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Application of Machine Learning for the Prediction of Solar Power Generation

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Abstract

The increasing percentage of grid power contributed by renewable sources is one of the main objectives of smart grid development. The intermittent and unpredictable nature of renewable energy sources' power supply makes grid integration difficult. Since dispatching generators of the grid to meet demand varies across the grid, forecasting future renewable generation is crucial. While manually creating complex prediction models for massive solar farms may be viable, doing so for the grid, for millions of households with distributed generation, is a difficult task. To address the issue of National Weather Service (NWS) weather forecasts, this research investigates the use of machine learning approaches to automatically generate solar power generation predictions through site-specific models. This research contrasts different methods of multiple regression, such as different kernel functions in support vector machines and linear least squares, for creating prediction models. Using historical NWS forecasts and solar intensity values from a weather station spanning almost a year, the work assesses each model's accuracy. NWS forecasts provide essential, current, and comprehensive information that can greatly enhance solar energy harvesting forecasts. These forecasts make expectation models more likely to record ongoing and anticipated weather patterns, leading to more accurate and dependable solar energy generation forecasts. The findings of this research demonstrate that existing forecast-based models are 36% less accurate than the prediction models of support vector machines developed using seven separate weather forecast parameters. The performance of the models is evaluated by the root mean square error.

Categories: Machine Learning (ML), Energy Efficiency and Sustainability, Green Computing and Sustainability
Keywords: solar intensity, least square regression, support vector machine, root mean square error, kernel function

Introduction

Increasing the prevalence of ecologically friendly renewable energy sources, such as solar and wind, is a primary objective of the smart grid initiative. For instance, the Renewables Portfolio Standard [1] sets a limit of 25% for intermittent renewable energy output, while California's Executive Order S-21-09 [2] mandates a target of 33% for renewable energy generation by 2020. The intermittent and unpredictable nature of renewable energy sources makes significant grid integration difficult. The modern electric grid does not currently have the capacity to handle massive amounts of unpredictable generation, but it does allow households to consume electricity in basically arbitrary amounts at any given time. Instead, the system continuously tracks electricity needs and assigns generators to meet fluctuating demand. Fortunately, when combined across thousands of structures and residences, electricity demand becomes remarkably predictable. As a result, today's grid can precisely predict in advance which generators will be dispatched to meet the demand.

The problem with widespread renewable integration is that it is hard to predict in advance how much electricity renewable sources will produce because it varies based on site-specific factors and weather conditions. Large-scale solar farms that generate multiple megawatts are not feasible, even though utilities may put effort into creating specialized models that accurately forecast the electricity output from a distributed generation at several small-scale facilities at intelligent homes and buildings across the grid. This fact is made evident by the fact that most states' current net metering laws permit individuals to sell energy produced locally using renewable resources back to the grid, but they usually place small restrictions on the total number of participating clients and/or the total amount of energy contributed by each client [3]. Massachusetts, for instance, limits the overall proportion of customers to all customers of 1% participating. Because renewable energy is less predictable than electricity demand and makes it more difficult to plan ahead for the grid's generator dispatch schedule, utilities limit the contribution from renewable.

This research concentrates on the issue of spontaneous models that correctly estimate nonconventional energy using weather forecasts from the National Weather Service (NWS) to improve forecasting and increasing the renewable fraction in the grid, as the barrier is lower. More specifically, the work tests and utilizes historical NWS forecast data, and a number of machine learning approaches are used to create prediction models, which are then correlated with the generating of solar panel data. The prediction

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models employ NWS forecasts for a local area to forecast the prospect after being trained on past forecast and generation data, with generation occurring over various time scales. Since solar intensity is inversely correlated with solar power harvesting, the work uses solar intensity as a stand-in for solar generation in the experiments in this study [4]. Importantly, because of the availability of historical site-specific power generation data, this research builds models that naturally take into account how local factors, such as nearby trees providing shade, affect each site's potential to generate power. Individuals must adjust the prediction models for specific site variables, as local factors affect electricity generation. To scale distributed production from renewable sources to millions of households across the grid, this work sees autonomous model generation as essential.

The main objective of this work is to automatically generate prediction models for smart houses with on-site renewable energy sources. These forecasting models can be used by the grid as well as specific smart houses to plan the generation and consumption of power in advance. As the grid's share of renewable energy rises, the models can be used in advance for planning the dispatch schedules of generators. With the aid of the models, smart homes may be able to better coordinate their energy consumption with their on-site generation. To improve efficiency and encourage wider deployment of generation which is distributed from the grid and at smart homes renewable sources, improved models of prediction are required in both situations. The work contributes the following to the study of prediction models for solar energy harvesting where forecast models for solar energy harvesting that rely on verifiable data are viable only to the extent that they account for relevant natural elements, the quality and preprocessing of the data, and the type of model used. Profound learning models and high-level machine learning techniques are particularly interesting because they can process large amounts of data and identify intricate examples, leading to incredibly accurate predictions.

Brief description of data

To match the weather metrics in the prediction with the intensity of solar radiation [5], measured in watts per square meter (W/m^2), the weather station recorded it, the study evaluates comprehensive historical data from NWS station, as well as the associated NWS weather forecasts, as shown in Table *1*. The research quantifies the interaction between each forecast parameter and the intensity of solar radiation. While there is a slight connection with each other by dew point, wind speed, temperature, and the intensity of solar radiation, this research finds that substantially correlated with one relative humidity, precipitation, sky cover, and the intensity of solar radiation [6].

Days	Solar intensity (W/m^2)
1	120, 180, 200, 280, 310, 350, 360, 365, 370, 400
50	50, 100, 200, 250, 300, 400, 500, 520, 540, 560
100	80, 100, 200, 250, 280, 300, 320, 330, 340, 350
150	150, 250, 280, 350, 400, 500, 600, 700, 800, 900
200	80, 200, 300, 340, 380, 400, 580, 680, 700, 800
250	150, 180, 280, 320, 360, 390, 560, 660, 680, 680
300	100, 160, 250, 300, 320, 340, 500, 640, 600, 660

TABLE 1: Datasheet for 10 months

Creation of models

This study uses various machine learning approaches to create predictive models for solar intensity based on a variety of forecast criteria. Forecasts made within one to seven days of an event are referred to as short-range forecasts. Typically, medium-range forecasts are released one to four weeks in advance, while long-term forecasts are made between one month and one year in advance. The research work then evaluates each model's predictive performance. Additionally, the research develops a model that calculates solar intensity over a specific time horizon, using a collection of anticipated weather variables. This model leverages machine learning techniques applied to historical solar intensity observations and forecasts, as detailed in the training dataset in Table *1*. This research develops models based on support vector machines (SVMs) and linear least squares regression. The study finds that the radial basis function (RBF) kernels for SVM, constructed from seven weather metrics, such as day, temperature, dew point, wind speed, sky cover, precipitation, and humidity, using historical data, are 68% more accurate than straightforward methods that rely only on sky condition, and when only sky condition is used for predictions, existing forecast-based models are 36% less accurate than these SVM-based models [7].

Accurate models for predicting solar power are essential for the efficient integration of solar energy into the grid. They contribute to a more stable, practical, and adaptable energy system in the context of sustainable resources. The implementation of solar energy prediction models in server farms and smart homes can help associations and mortgage holders maximize solar energy benefits, enhance energy efficiency, reduce expenses, and promote sustainable energy practices.

The understandable models provide clear and valuable insights into the factors influencing predictions for the solar energy sector. By enabling a deeper understanding of how environmental, temporal, and geographical elements interact to influence solar production, these models help stakeholders make well-informed decisions that enhance the efficiency, reliability, and integration of solar energy into the grid, as shown in Figure 1.

