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CONCERNING THE MATTER OF THE (IM)PRACTICALITY OF SOLAR FORECASTING MODELS

The availability of solar radiation data is crucial for determining the appropriate sizing of solar energy systems. As solar energy is widely used in electricity generation, numerous research efforts have been dedicated to developing models capable of estimating solar irradiance from various perspectives. These prediction models can be categorized as satellite-based, regression-based, statistical, artificial intelligence-driven, or hybrid in nature. While significant progress has been made during the development of these models, there are concerns among some researchers regarding their practical applicability. In this study, we aim to provide a comprehensive overview of existing solar irradiance prediction models and conduct a prospective and critical analysis of their practicality and accessibility based on the existing literature. Special emphasis is placed on the importance of researchers meticulously studying the current gaps in research and actively working to enhance and implement promising studies to overcome any shortcomings in the prediction models. It is worth noting that generalizing solar irradiance prediction models for locations without direct measuring instruments poses a challenging task. Thus, this article contributes valuable insights to researchers, practitioners, investors, and all stakeholders interested in advancing and utilizing solar irradiance prediction models to support the development of efficient solar energy systems. By shedding light on the strengths and weaknesses of existing models, we aim to facilitate more accurate and reliable solar energy estimations, thereby encouraging the broader adoption of sustainable and renewable energy sources. Ultimately, this research seeks to foster the growth and successful implementation of solar energy systems on a global scale.

Keywords: renewable energy, solar energy, solar radiation, global solar radiation model, forecasting model.

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ЩОДО ПИТАННЯ (НЕ)ПРАКТИЧНОСТІ МОДЕЛЕЙ СОНЯЧНОГО ПРОГНОЗУВАННЯ

Необхідність наявності даних щодо сонячного випромінювання є необхідною у визначенні розмірів об'єктів сонячної енергетики. З огляду на широке застосування сонячної енергії для виробництва електроенергії, багато досліджень спрямовані на розробку моделей, що здатні оцінювати сонячне випромінювання з різних перспектив. Моделі прогнозування сонячного випромінювання можуть бути супутниковими, регресійними, статистичними, заснованими на штучному інтелекті або гібридними. Незважаючи на те що, під час розробки цих моделей отримані значні успіхи, деякі дослідники мають сумніви у їхній практичній застосованості. У цьому дослідженні робиться огляд існуючих моделей прогнозування сонячного випромінювання, а також надається перспективний і критичний аналіз стосовно того, наскільки вони є практичними та доступними з літературного погляду. Підкреслюється, що дослідники мають ретельно вивчити прогалини в дослідженнях, які є наявними, аби вдосконалити і впровадити деякі перспективні дослідження для подолання недоліків у моделях прогнозування. Важливо зазначити, що узагальнення моделей прогнозування сонячного випромінювання для місць, де немає вимірювальних інструментів, є складним завданням. Отже, ця стаття містить цінний інформаційний внесок для дослідників, практиків, інвесторів та всіх зацікавлених у розвитку та використанні моделей прогнозування сонячного випромінювання з метою підтримки розвитку сонячної енергетики.

Ключові слова: *відновлювана енергетика, сонячна енергетика, сонячне випромінювання, модель глобального сонячного випромінювання, модель прогнозування.*

Introduction.

Obtaining historical data on solar radiation and its characteristics holds significant importance for various fields of human activity, such as hydrology, agriculture, and energy sector. The modern progress in using solar energy for electricity production and reducing the cost of solar technologies makes it a primary component of the world's energy complex. It is predicted that by 2040, solar and wind energy will account for approximately 48% of the world's electricity production [1]. According to statistics, the capacity of solar power plants has increased by approximately 100% from 2009 to 2015 [2] due to the widespread deployment of grid-connected and off-grid solar systems, as well as the development of rooftop solar photovoltaic installations. Solar resources that reach the earth are important for various applications, such as photosynthesis, heating, and electricity production through photovoltaic cells. This resource is renewable and almost everywhere available, although its flow is random and periodic. In the light of the need to decarbonize electricity systems, the use of solar resources becomes an integral part of the energy strategies. For the efficient use of solar technologies, it is important to have accurate data on solar radiation that reaches a specific land surface.

