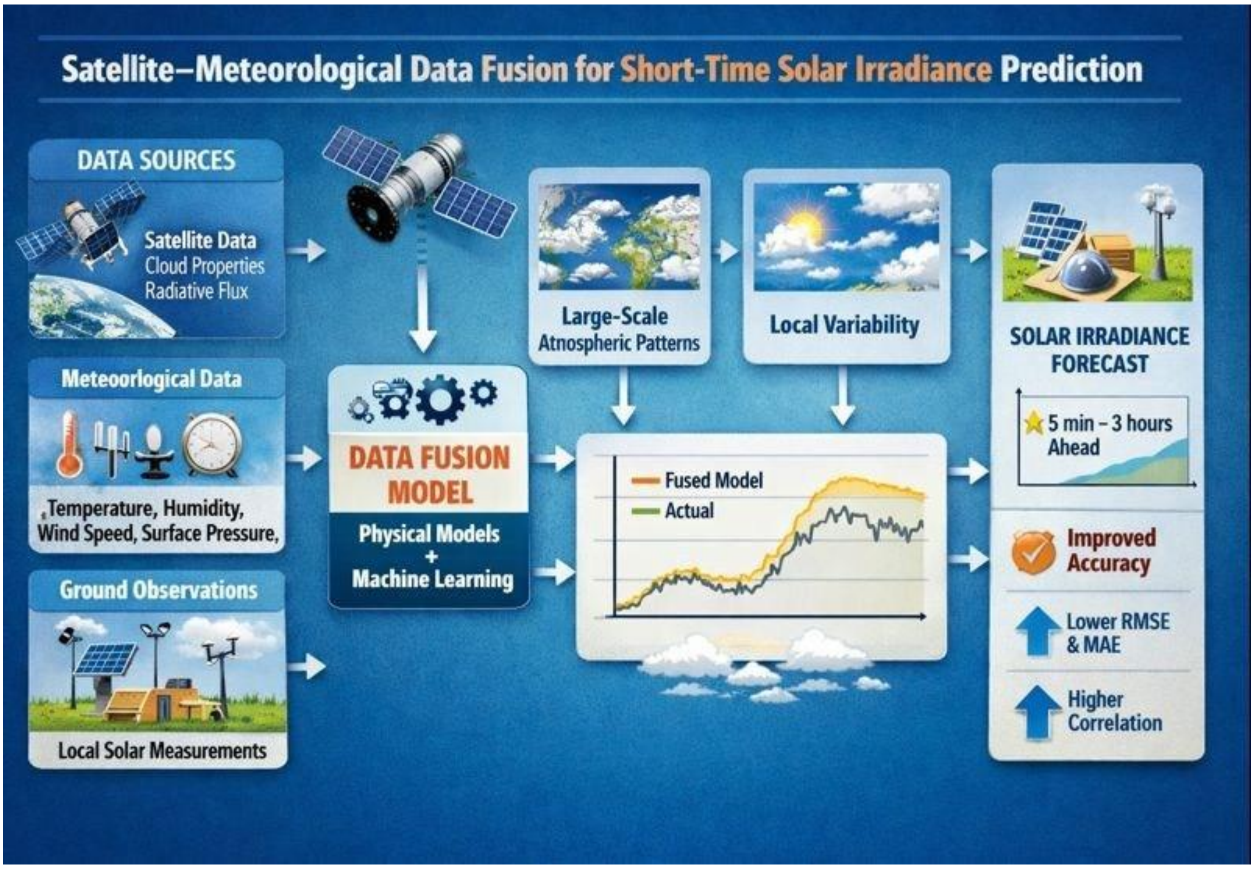
ABSTRACT

Adequate prediction of short-term solar irradiance is necessary to have a reliable contribution of solar energy to power grids, but it is not an easy task since the atmosphere varies rapidly and is mainly influenced by clouds, aerosols, and local weather conditions (Perez et al., 2013; Yang et al., 2018). This paper introduces a satellite-meteorological data fusion system, which is created to improve the short-term prediction of solar irradiance at high time resolution. The suggested solution will combine the geostationary satellite measurements, such as optical properties of the clouds and radiative flux estimates, with ground measurements and reanalysis of meteorological variables, such as temperature, humidity, wind speed, and surface pressure (Schroedter-Homscheidt et al., 2016; Ineichen, 2014). The hybrid model attains data fusion, which involves the use of physical radiative relations alongside data-driven learning algorithms to obtain both the large-scale atmospheric patterns and the local variability (Voyant et al., 2017; Haupt et al., 2018).