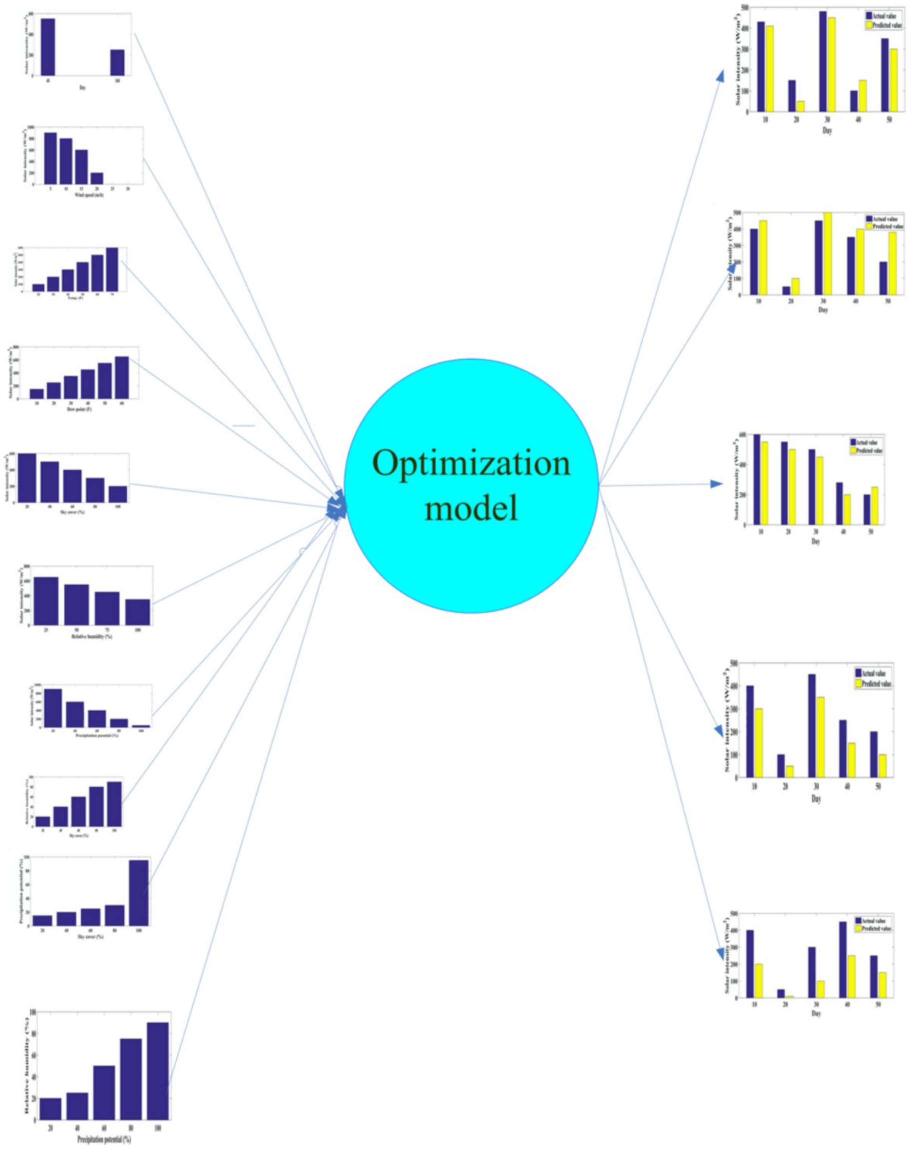

FIGURE 1: Optimization model of solar power generation

Materials And Methods

Starting in January 2010, this research collects information on solar intensity and weather forecasts over a period of 10 months. Solar intensity includes values for summer days with cloud cover (280 W/m²) and winter days with sunshine (500, 520, 540, and 560 W/m²), as shown in Table 1.

This research has been collecting historical forecast data for the past two years from weather.gov, operated by the NWS. For smaller city-sized regions across the United States, the NWS provides historical textual forecasts that include a variety of weather metrics for each hour of the day for the previous years. In the future, each prediction will include estimates for all measures at one-hour intervals, ranging from one hour to six days. Relative humidity, dew point, sky cover, precipitation probability, wind speed, and temperature are the few examples of weather measurements. The percentage estimation from 0 to 100 of clouds in the sky is called sky cover. The NWS offers historical forecasts, as well as an interface on the real-time web, that allow programs to programmatically access forecasts as they become available. Since the intensity of solar energy is influenced by daylight and fluctuates throughout the year for a particular site, this research also includes the precise time of day and day of the year as metrics. Changes in weather conditions variably affect the performance of solar energy forecast models. To provide accurate forecasts of solar energy generation in response to shifting environmental conditions, models must be able to adapt to real-time weather fluctuations, seasonal variations, extreme events, and long-term climate trends. The intensity of solar energy generation and meteorological parameters have a complicated and multidimensional relationship. While the focus is still on solar radiation, other factors such as temperature, humidity, air mass, geology, surrounding natural variables, transient elements, technological choices, and long-term environmental drifts all contribute to the complex relationship between weather patterns and solar energy production. These nuances should be accounted for in reliable solar energy forecasting models in order to provide accurate estimates under various ecological conditions.

The use of observational data on solar intensity from the University of Massachusetts Amherst's building, which has a weather station deployed on its roof for computer science purposes, was made possible. Every five minutes during the day, the station reports the intensity of solar radiation in W/m². Traces are available at traces.cs.umass.edu from the weather station. As demonstrated in earlier work [8-10], the intensity of solar radiation directly affects the amount of electricity generated by solar panels [11-13]. At the same location, solar panel inefficiencies generally lead to power production that is a fixed percentage lower than the raw intensity of solar readings. This work makes use of forecasts from the NWS for Amherst, Massachusetts. This section examines how each forecast component affects solar intensity, as well as how these forecast parameters are interconnected [14-18]. The data study aims to illustrate how solar intensity and solar panel electricity production depend on the combination of multiple climate variables, making them difficult to forecast from just a single weather metric. The investigation into automatically creating prediction models using machine learning approaches in the following section is motivated by the challenge of estimating solar intensity from multiple or equal weather metrics. The root mean square error (RMSE), provided in Eq. (1), is used to assess the performance of the models.

$$RMSE = \sqrt{1/N \sum (actualvalue - predictedvalue)^2} \qquad (1)$$

where N is the total dataset. For January 2010, as shown in Figure 2, analyzing the daily average value of solar intensity data at noon over the 10-month checking period starting from 1st January demonstrates the impact of solar intensity throughout the year, spanning 365 days.