Such data is essential for determining the dimensions of energy systems operating on solar panels, as it provides relevant information about the quantity, duration, and structure of solar energy received at a specific location on the Earth's surface [3]. These data help expand and improve research and utilization of solar energy. To obtain such data, specialized equipment is typically deployed to conduct measurements, which are then remotely transmitted to a data processing center, where they are analyzed and stored. However, due to the high cost of equipment, challenges in calibration, and ongoing maintenance expenses, many data recorded at data processing stations, especially in developing countries, are often limited, faulty, or inaccessible [4]. The utilization of such data poses numerous challenges and uncertainties in determining the dimensions of energy systems.

To mitigate the uncertainties associated with limited data, various algorithms and models have been proposed in the literature to estimate solar irradiance. These algorithms and models assess solar irradiance based on existing meteorological data, such as minimum and maximum temperature, relative humidity, hours of sunshine, and precipitation, available for the considered location(s). Some models even incorporate the interdependence between meteorological factors and solar radiation. Over the past few decades, different methodologies have been developed for solar irradiance forecasting, including satellite-based models, regression models, statistical models, artificial intelligence models, and hybridization of some of these models [5].

From the aforementioned points, it is evident that the amount of solar irradiance reaching the Earth's surface depends on the climatic characteristics of the location. This particularity has driven the development of various models capable of forecasting solar irradiance under specific local climatic conditions. Furthermore, some researchers have focused on improving existing models in terms of forecast accuracy and handling non-linearity. However, some thoughts have raised doubts about the ability of these models to be generalized. These concerns have led to the emergence of numerous solar irradiance prediction models that require proper contextualization for adequate understanding. While significant progress has been made during the development of these models, some researchers have questioned their suitability for practical applications. To address these concerns, this article provides a comprehensive review and perspective on the practicality or limitations of solar irradiance prediction models available in the literature. Additionally, research gaps that are desirable and necessary for future exploration are identified. It is expected that addressing these research gaps properly will contribute to the development of models or measurement equipment that effectively overcome the limitations of existing models.

Brief description of solar radiation prediction models

Earth's solar irradiance is influenced by various weather conditions that vary over time. These conditions serve as crucial factors for forecasting solar irradiance and are used as regressors in prediction models. Different types of models have been developed for solar irradiance forecasting, which can be classified into four main groups: regression-based, statistical, artificial intelligence-based, and satellite-based models, as illustrated in Fig. 1 [5].

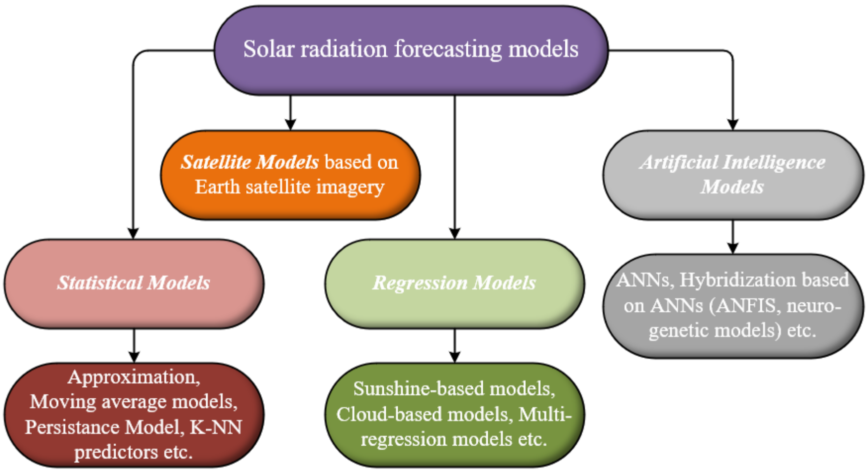

Figure 1. Classification of models developed for solar irradiance forecasting

Satellite-based models

Solar irradiance forecasting on the Earth's surface can be achieved using satellite data, utilizing imagery from satellites and other remote sensing data. By analyzing the intensity of cloud colors, the illumination of the Earth's surface can be estimated. However, satellite images have lower spatial and temporal resolutions compared to ground-based sources, leading to reduced short-term forecast accuracy. Thus, such images are more commonly used for long-term predictions.