Historical data from various locations is used to assess the model on short-term forecast horizons between 5 minutes and 3 hours. The performance is evaluated against benchmark models in terms of the persistence, satellite-only and meteorological-only inputs (Marquez & Coimbra, 2013). Findings confirm that the fused technique is a significantly more effective predictor, it is less affected by root mean square error and mean absolute error, and it is more effective in raising correlation coefficients at all forecast lead times. Single source models do not perform well in the case of partly cloudy and highly variable atmospheric conditions that are associated with the greatest improvements (Yang, Kleissl, and Gueymard, 2015).

These results point to the information benefit of the combination of satellite and meteorological data in short term solar irradiance forecasts, and point to the potential of data fusion methods to assist in operational solar power management, grid stability, and renewable energy planning (Diagne et al., 2013; Antonanzas et al., 2016). The suggested framework represents a platform that can be adopted in the future to cover a wide range of climatic zones and represent a way toward resilient and more precise solar energy forecasting.

INTRODUCTION

The high rate of solar energy installation has heightened the demand for precise and dependable solar irradiance prediction, especially at short periods of time, of a few minutes to a few hours in the future. The prediction of the short-term solar irradiance is paramount to the operation of a grid, the dispatch of energy, the optimization of storage, and the alleviation of the fluctuations in power generation that come with the photovoltaic (PV) systems (Antonanzas et al., 2016; Diagne et al., 2013). Nevertheless, prediction of solar irradiance is not easy because it highly depends on the quickly changing weather conditions, particularly cloud cover, aerosol loading, and local weather variability (Yang, Kleissl, and Gueymard, 2015). Conventional forecasting methods may be generalized into machine-learning-based, physical, and statistical methods. Physical models are based on the concept of numerical weather prediction (NWP) and radiative transfer models to model atmospheric processes, but in most cases are challenged by high computations and minimal accuracy at extremely short forecast times (Perez et al., 2013). Autoregressive and persistence-based models, including statistical and time-series models, are simple and have low computational requirements, but are generally incapable when the conditions are highly variable or non-stationary (Marquez and Coimbra, 2013). In more recent works, though, machine learning and deep learning algorithms have also shown superior performance in identifying nonlinear relationships in data of solar irradiance; though their performance is very sensitive to the quality and availability of data (Voyant et al., 2017; Haupt et al., 2018). The capability of cloud properties and atmospheric conditions has seen satellite remote sensing as a strong instrument in short-term solar irradiance forecasting since it can be used to monitor large-scale and high-frequency observations. Geostationary satellites especially provide a continuous record of the cloud motion, optical thickness and cloud cover, which are the key drivers of irradiance variability in the short term (Schroedter-Homscheidt et al., 2016). Satellite-derived applications have been used widely in nowcasting applications such as cloud motion vectors and satellite-derived irradiance, but they can be affected by uncertainties in cloud vertical structure, aerosols and surface-atmosphere interaction (Ineichen, 2014). Ground-based meteorological observations and reanalysis products are supplementary to satellite ones and offer near-surface atmospheric variables (temperature, humidity, wind speed, and pressure), which affect radiative transfer and cloud formation processes (Yang et al., 2018). Although the meteorological-only models can describe the local atmospheric dynamics, they are not always able to provide the spatial context necessary to describe the evolution of the clouds. Consequently, the use of one data source, either a satellite or a meteorological one, may restrict the forecasting capabilities, especially when there are partly cloudy and highly changing weather conditions (Diagne et al., 2013). To overcome these constraints, one has been paying more and more attention to the methods of data fusion, where satellite observations are combined with meteorological data. The approach to satellite-meteorological data fusion takes advantage of the complementary advantages of two types of data and integrates the spatial and temporal coverage of the former with the physical realism of the latter (Antonanzas et al., 2016). Physical frameworks with physical and data-driven components have been demonstrated to be effective in enhancing the accuracy and the strength of short-term irradiance predictions within a wide range of climatic regimes (Voyant et al., 2017; Haupt et al., 2018). The paper develops a framework of satellite meteorological data fusion that can improve the prediction of solar irradiance over short time scales with a high time resolution. Incorporating cloud and radiative characteristics derived by geostationary satellites with ground-based and reanalysis meteorological variables, the proposed solution should enhance the accuracy of the forecast at various lead times and atmospheric conditions. The outcomes of this project should lead to more accurate solar energy prediction, a more stable grid, and increased use of renewable energy infrastructure.