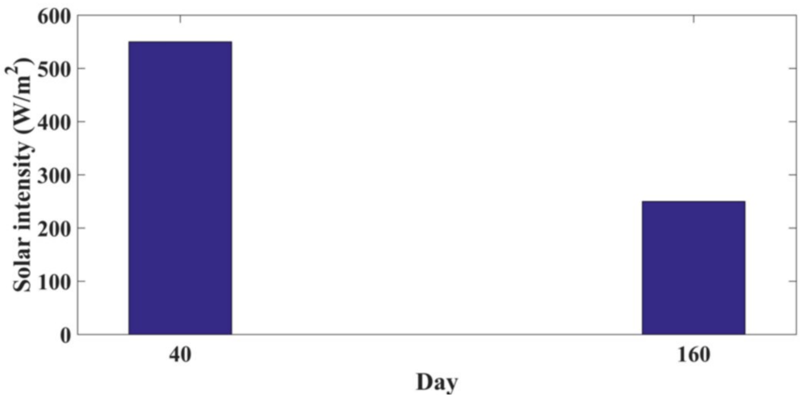

FIGURE 2: Comparison between solar intensity and day

Figure 2 confirms what was predicted, showing that the sun's intensity increases during the hot days and decreases following the vernal equinox. Only twice a year does the Earth's axis tilt in a direction that is neither toward nor away from the sun, resulting in "nearly" equal amounts of day and night at all latitudes. In January, solar intensity is at its lowest, close to the winter solstice. During winter, many days have lower solar intensity, so Figure 2 also suggests that other factors have a substantial effect on solar intensity. The graph demonstrates a loose correlation between solar intensity and the day of the year: a summer day will typically, but not always, have higher solar intensity than a winter day. However, as some sunny winter days obviously exhibit higher solar intensity values than certain foggy summer days, other variables must also influence solar intensity. This research builds comparable associations for other forecast indicators to understand correlations with additional weather metrics.

For instance, Figures 3-5 demonstrate that there is little correlation between solar intensity and wind speed, dew point, or temperature (Temp.).

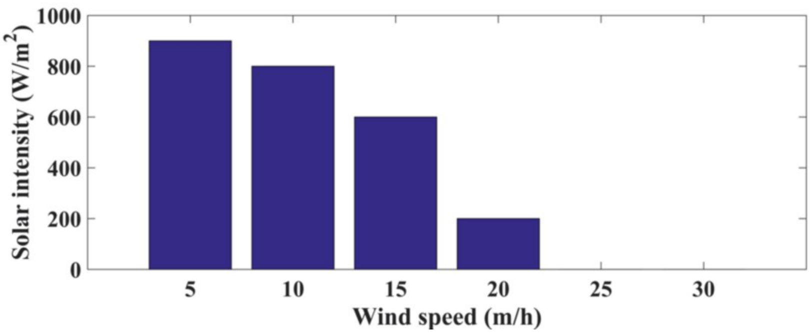

FIGURE 3: Comparison between solar intensity and wind speed

Figure 3 demonstrates that at any level of wind speed, solar intensity varies relatively consistently from maximum to minimum values, indicating a weak correlation. As a result, there is almost no relationship between wind speed and solar intensity, and wind speed alone neither predicts nor measures solar intensity.

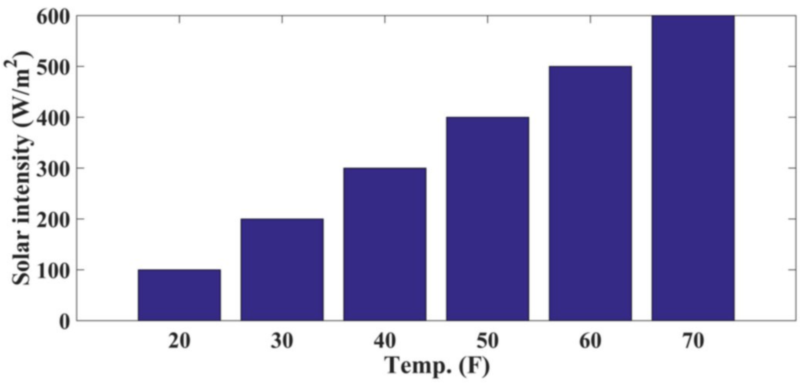

FIGURE 4: Comparison between solar intensity and temperature (Temp.)

At higher values, temperature exhibits a correlation with solar intensity: when one is high, the other is likely high as well, as shown in Figure 4.

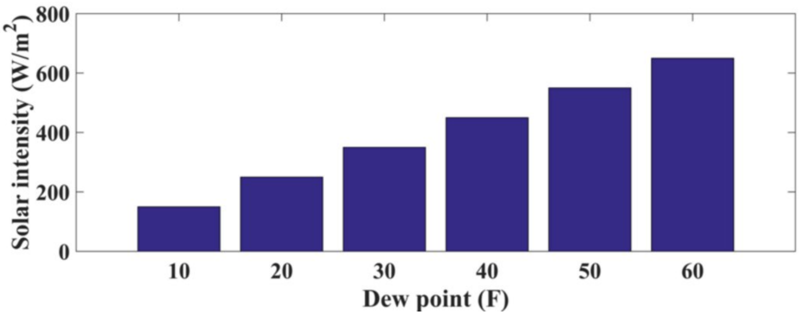

FIGURE 5: Comparison between solar intensity and dew point

For higher values of dew point, solar intensity is also high. As shown in Figure 5, solar intensity gradually increases from lower to higher values in relation to the dew point. Solar intensity, on the other hand, shows more pronounced oscillations between high and low values when temperature or dew point is low. For example, sunlight plays a more significant role in raising ambient temperature in the summer than in the winter.

In contrast, Figures 6-8 demonstrate that there are strong negative connections between solar intensity and sky cover, relative humidity, and the probability of precipitation. In each instance, solar intensity readings typically fall as the value of these metrics rises. Although certain days show high sky cover, relative humidity, and probability of precipitation with low solar intensity, there must be other elements that affect the solar intensity reading, just as there must be other things that affect the day of the year. Each weather metric not only displays intricate interactions with solar intensity but also displays complex relationships with other weather metrics. For instance, sky cover (the extent or amount of cloud cover observed or predicted in the sky at a given time and location) in Figure 9 and the chance of precipitation (the probability of rain, snow, or any form of water falling from the atmosphere to the ground within a specific timeframe and location) in Figure 10 show high values, but the connections are not strong with sky cover. Conversely, relative humidity (the amount of moisture or water vapor present in the air compared to the maximum amount of moisture the air can hold at a particular temperature) in Figure 8 and the chance of precipitation in Figure 10 demonstrate strong associations in Figure 11. Although the relationships are erratic due to the influence of other meteorological metrics such as mean atmospheric pressure and visibility, the measurements rise concurrently in all three instances, such as relative humidity, sky cover, and the chance of precipitation.

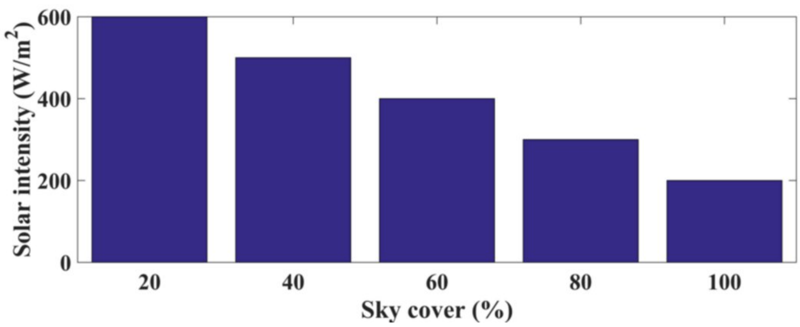

FIGURE 6: Comparison between solar intensity and sky cover

For higher values of sky cover, solar intensity decreases. Figure 6 shows how solar intensity gradually decreases from higher to lower values in relation to sky cover.