To construct cloud motion vectors using satellite imagery, a concept similar to that used in sky image analysis is employed. Cloud images are formed based on visible and/or infrared images obtained from satellite sensors. One of the advantages of this approach is that the spatial scale of satellite images is significantly larger [6]. The cloudiness index (considered proportional to cloud optical density) can be calculated with reasonable accuracy. Cloud motion vectors are determined using successive satellite images [6]. For predicting cloud cover for the next 2 hours, statistical methods based on conditional probabilities are used, and by minimizing the size of individual image elements, it is possible to make forecasts even up to 6 hours ahead. The obtained cloud motion vectors are also used to improve the results of numerical forecasting models [6].

Statistical models

Statistical models are based on the utilization of historical data and the establishment of correlation dependencies among them. These models do not require the inclusion of physical atmospheric parameters and focus on the analysis of digital data. To forecast solar irradiance, relevant data must first be collected. Such data is typically gathered using meteorological instruments on the ground, satellite imagery, or numerical models that simulate the behavior of the Sun and its influence on Earth's atmosphere.

The application of statistical methods relies on the quality of the available historical data. Selecting a time series requires adherence to specific rules, such as having observation results spanning from the beginning to the end of the time series, regularity in the time intervals, and the absence of missing data.

Forecasts must undergo thorough verification, especially when there are correlations between different trends or the potential for a "discontinuity" between the past and the future.

One of the subcategories of statistical models is the time series approach [7], where the dynamics of variables are ordered over time and used to build trends and forecast future values [8]. A simple regression model is represented as [9]:

$$y = \beta_0 + \beta_1 X_1 + \ldots + \beta_i X_i + \varepsilon\,, \tag{1}$$

where y is the target variable (the predicted value); $X_1, \ldots, X_i$ are independent variables; β_0 is the bias coefficient; $\beta_1, \ldots, \beta_i$ are coefficients of independent variables; ε is the error term (the residual).

The coefficient β_0 is the predicted value of y when the X is 0.

A multidimensional time series involves the numerical analysis of multiple variables in the time domain. The independent variable includes two types of data: exogenous data (influence data) and response data (response to the influence). The multidimensional model is described using a matrix that contains information about the relationships between variables and their changes over time [10]:

$$y = \begin{bmatrix} y_{11} & y_{21} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m1} & \cdots & y_{mn} \end{bmatrix}, \tag{2}$$

One of the drawbacks of the time series approach to forecasting is that forecast errors appear to increase for short-term predictions. In the literature, some time series models incorporate Autoregressive Moving Averages, K-Nearest Neighbors predictors, and Persistence Models [5].

Regression models

For forecasting solar irradiance, regression models are frequently used to establish correlations between various meteorological variables and solar irradiance measurement data. One of the key advantages of these regression models is that the instruments used to measure certain meteorological parameters, which serve as input data for the models, are readily available. This ensures data accessibility for most regions and locations [6]. However, regression models have a limitation in that they may not accurately capture the nonlinear nature of solar irradiance in their predictions. This limitation has been identified in the literature as one of the main drawbacks of these models [7]. Consequently, when forecasting solar irradiance, the accuracy of regression models may be lower compared to other types of models.

Solar irradiance forecasting employs various regression models, among which the following can be highlighted:

- Cloud-based models [11-13]: In these models, cloud cover is utilized as a significant input variable, as clouds have a substantial impact on the amount of solar irradiance reaching the Earth's surface.
- Sunshine-based models [14]: Such models use data on sunshine duration as an input parameter for solar irradiance forecasting.
- Temperature-based models [15]: In this type of model, temperature is used as an input variable, as it can also influence the magnitude of solar irradiance.
- Hybrid models [5]: Some forecasting models combine cloud cover, sunshine duration, temperature, and other meteorological data such as atmospheric pressure, solar elevation angle, precipitation, relative humidity, atmospheric pressure, and wind speed to achieve more accurate predictions.

In [16], it is noted that among regression models, the most advanced and widely used is the model based on cloud cover, sunshine duration, and temperature. This model takes into account the influence of important meteorological parameters, enabling more accurate solar irradiance forecasts.

Sunshine-based model

The solar irradiance forecasting model based on sunshine duration establishes a relationship between the hours of sunshine recorded at the meteorological station and the extraterrestrial irradiance [17, 18]. Mathematically, the original model is presented as follows [10]:

$$\frac{G_t}{G_{t,0}} = B_0 + B_1\left(\frac{S}{S_0}\right), \tag{3}$$

where G_t is the mean global solar irradiance, $G_{t,0}$ is the monthly average daily global irradiance under clear sky conditions, S is the mean number of hours of sunshine, S_0 is the mean duration of the day, B_0 and B_1 are parameters of the model determined using statistical methods of analysis and regression.