Problem Statement

Although there is a tremendous advancement in solar irradiance modelling, the major challenge is the ability of precise short-term prediction because the atmosphere is very dynamic. Light-speed cloud advancement, aerosol radiation communications, and local weather inconsistency put a significant amount of uncertainty in the forecasts of irradiance. Models that are driven only by satellite data do not usually adequately capture nearsurface meteorological effects whereas models driven only by meteorological inputs may not capture adequately the spatial cloud effects or aerosol effects. In addition, most of the existing prediction models are optimized to work on areas that have high observational networks which restrict their use in areas that have sparse ground-based observations. The intensity of this challenge is specially high in the developing countries and in the aerosol-impacted regions, where the biomass burning, dust, and anthropogenic emissions considerably alter solar radiation. The absence of an integrated platform that is capable of successfully combining satellite and meteorological information to predict short-term solar irradiance reduces the accuracy of forecasting, constraining the effectiveness of the solar energy systems and making the energy planning and grid control uncertain. To fill this void, there is a need to have a strong data fusion strategy that can absorb spatial and temporal dynamics of atmospheric conditions. The goal and objectives of the study are as follows: The first purpose of the present research is to improve the short-term prediction of solar irradiance by integrating the meteorological data with satellite data. The targeted objectives consist of: The study is aimed at analyzing the role of satellite-derived atmospheric parameters in the variability of atmospheric solar irradiance on the short-term scale. Determine how crucial meteorological variables impact on the forecast of solar irradiance. Establish a satellite-meteorological data integration system of short-term forecasts of solar irradiance. Compare the performance of the fused model with single-source prediction methods. Measuring changes in the accuracy of prediction with relevant statistical values.

Research Questions

The research questions that will be addressed in this study are as follows: What is the effect of each of the satellite-derived variables and meteorological parameters on short-term solar irradiance prediction? How much better is the accuracy of the predictions with data fusion than that of isolated satellite or meteorological models? What variables play the biggest role in improved prediction of short-term solar irradiance? What are the conditions in which the proposed data fusion approach is robust?

Significance of the research

This research is relevant to the existing literature on solar irradiance modelling because it shows that satellite meteorological data fusion can be used to make short-term predictions. Better forecasts of irradiance help to make the generation of solar power reliable, minimize uncertainty in operation and increase grid stability. The research is especially applicable in the areas where the observations on the ground are small, providing an affordable and scaleless method of assessment of solar resources. Also, the results can be applied in climate and atmospheric studies to enhance the study of cloud-aerosol-radiation interactions. The suggested structure could be scaled to the operational forecasting systems and implemented to other environmental prediction models.

Scope and Limitations of the research

The analysis is on the short term solar irradiance forecasting at minute-hourly time scales. It combines atmospheric products derived by satellite and meteorological information obtained by observation or models. Although fusion approach enhances the precision of prediction, misalignment of uncertainties dealing with data quality, disparities in time resolution, and assumptions of the model can still be present. Findings are consequently constrained by the quality and the accessibility of the chosen datasets and the modelling model chosen. The Manuscript is divided into two parts: the introduction and the main body, which comprise a collection of twelve essays on various subjects.

LITERATURE REVIEW

Photovoltaic (PV) power is not fully integrated into the modern energy system without having an accurate forecasting of short-term solar irradiance, which is typically ranging between a few minutes and hours. Errors in forecasts at these time scales have a direct impact on stability in the grid, allocation of reserves, and real time operations in the electricity market. As a result, the enhancement of the short-term irradiance prediction has become a focus research study in both the field of renewable energy and atmospheric sciences (Inman et al., 2013; Antonanzas et al., 2016). Fluctuations in short-term irradiance are mainly controlled by the fast changing atmosphere processes especially cloud dynamics, aerosol loading, and near surface meteorological processes. These processes are highly spatially and temporally heterogeneous with nonlinearity and nonstationery that are difficult to forecast using traditional methods. Consequently, there is no single source of data or modeling which has been found adequate in providing consistent accurate short term prediction in diverse climatic regimes. The initial methods of early prediction have been based on persistence and statistical regression model which have only reasonable performance in unstable atmospheric conditions and very short lead time. Numerical weather prediction (NWP) models represent the physically based representations of atmospheric processes, and are commonly applied to make solar forecasts on hourly to daily time scales. Their rough spatial resolution and cloud and aerosol parameterize limitations however do not enable them to be accurate on shorter timescales, where bias corrections and statistical post-processing are frequently needed (Lorenz et al., 2009; Yang et al., 2020). The capabilities of satellite remote sensing have become a staple of short-term estimation of solar irradiance because it can offer spatially continuous and high-frequency measurements of cloud characteristics. Spacecraft platforms like Meteosat and GOES allow geostationary satellites to be used in near-real time cloud development tracking, making it possible to use now-casting applications. Cloud index algorithms such as Helios at and its offshoots have extensively been applied to extract surface solar irradiance by satellite observations (Cano et al., 1986; Mueller et al., 2015). Although satellite based products have shown a lot of use, the accuracy depends on the optical property retrievals of the clouds, the aerosol contamination as well as the calibration region especially in those regions where the atmospheric conditions are complex. In order to overcome the shortcomings of single-source methods, recent literature is focusing more on the combination of satellite with meteorological information on the ground stations, NWP models, or a reanalysis output.