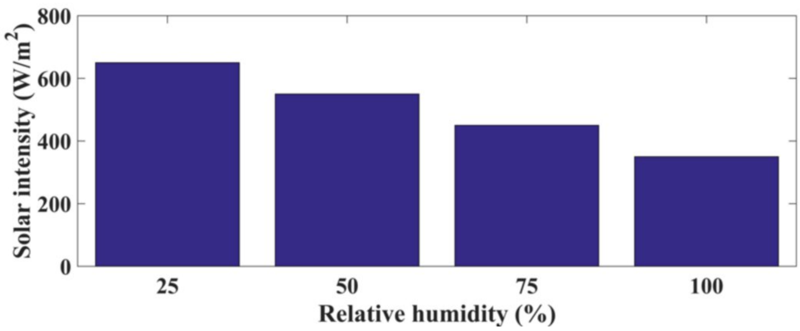

FIGURE 7: Comparison between solar intensity and relative humidity

For higher values of relative humidity, solar intensity decreases. Figure 7 shows how solar intensity changes as relative humidity shifts from higher to lower values.

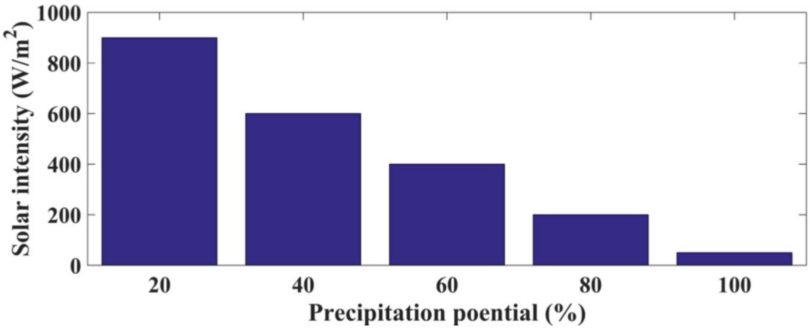

FIGURE 8: Comparison between solar intensity and precipitation potential

Figure 8 shows that the precipitation potential value also affects solar intensity. As the precipitation potential increases, solar intensity decreases. In Figure 9, the relative humidity value changes as the sky cover values fluctuate. The relative humidity gradually increases as the sky cover value rises.

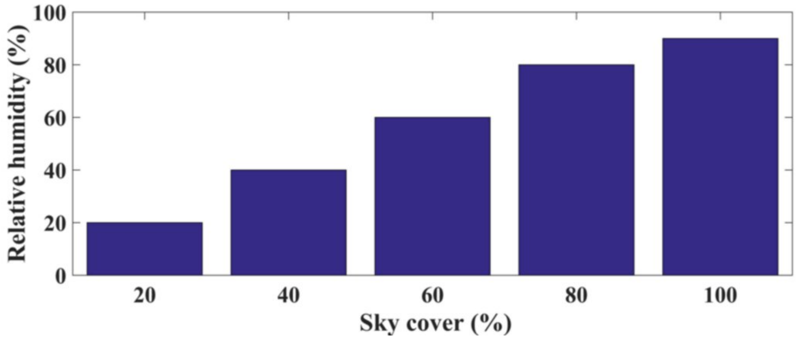

FIGURE 9: Relation between relative humidity and sky cover

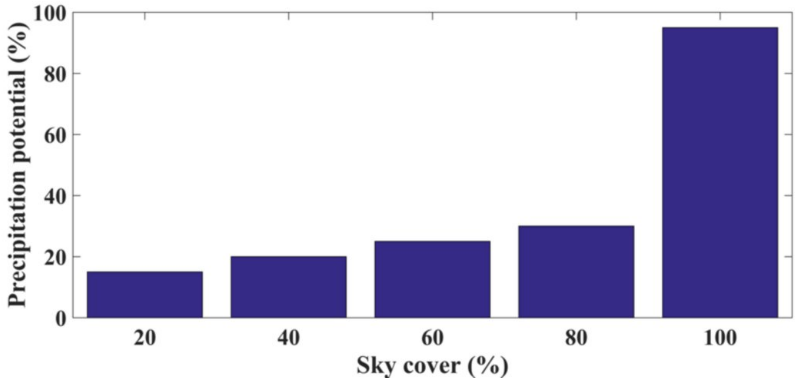

FIGURE 10: Relation between precipitation potential and sky cover

In Figure 10, the precipitation potential value varies with each value of the sky cover. For each sky cover value, the precipitation potential is different.

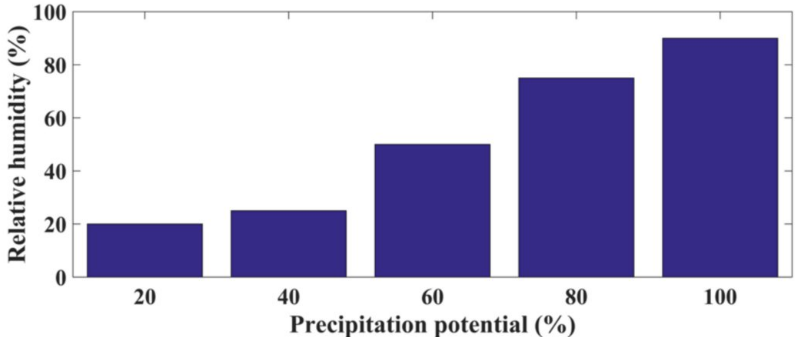

FIGURE 11: Relation between relative humidity and precipitation potential

The relative humidity is also influenced by the precipitation potential value. The maximum value of precipitation potential gives the highest value of relative humidity, as shown in Figure *11*.

The Pearson product-moment correlation coefficient (a measure of the strength and direction of the linear relationship), which divides the covariance of the two variables by the product of their standard deviations, is used in Table *1* to display the correlation coefficients for each weather metric. A positive correlation suggests an increasing linear relationship, whereas a negative correlation shows a decreasing linear relationship. The larger the absolute value of the correlation coefficient, the stronger the association between the two meteorological indicators. The investigation of automated prediction models using machine learning techniques is motivated by the nuanced correlations between meteorological variables and solar intensity, as illustrated in the following section. The predicted values are provided in Table *2*, which also explains the different parameter values used in the prediction of solar intensity. These parameters have yielded good results in reducing the root mean square error value.

Quantities	Value of day	Value of temp.	Value of dew point	Value of wind speed	Value of sky cover	Value of precipitation potential	Value of relative humidity
Value of day	1.0000	0.6234	0.6434	-0.0443	-0.0231	-0.0023	0.0451
Value of temp.	0.6055	0.5674	0.8543	-0.0231	-0.1254	-0.0132	-0.0658
Value of dew point	0.8080	0.8345	0.9754	-0.1223	0.2354	0.2312	0.2053
Value of wind speed	-0.5089	-0.0234	-0.1221	0.9832	-0.0056	0.0012	-0.0034
Value of sky cover	-0.0034	-0.3425	0.0034	-0.0034	0.3421	0.3241	0.6554
Value of precipitation potential	-0.0658	-0.0365	0.0132	0.0032	0.2354	0.3456	0.3427
Value of relative humidity	0.03452	-0.0567	0.2354	-0.0341	0.5345	0.5467	0.9956

TABLE 2: Correlation matrix demonstrating the relationship among various forecast parameters

Results

Model prediction

This work presents both observed and predicted weather metrics as a time series that varies with the seasons and weather patterns [19]. As discussed in the preceding section, creating a reliable prediction model is challenging because solar intensity depends on various weather indicators. The investigation into regression techniques for creating a solar intensity prediction model is driven by the high dimensionality of the time-series data [20-22]. The investigation used training data for eight months, i.e., from January to August (up to 240 days), for each model. This data includes solar intensity values and NWS projections for seven weather indicators, as shown in Table *1*. The seven weather metrics such as day, temperature, dew point, wind speed, sky cover, precipitation with relative humidity, and the year's day (240 days) are automatically combined into a function that the machine learning techniques generate [23]. This research evaluates the model's precision using the final two months (60 days) of the dataset, as shown in Table *1*. Normally, the more training data provided, the more precise the model will be, which is one advantage of using machine learning to mechanically produce models of prediction.