The model expresses the statistical relationship between a variable representing the ratio of the monthly average daily hours of bright sunshine to the monthly average maximum possible daily hours of sunshine $\left(S/S_c \right)$, and a variable representing the ratio of the monthly average daily global irradiance to the monthly average daily global irradiance under clear sky conditions $\left(G_t/G_{t,0} \right)$ [10].

The duration of sunshine is typically accessible and measured using appropriate instruments at meteorological stations. On the other hand, the extraterrestrial irradiance is obtained from the following expressions [10, 19]:

$$G_{t,0} = \frac{24I_D}{\pi}\left[\cos\varphi\cos\delta\sin\omega_S + \frac{2\pi\omega_S}{360}\sin\varphi\cos\delta\right]\left[1+0{,}033\cos\left(\frac{360n}{365}\right)\right]; \tag{4}$$

$$\delta = 23{,}45^{\circ}\, sin\left[\frac{360\left(d_n+284\right)}{365}\right], \tag{5}$$

The latitude of the selected location is denoted as φ, n is the day of the year starting from January 1. The value of the solar constant is denoted as I_D and it is equal to 1367 W/m².

Cloud-based models

Clouds influence the distribution and scattering of solar radiation, which in turn alters weather conditions and impacts the amount of solar radiation reaching the Earth's surface [16]. Meteorological satellites are used to obtain data on clouds, and they perform measurements for various types and layers of clouds [20]. The obtained cloud data can be utilized in the development of different models that allow for the estimation of global solar radiation at the Earth's surface.

One of the drawbacks of such models can be the presence of different cloud layers with varying movement characteristics. For instance, clouds at higher altitudes may be partially obscured by clouds at lower altitudes. Such differences in cloud movement can impact the accuracy of the forecast. The actual forecasting time also depends on the speed and altitude of cloud movement. Fast-moving and low clouds may only remain in the field of view for a few minutes, while high and slow-moving clouds can remain visible for 30 minutes or even longer. Common forecast horizons range from 5 to 20 minutes.

Indeed, even if the size and speed of clouds can be accurately measured, the forecast accuracy will depend on how quickly the cloud field shifts relative to its initial position, which is determined by vectors of their movement (such as development, dissipation, and other factors) [21]. Such complexities can lead to deviations in forecasts and reduce the precision of solar radiation forecasting.

Temperature-based models

The measurement instruments required to collect sunshine and cloud data can be expensive and may not be commonly available in all weather stations, unlike temperature measuring instruments. As a result, accessing reliable sunshine and cloud data is often challenging. In response to this limitation, researchers have developed models that utilize readily available meteorological data, such as air temperature, to estimate solar radiation. These empirical models use daily minimum and maximum air temperatures as inputs and calculate solar radiation as outputs. In temperature-based models, it is assumed that the fraction of extraterrestrial radiation reaching the ground is directly related to the difference between maximum and minimum temperatures [16].

Expression (6) serves as the foundation for many temperature-based models [10].

$$\frac{G_t}{G_{t,0}} = A_1\left(\Delta T\right)^{0,5}, \tag{6}$$

where ΔT represents the difference between the daily maximum temperature (t_{max}) and the daily minimum temperature (t_{min}).

Models based on artificial intelligence

Techniques of Artificial Intelligence (AI) are used to create machines that mimic biological processes. Solar radiation forecasting using AI methods involves the utilization of Machine Learning algorithms [22, 23], which assess historical meteorological data, such as cloud cover, temperature, and wind speed, to predict future levels of solar radiation. Among the AI algorithms widely employed for solar radiation prediction are Artificial Neural Networks [24, 25], Decision Trees [26], Support Vector Machines [4] etc. Additionally, other methods like Deep Learning [27-28] and Convolutional Neural Networks are being investigated for solar radiation forecasting [28, 29]. These methods show potential in providing more accurate and sophisticated predictions of solar radiation.