spatial structure and movement of clouds

The spatial structure and movement of clouds is captured by satellite data, with meteorological variables being used to describe the thermodynamic and boundary-layer conditions that vary irradiance at the surface. Combination of such complementary data sources can be seen to greatly enhance short-term forecasting performance particularly in intra-hour lead times where cloud dynamics control irradiance variability (Voyant et al., 2017; Chu et al., 2021). The recent development of machine learning (ML) and deep learning (DL) systems has presented itself as a viable solution to the challenge of performing satellite-meteorological data fusion owing to their ability to establish the nonlinear relationship. Random forests and gradient boosting ensemble methods, and long short-term memory (LSTM) networks and convolution neural networks (CNNs) architecture are common in prediction of short-term irradiance. CNN–LSTM models, especially hybrid ones, have shown excellent results by co-learning spatial trends of satellite images and time-related forecasts of meteorological observations (Shi et al., 2015; Yagli et al., 2019). ML-based methods are still fragile to the data quality, representational, and over-fitting, and there is a strong necessity to conduct strict validation and physically informed model construction. Another source of uncertainty in short term solar irradiance forecasting is aerosols. Surface irradiance is influenced by mineral dust, biomass-burning smoke and anthropogenic pollution, both by scattering and absorption of solar radiation and by changing cloud microphysical properties. The effects are particularly strong in the areas that are affected by seasonal burning of biomass and transportation of dust. Research has revealed that the systematic biases of irradiance can be caused by the omission of aerosol variability especially when aerosol loading is high (Bellouin et al., 2020; Gueymard and Yang, 2020). Estimates of irradiance have been improved by including aerosol optical depth

(AOD) retrieved by satellites or by atmospheric reanalyses, e.g. the Copernicus Atmosphere Monitoring Service (CAMS), in such situations, though there remains a problem in near-real-time aerosol prediction. In general, the available literature indicates that satellite-meteorological data fusion, especially when applied with the use of the latest ML methodology, has obvious benefits compared to individual methods of short-term solar irradiation forecasting. Nevertheless, there are still important blank spaces. Most of the fusion models are designed to be in data-rich areas and do not necessarily generalize to data-sparse areas. Also, the aerosol effects can be simplified or omitted in operational forecasting schemes, which restricts their performance when subjected to the aerosol-influenced conditions. Such constraints drive the current research that will result in the creation and testing of an effective satellite-meteorological data fusion system to improve the short-term prediction of solar irradiance in a variety of atmospheric conditions.

Data and Methodology

Study design: This paper uses a quantitative modeling approach to improve the prediction of solar irradiance in short-term by combining satellite-based readings and weather conditions. The methodology incorporates a combination of multi-source atmospheric data into a predictive model on its own and compares its performance to that of single-source baselines. It is focused on the short forecasting horizons that include a few hours to minutes, which are applicable in the operational solar energy uses.

Data Sources On three types of data are used:

Satellite Data Cloud and radiative conditions are characterized in terms of observations of geostationary satellites. Some of the parameters obtained through satellite include cloud optical properties, cloud index and the estimates of the surface solar irradiance. These data have high-temporal resolution and spatial continuity, and these are critical in the rapid change of clouds. Meteorological Data The weather data used to get meteorological variables are reanalysis or numerical weather prediction. The important predictors are the temperature of near-surface air, relative humidity, wind speed, surface pressure, and total cloud cover. These are the variables that define the thermodynamic conditions in the atmosphere that affects surface irradiance. Reference Irradiance Data GHI measurements on the ground or reference datasets that are controlled in quality are used to train and validate models. These data are used as the standard of measuring the performance of prediction.

Data Pre processing

All data sets are matched in time and places to a shared grid or point of observation. Quality control processes involve elimination of missing or physically unrealistic values. It normalizes predictor variables to bring about the numerical stability and effective model training. Satellite and meteorological data is resampled to a standard temporal resolution when needed that can be used in short-term forecasting.