The investigations concentrate on the research on short-term forecasts for the next three hours [24]. To conduct the experiments, the work creates models that establish a correlation between the solar intensity and the projected weather parameters at each time t (t − 3). Noting that the methods can be used for forecasts of any length, this work uses a three-hour forecast as a straightforward example. Using the models and the three-hour forecast, this work can predict solar intensity three hours into the future. The models that the research work produces are straightforward functions that compute solar intensity from a variety of weather indicators, such as the year's day [25,26]. The day's time may be added as an extra parameter; however, for the sake of clarity, the studies only consider forecasts made around noon because, at noon, the Sun is generally at its highest point in the sky during the day, reaching its maximum elevation. This research assesses the model's accuracy against one another, against the model of this research work created in earlier work [27] that relied just on the condition of sky measure, and against a straightforward model of past to future. By multiplying the maximum power output by 1 − sky cover, the model adjusts the estimated power generation based on the extent of sky cover. Thus, the solar intensity (SI) is represented by Eqs. (2-13).

$$SI = F(Temperature, Day, Windspeed, Dewpoint, Humidity, Skycover, Precipitation) \tag{2}$$

Because of this, the phenomenon of extraterrestrial bar radiation is split into two particular parts: Diffuse Horizontal Irradiance (i_h) and Direct Normal Irradiance (i_n). The Global Horizontal Irradiance i_{gh} and ϕ are the zenith angles of the sun in Eq. (3):

$$i_{gh} = i_h + i_n * \cos\phi \tag{3}$$

The Linke turbidity coefficient, t_{cl}, and the optical density of a dry, clear atmosphere, α_a, could be used to calculate the overall optical thickness of an atmosphere without clouds in Eq. (4) with the mass of atmosphere a_m:

$$i_n = i_o * e^{-\alpha_a * t_{cl} * a_m} \tag{4}$$

One of the most basic clear sky models is a location-specific polynomial of the cosine of the solar zenith angle $\cos\phi$, which is given in Eq. (5):

$$i^m = \sum_{i=0}^{n} b_i (\cos\phi)^n \tag{5}$$

The polynomial fit of the third order (n = 3) is sufficient. In Eq. (6), the third-order polynomial can be written:

$$i_t^m = b_0 + b_1 (\cos\phi_t) + b_2 (\cos\phi_t)^2 + b_3 (\cos\phi_t)^3 \tag{6}$$

The proportion between the ground-level measured and modeled clear sky irradiance is the clear sky index, or c_t, in Eq. (7):

$$c_t = \frac{i_t}{i_t^r} \tag{7}$$

The clearness index c_t is also defined by normalizing the ground-level and extraterrestrial irradiances in relation to one another in Eq. (8):

$$c_t = \frac{i_t}{i_t^x} \tag{8}$$

Extraterrestrial irradiance is a lot simpler to demonstrate than reasonable sky irradiance because of the shortfall of actual climatic changes. A straightforward model of extraterrestrial radiation can be written as in Eq. (9):

$$i_t^x = i_0 \cos(\phi_t) \tag{9}$$

where i_t = 300 W/m^2 is the sun-powered consistent and ϕ_t is the sun-based apex point at time t.

This research defines the following persistence condition for the clear sky persistence forecast in Eq. (10):

$$c_{t+\Delta t} = c_t = \frac{i_t}{i_t^r} \tag{10}$$

In a similar way, this research defines a corresponding persistence condition for the clearness persistence forecast, with the forecast horizon as Δt in Eq. (11):

$$c_{t+\Delta t} = c_t = \frac{i_t}{i_t^x} \tag{11}$$

The solar irradiance prediction for the next time step is calculated using these indices in Eqs. (12 and 13):

$$i_{t+\Delta t}^k = c_t i_{t+\Delta t}^r \tag{12}$$

$$i_{t+\Delta t}^k = c_t i_{t+\Delta t}^x \tag{13}$$

The function that the research work identifies using various regression techniques is called F. This research maintains the units for each metric: this work produces every day as a number between 0 and 365, temperature is in degrees Fahrenheit, wind speed is in miles per hour, sky cover is given as a percentage between 0% and 100%, the probability of precipitation is between 0% and 100%, and the percentage of humidity is between 0% and 100%. However, this research standardizes the data of all features to have a mean of zero and a variance of units before using any of the regression procedures. This work utilizes the RMSE in the prediction of the solar intensity at any moment and the exact solar intensity observed to measure each model's accuracy. RMSE is a well-known statistical indicator of how effectively a model predicts values.

Discussion

Linear least square regression

To forecast the intensity of solar radiation, this research first uses the technique of linear least squares regression [28-30]. Linear least squares regression is a simple and popular method for determining the relationship between a set of independent or forecaster variables and a dependent or response variable, such as solar intensity. The sum of the squared differences between the observed and predicted solar intensities is minimized by the linear approximation of the weather metrics forecast, as indicated by Eq. (14). The model for prediction given below, which includes coefficients for each metric, is obtained when the linear least squares method is applied to the training data for 8 months [31-34].

$$SI = F(77.9*Temperature+1.11*Day+22.8*Windspeed+33.11*DewPoint-43.4*Humidity-96.9*Skycover-49.15*Precipitation) \tag{14}$$

Using the remaining months of the year’s test data (the final two months, or 60 days, of the dataset as shown in Table *1*), this research confirms the prediction accuracy. The research observes an RMSE of 150 W/m^2 for cross-validation and 100 W/m^2 for solar intensity, considering the actual and predicted values as shown in Figure *12*, respectively. The training dataset from January to August 2010, as shown in Table *1*, is used in the regression model for cross-validation, while the testing dataset, which consists of the last two months, is used to assess the regression model's predictive power for September and October 2010. While the expectation RMSE forecasts how well the model predicts values in the testing dataset, the cross-validation RMSE evaluates how well the model's predictions perform in the training dataset. The solar intensity for September and October 2010 is depicted in Figure *12*, both measured and forecasted. The model closely follows the predicted solar intensity, although with some deviations, since predicting solar intensity is a complex task influenced by multiple factors such as the day, temperature, etc. Achieving perfect accuracy may not always be feasible. However, with careful analysis and improvement of the model and data, these deviations can be reduced, leading to a more reliable solar intensity prediction system, as shown in Figure *12*.

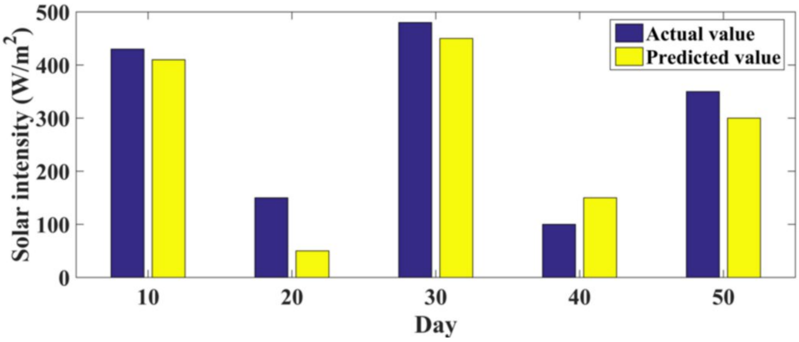

FIGURE 12: Solar intensity with the linear regression model

Figure *12* illustrates the performance of the SVM regression-RBF model for solar intensity, as RBF can be a strong choice due to its flexibility and universal approximation property. However, it is always essential to try different kernels and perform cross-validation to determine the best kernel for the specific data and problem. The predicted values are lower than the actual values for almost all days.