AI models for solar radiation forecasting encompass various approaches, among which the following are the most popular:

- *Artificial Neural Networks (ANNs)*: ANNs simulate the biological nervous system of the human brain and enable understanding complex relationships between input and output data. They consist of three layers - input, hidden, and output layers [30]. ANNs can forecast solar radiation without making specific assumptions about the underlying process, utilizing neurons to establish connections between variables.

- *Recurrent Neural Network Models (RNNs)*: These models are specifically designed to handle sequential data, such as time series. They are trained on historical data to predict future solar radiation values based on past observations.
- *Random Forest Models*: These models employ an ensemble of decision trees to forecast solar radiation. They are trained using various meteorological parameters and past observations as input data and then derive the final prediction by averaging the values produced by each tree.
- *Support Vector Machines (SVM)*: These models can forecast both linear and nonlinear data. They are trained on historical data to obtain an optimal boundary that separates solar radiation into two classes.

The application of ANNs offers numerous advantages, such as self-learning ability, flexibility, compactness, and the capability to model complex nonlinear processes without assuming explicit relationships between input and output variables [31]. However, they also come with certain drawbacks, such as overfitting, local minimal tendencies, poor generalization, which can impact model accuracy and complexity [32]. To enhance the performance of ANNs in solar radiation forecasting, they can be combined with global algorithms [32, 33].

In general, AI models, such as ANNs, RNNs, Random Forest Models, and SVMs, are notable for their ability to provide accurate real-time forecasts, making them valuable for optimizing energy generation systems utilizing solar technologies.

Performance assessment: predictive models and indicators of forecast quality

Performance metrics provide a quantitative assessment of the accuracy and reliability of solar radiation forecasting algorithms, enabling model comparisons. These evaluations help determine which models are most suitable for specific applications, contributing to the overall improvement of solar radiation prediction quality. Table 1 presents a comparison of the effectiveness of various forecasting models, each with its own advantages and limitations.

Table 1

Evaluation of the effectiveness of the considered models for solar radiation forecasting

Forecasting Model	Strengths	Weaknesses
Satellite-based Models	▪ Capture large-scale weather patterns; ▪ Good spatial coverage	▪ Limited accuracy in capturing local weather phenomena; ▪ Dependence on the quality of satellite data; ▪ Struggles with complex atmospheric conditions
Statistical Models	▪ Can capture nonlinear relationships and complex patterns; ▪ Better accuracy compared to regression models	▪ Requires significant and diverse training datasets; ▪ Model selection and tuning are crucial for optimal performance
Regression Models	▪ Relatively simple to implement; ▪ Acceptable accuracy for short-term forecasting	▪ Limited effectiveness during significant weather variations or unexpected fluctuations; ▪ Constraint in solving complex nonlinear relationships
Artificial Intelligence Models	▪ Can automatically learn complex patterns and dependencies; ▪ Often outperform traditional statistical models	▪ Requires large volumes of training data; ▪ Demands significant computational resources; ▪ Interpretation and explainability can be challenging
Hybrid Models	▪ Combine strengths of individual models	▪ Effectiveness can vary depending on the specific combination and integration methodology

To assess the effectiveness of solar radiation forecasting models, several accuracy metrics are commonly used. Among these indicators, the following can be highlighted: Mean Absolute Error, Root Mean Squared Error, Mean Bias Error, Mean Percentage Error, Mean Absolute Percentage Error, R-squared (R^2), and Forecast Benchmarking. Additional details regarding these metrics are provided in Table 2.

Although satellite models offer wide spatial coverage [34], their accuracy suffers from the influence of cloud cover and atmospheric conditions. Consequently, satellite models tend to exhibit higher values of MAE, RMSE, and MAPE. On the other hand, regression models, while easy to implement and interpret, often fail to adequately capture complex nonlinear relationships and rapid weather changes, leading to moderate performance metrics. Regarding statistical models, they are also straightforward to use and computationally efficient, but during rapidly changing weather conditions, they may suffer from insufficient accuracy. Certainly, performance metrics for statistical models, such as MAE, RMSE, and MAPE, often fall within a moderate range. Nevertheless, despite their limitations, statistical models can be valuable for short-term forecasts when relevant historical data is available. Other models, such as those based on AI, typically demonstrate superior results in identifying complex patterns and relationships. These models often exhibit lower values of MAE, RMSE, and MAPE, indicating higher accuracy. Hybrid models, which combine multiple forecasting methods and leverage the advantages of different approaches, also garner significant attention. Research has shown that hybrid models tend to achieve improved efficiency, as reflected by lower values of MAE, RMSE, and MAPE compared to individual models [35]. For instance, a study described in [36] demonstrated that employing Deep Learning-based optimization in hybrid solar radiation forecasting models can lead to achieving a maximum R^2 value of 100%.