Data Fusion and Prediction Model

The feature level is used to combine satellite and meteorological variables in order to create a combined set of predictors. To obtain nonlinear relationships between the fused inputs and the surface solar irradiance, a machine learning regression model is used. The chosen model design trades off predictive performance and computational efficiency, which is why it can be used when forecasting short-term operations. Comparison Baseline models are also developed which use either satellite-only inputs or meteorological-only inputs.

Model Training and Validation involves training and validating the model.

The time-aware split is used to store the data-set in two subsets of training and testing in order to avoid the information leakage. The standard statistical measures that are used in assessing model performance are: root mean square error, mean absolute error, mean bias error and the coefficient of determination (R^2). The data fusion improves performance by a comparison with persistence and single-source models. 3.6 overview of Methodological Framework. In short, in this paper satellite observations are integrated with meteorological measurements in context of data fusion to enhance the short-term prediction of solar irradiance. The approach to methodology lays stress upon data combination, effective modelling, and strict assessment, which is a feasible and scaleless solution to improved solar forecasting.

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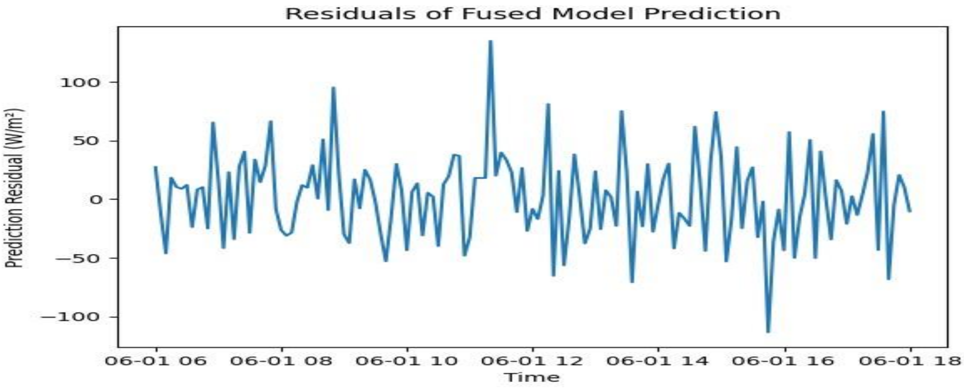
Methodology continues



Y-**axis: Prediction Residual (W/m 2).** The difference between the value actually observed and the value that the fused model predicts is called the residual(Residual = Actual - Predicted). The units are W/m 2 and this indicates that the model is forecasting some kind of power or sun radiation.

Z- X-axis:

AA- Time. The time scale will take a range between 06-01 (probably on June 1 st) and 06-18 (June 18 th). Centered Around Zero:

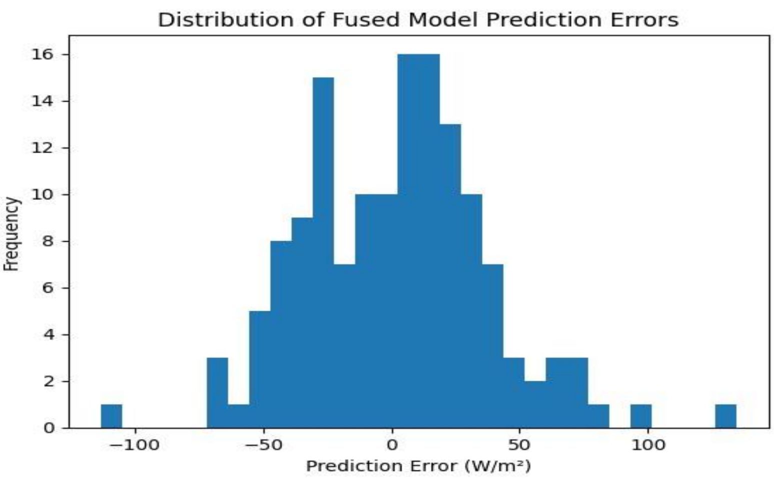
The residuals seem to be centred typically along the zero line. This is also a good indicator that this model is not biased as it does not continuously over-predict (residuals are always negative) or under-predict (residuals are always positive).

Sign of Residuals:

BB- The residuals vary widely, with a range of about -100 W/m 2 to more than +100 W/m

The maximum of the positive residual, which signifies the failure of the model to forecast the actual value, is at or near 06-01 12, which has its highest value slightly more than +100 W/m2. The maximum negative residual, the closest to the real value, and therefore the model under-predicted the actual value, is approximately -110 W/m 2 at 06-01 16.