Support vector machine

The use of SVM to analyze several kinds of supervised learning techniques is what follows [35-37]. For classification and regression analysis, in a multidimensional space, SVMs create hyperplanes, which have lately grown in prominence. The kernel function and parameters appropriate choice affect how accurate SVM regression is. This work investigated three different SVM kernel functions: linear, polynomial, and RBF kernels. [38,39]. Data are transformed from the input space to the high-dimensional feature space using an SVM with the kernel function. Due to their capacity to handle the data for non-linearity and their sparsity property, SVMs were selected above other supervised learning techniques. In the training dataset, this research applies SVM regression with a linear kernel function using the LibSVM library, which contains a wide range of SVM regression methods [40]. This study found that the performance of the linear and polynomial kernels was subpar, with RMSE values of 50 W/m^2 and 200 W/m^2, respectively, as shown in Figure *13*, compared to the linear least squares method. Figure *13* explains the work of the SVM regression-RBF model for solar intensity. The predicted values are higher as compared to the actual value. Therefore, this research concentrates on the outcomes obtained using the RBF kernel.

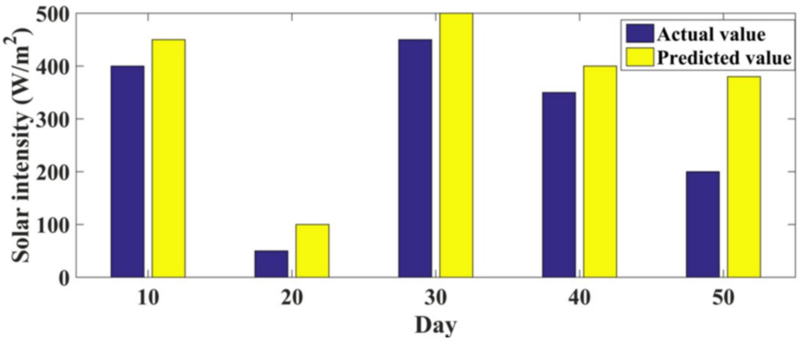

FIGURE 13: Solar intensity with SVM regression-RBF model

SVM: Support Vector Machine; RBF: Radial Basis Function

Using the LibSVM library and the training data for 8 months as given in Table *1* for 240 days, this research evaluated the kernel RBF of SVM. This study used a grid search tool from the LibSVM library in the dataset of training to determine the best parameters of the RBF kernel, because the parameters typically considered for the RBF kernel are the gamma (γ) and the cost (C) with the help of accuracy on the training dataset, i.e. days 1 to 240, and the accuracy on the validation dataset, i.e. days 250, from Table *1* and the margin of tolerance for LibSVM, which helps to avoid penalizing for fewer accuracy results. The kernel of RBF ideal parameters, according to the research, are $C = 280$ and $\gamma = 0.0251$. With the help of these parameters, this work found that the kernel of RBF with all seven dimensions (day, temperature, dew point, wind speed, sky cover, precipitation, and relative humidity) for the seven weather metrics (day, dew point, wind speed, temperature, precipitation, sky cover, and relative humidity) offers a better model of regression than the other techniques of regression, as shown in Table *3*, by its less cross-validation and errors of prediction with the calculation of RMSE, significantly both of which are less than either the kernels of linear or the polynomial, in Table 2, by comparison of the linear regression model, SVM regression-RBF model, SVM-RBF kernel model, Cloudy PPF model, and PPF model with their actual and predicted values. This fact is also depicted in the histogram time series of the observed and anticipated values in Figure 13 on day 20. With slightly higher prediction RMSE (76.55 W/m^2) and slightly lower cross-validation RMSE (66 W/m^2) compared to the linear least squares approach, the results demonstrate that the RBF kernel also outperforms it, as shown in Tables 3 and 4, by comparison of their actual and predicted values with the calculation of RMSE. The choice between linear least squares and SVMs with RBF kernels for solar energy prediction is determined by the dataset's specific characteristics, desired level of interpretability, and computational considerations.

Day	Linear regression model		SVM regression-RBF model		SVM-RBF kernel model		Cloudy PPF model		PPF model	
	Actual value	Predicted value	Actual value	Predicted value	Actual value	Predicted value	Actual value	Predicted value	Actual value	Predicted value
10	430	410	400	450	600	550	400	300	400	200
20	150	50	50	100	550	500	100	50	50	10
30	480	450	450	500	500	450	450	350	300	100
40	210	150	350	400	280	200	250	150	450	250
50	350	230	200	380	200	250	200	100	250	150

TABLE 3: Comparison of solar intensity (in watts per square meter) for different models

SVM: Support Vector Machine; RBF: Radial Basis Function; PPF: Past that Predicts the Future

Days	Linear regression model	SVM regression-RBF model	SVM-RBF kernel model	Cloudy PPF model	PPF model
10	400	2,500	2,500	10,000	40,000
20	10,000	2,500	2,500	2,500	1,600
30	900	2,500	2,500	10,000	40,000
40	3,600	2,500	6,400	10,000	40,000
50	14,400	32,400	2,500	10,000	10,000
	RMSE = 76.55 Cross-validation = 66	RMSE = 92.08 Cross-validation = 76	RMSE= 57.27 Cross-validation = 56	RMSE = 92.19 Cross-validation = 90	RMSE = 362.76 Cross-validation = 148

TABLE 4: Comparisons of RMSE and cross-validation values for different models

SVM: Support Vector Machine; RBF: Radial Basis Function; PPF: Past that Predicts the Future; RMSE: Root Mean Square Error

Redundant information elimination

Numerous meteorological metrics exhibit a high correlation with one another, as demonstrated in the preceding section. As a result, the SVM regression models include redundant data, frequently lowers each model's prediction accuracy. A common technique for removing extraneous data from an input dataset and consequently lowering its dimensionality is principal component analysis (PCA) [41]. To eliminate unnecessary information from the feature collection, this work applies the PCA algorithm. A set of input variables with the potential to be correlated are transformed orthogonally by the PCA algorithm into a set of principle components, which are a set of uncorrelated variables. There are fewer or the same number of primary components as there were original variables [42-44]. The variance of the first principal component is as high as it can be, and the variance of the second principle component is as high as it can be while still having to be orthogonal to the first component, etc., as shown in Figure 14 with the application of PCA algorithm.

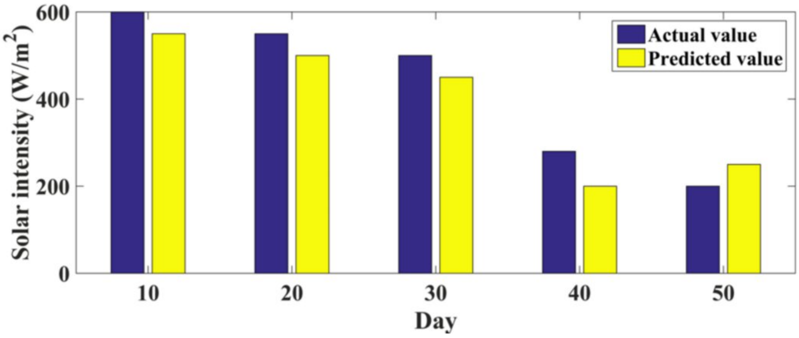

FIGURE 14: Solar intensity with SVM-RBF-Kernel model

SVM: Support Vector Machine; RBF: Radial Basis Function

This study uses the RBF-SVM regression method on a condensed feature set (day, dew point, temperature, sky cover, wind speed, precipitation, and relative humidity) from Table *1*, selecting the first four principal components that correspond to the first four maximum eigenvalues. The results in Figure *14* show that the RBF kernel outperforms the linear least squares model, with a cross-validation RMSE of 56 W/m² and a prediction RMSE of 57.27 W/m² following PCA analysis. This research work also conducted tests that further lowered the feature set's dimension from 4 to 2, as shown in Table *4*. However, this work discovered that when compared to the four-dimensional feature set, all three SVM regression algorithms (linear, polynomial, and radial basis functions) underperformed. The extra decrease in dimensionality eliminates information that is useful for prediction and is not redundant, which leads to performance degradation.