Table 2

Performance metrics used for evaluating solar radiation forecasting models

Performance Metric	**Description**	**Mathematical Expression**	**Ideal Value**
Mean Absolute Error (MAE)	MAE calculates the average absolute difference between forecasted ($\hat{y}_i$) and actual values (y_i). This metric measures the average magnitude of the forecast error and is widely used in solar radiation forecasting evaluations	$\frac{1}{N}\sum_{i=1}^{N}\lvert\hat{y}_i - y_i\rvert$	0
Root Mean Squared Error (RMSE)	RMSE calculates the square root of the average of squared differences between forecasted and actual values. It is more sensitive to large errors than MAE and offers an overall assessment of model performance	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$	0
Mean Bias Error (MBE)	MBE indicates the average forecasting error, reflecting the systematic tendency of the forecasting model to under- or over-predict. This metric helps understand the model's systematic bias	$\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)$	0
Mean Absolute Percentage Error (MAPE)	MAPE is commonly used as a loss function for regression and model evaluation due to its intuitive measure of relative error. In solar forecasting, it is normalized by the nominal power to facilitate meaningful comparisons P_0	$\frac{100}{N}\sum_{i=1}^{N}\left\lvert\frac{y_i - \hat{y}_i}{P_0}\right\rvert$	0
R-squared (R^2)	R-squared defines the ratio of the variance in actual values that can be predicted based on forecasted values. It indicates how well the model fits the data and explains the variation in solar radiation	$1-\frac{\sum_i (y_i - \hat{y})^2}{\sum_i (y_i - \bar{y})^2}$	1
Forecast Benchmarking	Forecast benchmarking compares a model's improvement to a benchmark relative to the best possible forecast without errors	$1-\frac{Metric_{forecast}}{Metric_{perfect\ forecast}}$	The closer the value to 1, the better the model's effectiveness

The (im)practicality of solar forecasting models

An overview of contributions presented in the scientific literature regarding solar radiation forecasting models based on regression indicates the effectiveness of such approaches in determining solar radiation with a significant level of accuracy. Regression models have successfully established a strong and positive relationship between measured meteorological data and solar radiation in various geographical regions. However, in [37], it is noted that regression models can only be deployed and applied in locations where accurate data on solar radiation and other relevant climatic data are guaranteed. It is important to highlight that instruments for collecting data on solar radiation have high costs and are usually only available in developed countries that can afford them. In countries where measuring devices capturing solar radiation data exist, such devices are only available at a limited number of stations [38]. Such constraints raise doubts about the generalizability of regression-based solar radiation forecasting models. Real-time data collection from measurement devices can create problems concerning the use of regression models in such locations. Crucial questions arise:

1) How useful can solar radiation models be in places where meteorological instruments are available for measuring radiation and other meteorological data?

2) What is the contribution of solar radiation forecasting models in regions where measuring devices are not accessible?

These questions cast doubt on the practical applicability of regression-based solar radiation forecasting models, which occupy a significant place in research within the scientific community. Clearly, the majority of researchers in this field are improving initial models based on limited measurement data.

To address the provided questions, it is necessary to thoroughly assess the effectiveness of solar radiation forecasting models at a practical level. In cases where solar radiation data is unavailable due to instrument malfunction or technical maintenance, solar radiation forecasting models can be employed to correct for these missing data [37], thus generating synthetic data. However, the purposefulness of data correction must be carefully considered. Introducing solar radiation data with missing points into the energy generation model may lead to various levels of uncertainty in the obtained results. Although the consequences may be insignificant in small-scale energy system projects, the severity of uncertainties increases as the size of the designed system grows. For example, if data absence results in a 5% error for a 5 kW and 1 MW solar energy systems, operators or energy companies would need to compensate for 0,25 kW and 50 kW, respectively. Nevertheless, the technical, legal, and economic burden caused by a 50 kW deficit would be significantly greater than a loss of 0,25 kW. Considering these factors, it appears that solar radiation forecasting models could play a vital role in providing synthetic data to correct for missing data caused by instrument malfunction or failure [37].