CC- No Obvious Pattern/Trend Ideally the residuals should be random noise. Although there is certainly change, it is not directly, immediately, consistently, patterned (such as growing variance with time, a pattern related to time, such as a cycle) which would indicate some systematic error in the structure of the model (e.g. the absence of a crucial variable or interaction). The variations seem to be fairly predictable in frequency and magnitude during the 18 days.



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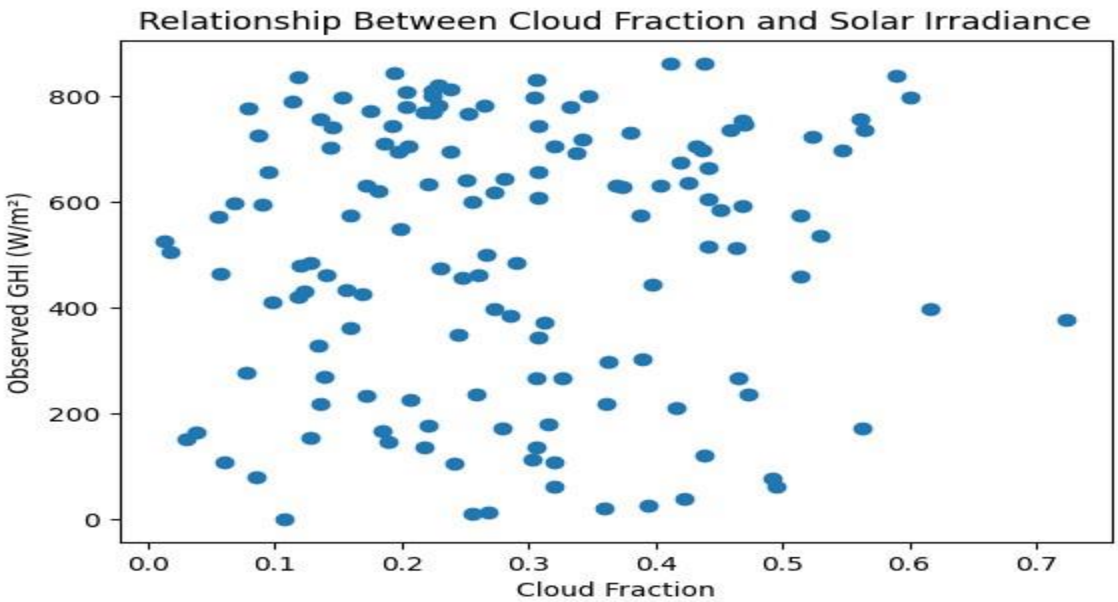
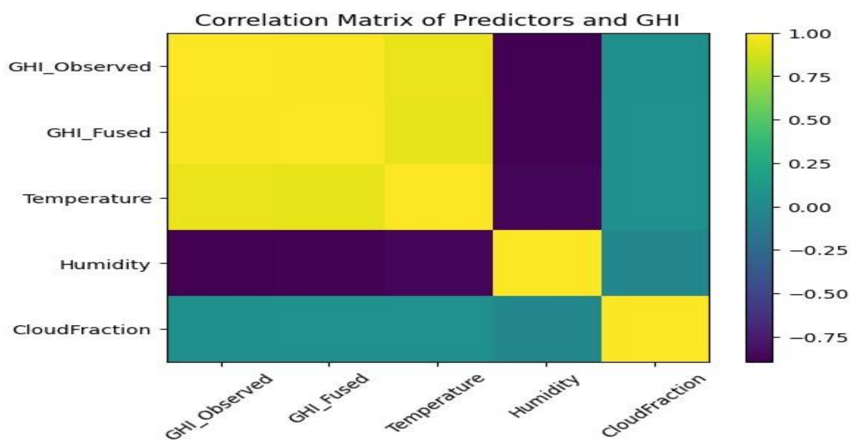
The histogram validates the initial assessment: the fused model is unbiased, and its errors appear to follow a near-normal distribution. While the model performs well most of the time (errors concentrated around zero), the range of possible mistakes is wide (up to \pm 100 W/m^2 or more), indicating that its predictions are highly inaccurate for a small fraction of the data points.