Existing models comparison

At last, this research evaluates the prediction models of regression based on other models. First, this work compares the model of the past that predicts the future (PPF), which forecasts solar intensity based on the previous day's data. When forecasts are unavailable, historical prediction models are frequently utilized, because, if the weather does not change, the past is a relatively better predictor of the prospect. The models cannot foresee abrupt changes in the weather, despite the fact that they are very accurate if the meteorological conditions remain the same. Second, this research compared the results with the cloudy model, which was developed in earlier work [45], which is a straightforward model that bases predictions on the state of the sky. This research demonstrated that the clouded model outperforms the PPF variations that are currently used in the literature [46-49]. The model can forecast changes in the weather, but it does not take into account the effects of different meteorological measures on solar intensity.

The accuracy of the cloudy model and PPF in predicting the weather on the test dataset (day 300) from Table *1* is shown in Figures *15* and 16, respectively. The findings demonstrate that although the cloudy model often predicts the weather correctly, it frequently makes mistakes. As expected, whenever the weather changes, which happens almost every day, PPF's results are incorrect. The first four principal components are selected based on the highest eigenvalues. Performing PCA and obtaining the reduced feature set (using the first four principal components) offer a model that is significantly more accurate. This finding is highlighted by the RMSE for each model: 57.27 W/m² for SVM-RBF with four dimensions, 90 W/m² for the overcast model, and 148 W/m² for the PPF. As a result, SVM-RBF with four dimensions is 61% and 36% more accurate than the PPF model and the basic cloudy model, respectively, as shown in Table *4*.

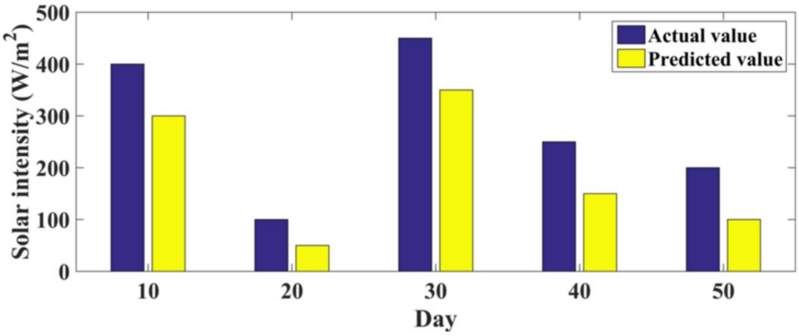

FIGURE 15: Solar intensity with Cloudy-PPF model

PPF: Past that Predicts the Future

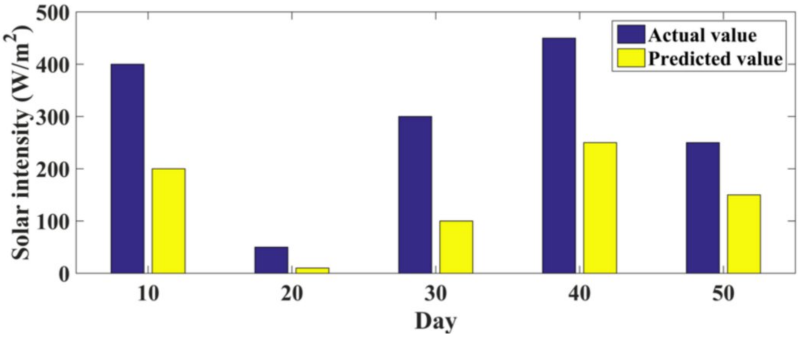

FIGURE 16: Solar intensity with PPF model

PPF: Past that Predicts the Future

Figure *14* presents the predicted solar intensity values using the SVM-RBF kernel model. The predicted values show a decrease in RMSE, as shown in Table *4*.

Figure *15* presents the predicted solar intensity values using the cloudy-PPF model. The predicted values are lower compared to the actual value, as given in Table *3*.

Figure *16* presents the actual and predicted values of solar intensity using the PPF model. The PPF model decreased the predicted values of solar intensity, as shown in Table *3*.

Table *3* presents the predicted values from different models. Every predicted value is closely equal to the actual value. These predicted values help in reducing the RMSE value, as shown in Figure *16*. Therefore, this work can choose the appropriate machine learning method for solar power generation, which is explained in the conclusion section.

Table *4* shows that comparing the RMSE and cross-validation values for these models is crucial for selecting the model that provides the most accurate and reliable solar power forecasts. Lower RMSE (57.27 W/m^2) and consistent cross-validation (56 W/m^2) results indicate better predictive performance and generalization ability.

Figure *17* presents the different RMSE values for different models such as linear regression, SVM regression-RBF, SVM-RBF kernel, cloudy PPF, and PPF models, and it has cleared that the SVM-RBF kernel model has the lowest RMSE value, i.e., 57.27, which is the best model for energy efficiency from weather forecast using solar power, and this analysis is carried through Figures *18*-*23*.

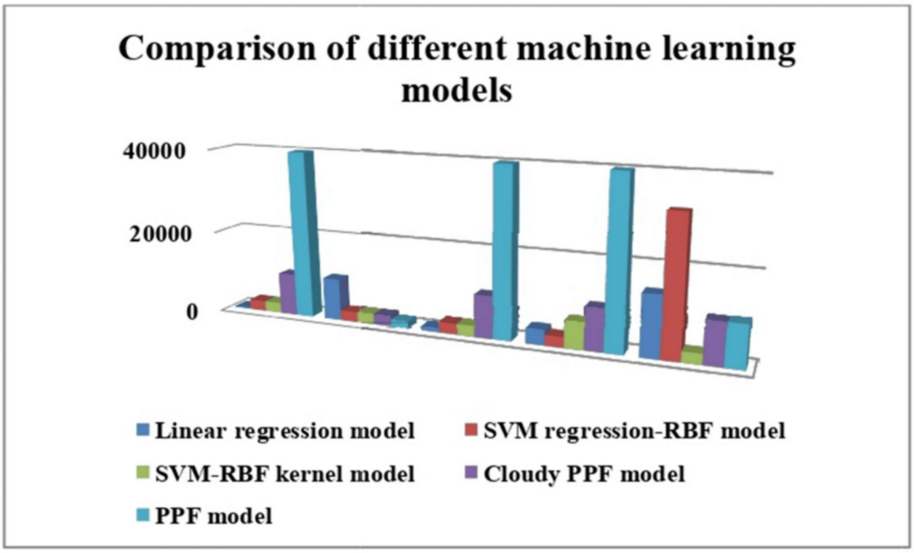

FIGURE 17: Comparison of different machine learning models

SVM: Support Vector Machine; RBF: Radial Basis Function; PPF: Past that Predicts the Future