With the increasing deployment of municipal solar energy systems, the demand for accurate energy generation forecasting in power grids is growing. Consequently, more attention is being directed towards solar activity forecasting models. Essentially, solar activity forecasting models provide tools that operators can use to assess and balance energy production and consumption in electric grids composed of various energy sources, including solar technologies. Adequate solar activity forecasts enable operators to efficiently dispatch different controllable generating units, ensuring the necessary availability, stability, and flexibility critical for optimizing the electric grid's operations.

Therefore, from the perspective of energy production forecasting, solar activity forecasting for periods ranging from daily to minute intervals is crucial for the efficient management of operational energy systems, particularly those integrated with solar technologies. This is because solar radiation exhibits variable characteristics and requires accurate forecasting to ensure the stability and reliability of the electrical grid. Hybrid energy systems, combining solar technologies with other sources, greatly benefit from precise solar activity predictions to optimize their performance and maintain grid stability.

In addition to their practicality, as mentioned earlier, solar radiation forecasting models find extensive applications in the financial aspects of solar energy projects. For instance, large-scale solar energy projects often require financing from financial institutions at competitive rates. Securing such funding depends on a thorough analysis of cash flows, demonstrating that the project can ensure a stable income stream throughout the loan term. Solar forecasting models can assist companies in effectively planning and managing their projects. Thus, the quality of solar resources and the accuracy of solar radiation forecasting are critical factors influencing the possibility of obtaining competitive credit financing for solar energy projects. Reliable solar radiation data is an essential component for cash flow analysis and project viability assessment. Lenders also require a verification dataset of solar radiation, confirming the potential income level that the project can generate. Accurate solar radiation forecasts at different time scales, including hourly, daily, monthly, and yearly forecasts, are key requirements for determining project economic viability. Overall, solar radiation forecasting models play a significant role in contributing to the success of solar energy projects by enabling efficient energy grid management and ensuring reliable project financing.

During the literature search, significant gaps in research related to solar radiation estimation in locations without measurement instruments were identified. Nevertheless, the use of data-driven AI methods showed promise in solar radiation forecasting for such areas [39]. Researchers utilized data-driven methods that allowed them to handle situations where real models were impractical or unavailable to obtain information about solar radiation in locations without direct measurements. In [39], the feasibility of obtaining solar radiation data from places without measurements was investigated, and a forecasting model using the SVM method was developed. This model could estimate and establish the relationship between meteorological variables and global solar radiation for locations with available data and predict global solar radiation for places where data were absent in the model's training data. Even when testing the model on new data for an another location not included in the training dataset, the model demonstrated an accuracy of 95% and MAPE of 5,43%. In another study [40], a different approach was presented, where solar radiation data measured at various locations with similar radiation patterns were used to train accurate forecasting models for the target location. A multi-dimensional space was constructed based on measurements of humidity, temperature, and satellite data, where each location was interconnected with a point in this space. A directionality diagram-based metric was then utilized to compare the relationships between measurement locations. Consequently, "candidate sites" were identified, providing data for training the forecasting model for the target location. The results of these studies emphasized the practicality of solar radiation forecasting models in locations without measurement instruments, warranting further detailed exploration [40].

Conclusions

Solar radiation forecasting models play a vital role in the successful integration of solar energy into the energy balance and the planning and operation of solar technologies. While their significance is clear, challenges exist in developing generalized models for regions without measurement instruments. Nevertheless, promising progress has been made in this area, and further research efforts should be directed towards creating effective models for such regions.

The development and implementation of advanced solar radiation forecasting models require substantial resources, which can be particularly challenging for organizations operating in developing regions with limited means. To make these models accessible in resource-constrained countries, it is crucial to focus on the production of cost-effective devices for measuring solar radiation.

Additionally, the accuracy of solar radiation forecasts is crucial for rational decision-making regarding electricity generation and grid management. Thus, research efforts should concentrate on enhancing the precision of these models through the availability of real-time data on solar radiation levels and weather conditions.

In summary, solar radiation forecasting models are essential for the successful integration of solar technologies into the energy sector, leading to a more efficient transition to green energy and a sustainable future. However, ensuring their practical application and accessibility worldwide requires further research and technological advancements.

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