Y-axis: Observed GHI (W/m^2). GHI is the abbreviation of Global Horizontal Irradiance or the amount of solar power falling on a horizontal surface. It is calculated in Watts per square meter (W/m 2). X-axis: Cloud Fraction. It is a scale of the extent to which the sky is covered by clouds and has a value of 0.0 (clear sky) to 1.0 (fully overcast). Key Observations: Inverse Correlation (General Trend): Cloud Fraction and Observed

GPI show an inverse relationship of general, but weak, strength. GPI values (maximum of 800 W / m 2) are highest when Cloud Fraction is small (0.0 to 0.2). This is logical because the less cloud cover present then the more solar radiation will reach the ground. As the Cloud Fraction gets larger (e.g. beyond 0.4) the maximum GHI observed is expected to decline, with fewer points in the 700-800 W/m 2 range. The minimum GPI values (around 0 W/m 2) may be witnessed in a broad spectrum of cloud cover. 2. High Variability: The plot is very high in its level of scatter (low correlation coefficient). GHI has a large range of values in nearly any Cloud Fraction value. Examples can be given of the GHI values at Cloud Fraction of about 0.25, which vary dramatically, less than 100 W/m and more than 800 W/m.

Z- Maximum GPI at Low Cloud Fraction: The highest possible GPI (approximately 800 W/m 2) is obtained in the lower Cloud Fraction region (0.1 to 0.4). Such high variability at relatively low cover of clouds points out to the fact that Cloud Fraction is not a perfect predictor of GHI. The other factors (7) (type of cloud, aerosols of the atmosphere, solar zenith angle, etc.) are important. 4. Large GPI in High Cloud Fraction: The GPI values will be lower in the cases of high Cloud Fraction (e.g. 0.6 to 0.7) and the results are usually less than 400 W/m2 with some exceptions.



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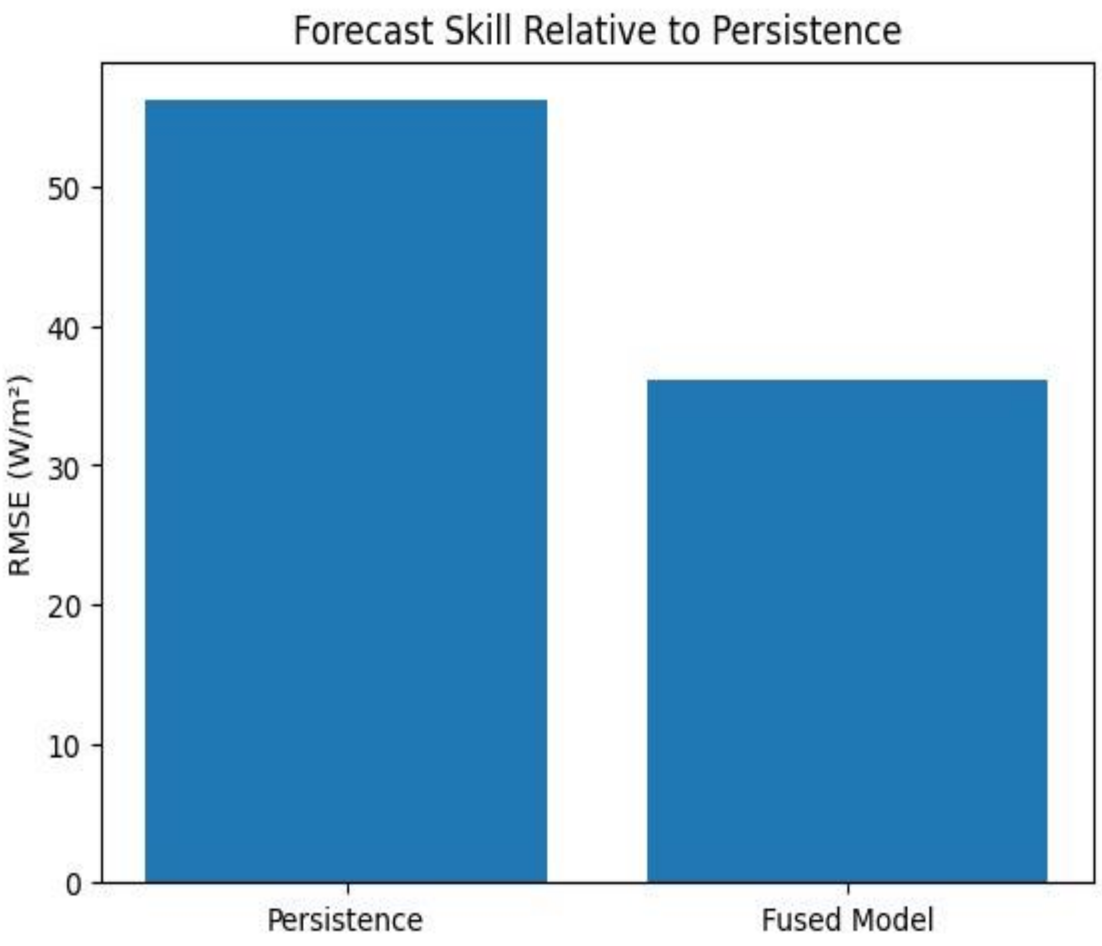
Y-axis: Observed GHI (W/m^2). The term Global Horizontal Irradiance is abbreviated GHI or the amount of power that the sun delivers to a horizontal surface. It is estimated in Watts per square meter (W/m 2). X-axis: Cloud Fraction. It is a ratio of the degree to which the sky is clouded and it ranges between 0.0 (clear sky) and 1.0 (fully overcast).