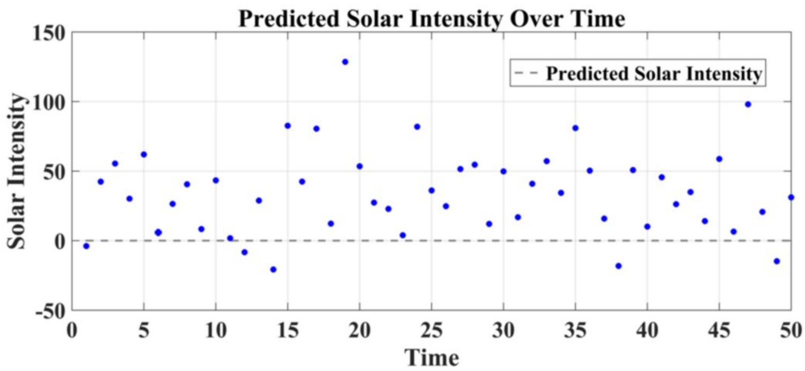

FIGURE 18: Comparison of solar intensity with time

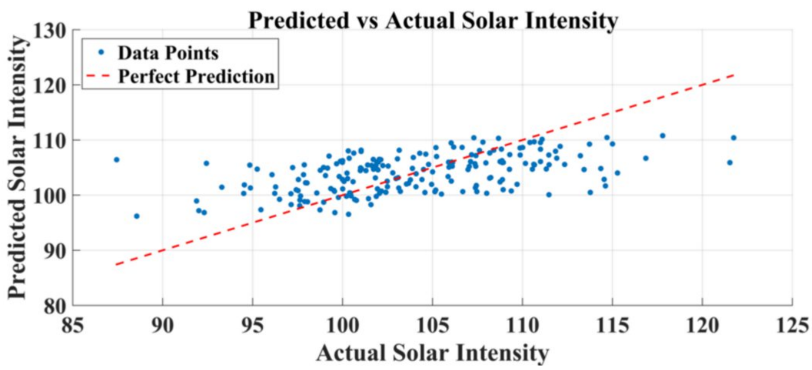

FIGURE 19: Scatter plot showing comparison of predicted and actual solar intensity

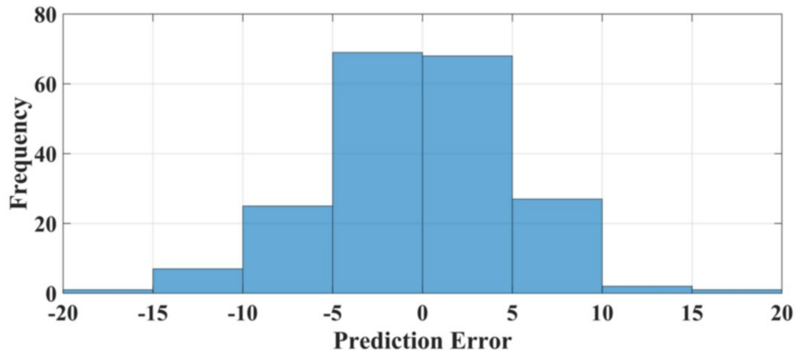

FIGURE 20: Bar chart showing comparison of predicted and actual solar intensity

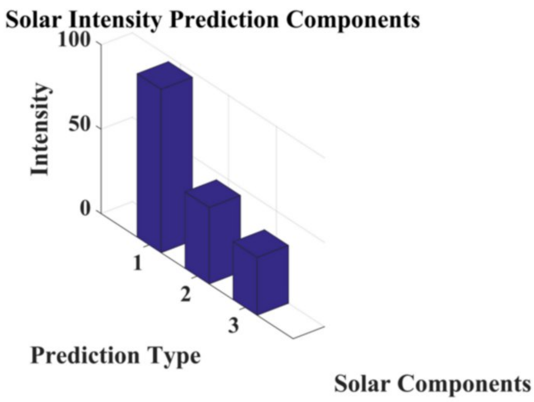

FIGURE 21: Comparison of solar intensity and solar components

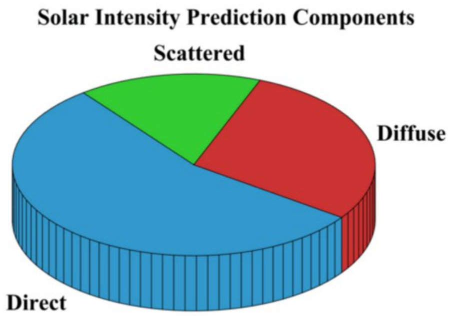

FIGURE 22: Comparison of solar intensity and solar components in pi chart

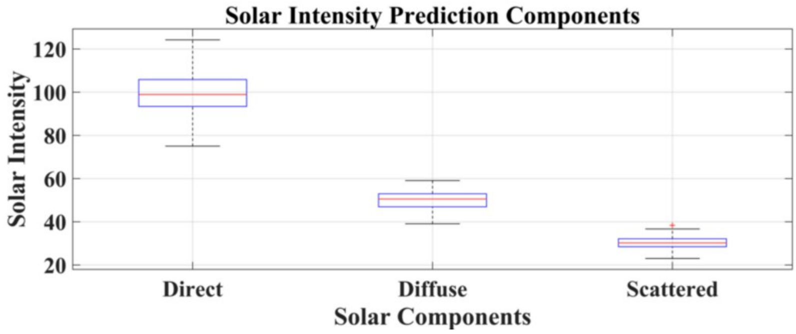

FIGURE 23: Comparison of solar intensity and solar components in box plot

Conclusions

Previous solar energy harvesting prediction models mostly relied on recent history. Unfortunately, these techniques cannot foresee changes in weather patterns. Integrating a larger, verifiable dataset can improve the power and accuracy of predictions by providing a more comprehensive view of the factors influencing solar energy age. However, relying solely on recent history to predict sun-based energy age restricts the model's ability to represent long-term patterns, sporadic variations, extreme events, and mechanical progressions. Since the NWS's weather forecasts are based on compilations of data from numerous sources across the nation, they can offer early warnings. The NWS produces forecasts using a variety of highly developed forecasting models that combine a wide range of observational data. This research work demonstrates the nuanced nature of the association among these anticipated weather metrics and solar intensity. As a result, this study uses machine learning approaches to automatically generate predictive models from historical solar intensity and forecast data. The findings suggest that a promising field is the automatic generation of precise models that anticipate solar intensity and, consequently, the harvesting of energy from solar arrays. According to this study, models constructed with SVMs with RBF kernels and linear least squares perform better than models constructed with PPF and a basic model constructed using sky condition forecasts from earlier research. This is because, when comparing ML techniques to other strategies like PPF and simple sky condition forecasts, their feasibility depends on how well they adjust in terms of complexity, accuracy, interpretability, and suitability for the specific solar energy prediction task at hand. This topic holds the potential for enhancing the accuracy of solar power generation predictions, which is essential for increasing the proportion of renewable energy in the grid. One strategy to maximize energy efficiency using weather forecasts and solar power is to use predictive capabilities to optimize energy generation, distribution, and consumption. Partners may reduce their impact on the environment, increase energy productivity, and achieve attainable energy goals by combining weather condition gauges with sunlight-based energy frameworks and matrix the board approaches. This research work plans to use the prediction algorithms in the future to better match the production and use of renewable energy in data centers and smart homes that are powered by on-site solar panels.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Saroj Kumar Panda, Manoj Kumar Panda

Acquisition, analysis, or interpretation of data: Saroj Kumar Panda, Manoj Kumar Panda

Drafting of the manuscript: Saroj Kumar Panda, Manoj Kumar Panda

Critical review of the manuscript for important intellectual content: Saroj Kumar Panda, Manoj Kumar Panda

Supervision: Saroj Kumar Panda, Manoj Kumar Panda

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.
Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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