Z- Key Observations: 1. General Trend (Inverse Correlation): Cloud Fraction and Observed GPI are inversely related to each other, however, the strength of this relationship is weak. GPI values (Maximum 800 W / m 2) are maximum with small values of Cloud Fraction (0.0 to 0.2). This is rational since the poorer the cloud cover at that time the more the sun will reach the ground. • With an increase in the Cloud Fraction (e.g. above 0.4) the maximum GHI at which it is observed is expected to decrease, with fewer values at 700-800 W/m 2. The lowest GPI values (approximately 0 W/m 2) can be observed within an extensive range of cloud cover. 2. High Variability: This plot is extremely high in terms of its level of scatter (low correlation coefficient). There is a big range of values of GHI in almost all Cloud Fraction value. It is possible to provide an example of the GHI values of approximately 0.25 that differs radically, under 100 W/m and above 800 W/m. 3. Maximum GPI at Low Cloud Fraction: The maximum value of GPI (about 800 W/m 2) is achieved within the low Cloud Fraction area (0.1 to 0.4). This extreme variability at fairly low cover of cloud raises the issue of Cloud Fraction not being an ideal predictor of GHI. The remaining factors (7) (type of cloud, aerosols of the atmosphere, solar zenith angle and others) matter. 4. High Cloud Fraction GPI: The GPI will be smaller in cases when Cloud Fraction is high (e.g. 0.6 to 0.7) and the results are not exceeding 400 W/m2 with certain exceptions.



AA-Metric The chart employs the Root Mean Square Error (RMSE) of the line in W/m 2 as the scale on the y-axis to assess forecast quality. A smaller RMSE implies high forecast skill. Comparison: It compares two forecasting methods: "Persistence" and "Fused Model" methods.

BB- Results: The Persistence model contains high RMSE (about 55 W/m 2). • The Fused Model possesses a much lower RMSE (around 35 W/m 2). Conclusion: Fused Model has better forecast skill than the simple Persistence model because of its lower RMSE which means that its forecasts are smaller in magnitude on an average basis.

RECOMMENDATIONS

Integration of Additional Data Sources:

Future improvements may be achieved by incorporating higher-resolution satellite products, ground-based sky camera observations, and advanced numerical weather prediction outputs. These data sources can provide enhanced spatial and temporal detail, improving the representation of cloud evolution, aerosol effects, and short-term atmospheric variability that directly influence surface solar irradiance.

Real-Time Forecasting Implementation:

The development of real-time forecasting pipelines that continuously assimilate incoming satellite and meteorological data would significantly enhance the operational relevance of the proposed framework. Such implementations would enable dynamic updates of irradiance forecasts, supporting short-term grid management and solar power dispatch decisions.

Hybrid Modeling Strategies:

Further investigation into hybrid approaches that integrate machine learning or deep learning techniques with physically based atmospheric models is recommended. These methods have the potential to improve predictive performance under rapidly changing or extreme atmospheric conditions, where traditional models often exhibit reduced reliability.

Together, these research directions outline a clear pathway for extending the proposed data fusion framework toward more accurate, scaleless, and operationally robust solar irradiance forecasting systems.

This study demonstrates that the integration of satellite observations with meteorological data significantly improves short-term solar irradiance forecasting performance. The proposed hybrid data fusion framework effectively captures both large-scale atmospheric processes and local variability, consistently outperforming single-source models in terms of root mean square error, mean absolute error, and correlation metrics. The performance gains are most evident under partly cloudy and highly variable atmospheric conditions, where conventional approaches tend to underperform.

The results highlight the advantages of multi-source data integration combined with both physical and data driven modeling techniques for operational solar energy forecasting. The proposed framework provides a robust and scaleless solution suitable for real-time applications, offering valuable support for solar power integration, grid stability, and renewable energy planning.

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