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Numerical Simulation and Analysis of Solar Energy Forecasting Using Machine Learning Methodologies

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Abstract— India is a developing country with a high energy demand that is hard to meet with traditional ways of making power. As of July 30, 2012, New Delhi to Kolkata were all affected by the world's biggest power outage. In the next five years, India's ability to make electricity will grow by 44%. India's need for electricity goes up as the country's population and economy grow. So, what needs to change to cut down on power outages and meet the energy needs of the future? India has decided to use renewable energy sources instead of fossil fuels because it is cheaper and better for the environment. In recent years, more PV panels have been installed because they are becoming more cost-effective as a source of renewable energy. In the meantime, more data and more powerful computers have made it possible for machine-learning algorithms to make better predictions. Machine learning and time series models can help people in the energy business make accurate predictions about how much energy solar PV panels will produce. In this study, different sites are used to compare different machine learning approaches and time series models to see which one works best. Wind energy forecasting has already had a lot of research done on it, but solar energy forecasting is just now getting more and more attention. This study gives a model for a thorough review and analysis. Power system operational planning is one of the most important things to think about right now. For the power system to work well, many different factors must be predicted as accurately as possible over different forecasting horizons. But different variables have different characteristics, and academics have come up with different ways to predict them in the literature. But putting into action and analyzing recently published forecasting models is hard because there are a lot of outside factors that interact with each other in a complicated way. To plan for renewable energy sources, it is important to come up with a smart plan. Because the power system is getting more and more complicated, it is still a work in progress to find the best way to predict these variables with the least amount of computer work.

Keywords: Solar Power Prediction, Machine-Learning, Time Series, Artificial- Intelligence, Renewable Energy Forecasting, PV Forecasting, Wind Energy Forecasting

I. INTRODUCTION

Global energy demand is predicted to have more than tripled by the end of the century and more than doubled again by 2050, according to the International Energy Agency. This demand will not be met by incremental improvements to existing energy networks in the long term. Society's top priority is ensuring that we have enough renewable energy in the future. Changes in global energy supply and demand affect everything we do as humans. We cannot have a peaceful and prosperous world unless we have reliable access to affordable and clean energy. As global energy demand rises over the next half-century, we'll need to keep looking for new renewable energy sources. Addressing this broad problem and its bewildering technical complexity will require an all-out national effort using our most cutting-edge scientific and technological capabilities. For many countries, deregulation of the economy has become a priority in order to maximize resources and provide consumers with a wide range of high-quality

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services at reasonable prices. In the current deregulated environment, solar and wind power forecasting has emerged as one of the most important research fields in electrical engineering. [33]

Academics and researchers are developing tools and algorithms for forecasting renewable energy. Energy forecasting on the other hand, on the other hand, is at a very advanced stage of development. [37]

Because of the widespread consensus that global warming is one of the most pressing issues facing humanity, clean renewable energy sources like solar, wind, and geothermal have received a lot of attention. Wind and solar energy are expected to play a major role in achieving many countries' lofty goals for increasing the percentage of renewable energy in electric power generation. Wind and solar power, on the other hand, face major obstacles to deep penetration in the energy system because of their inherent volatility and uncertainty. Feed-in tariffs that guarantee grid access and favourable set feed-in pricing are common in many parts of the world for wind and solar power.Power system operational planning is one of the most pressing issues of the day. In order for the power system to function properly, a variety of factors must be anticipated with the greatest accuracy over various forecasting horizons..

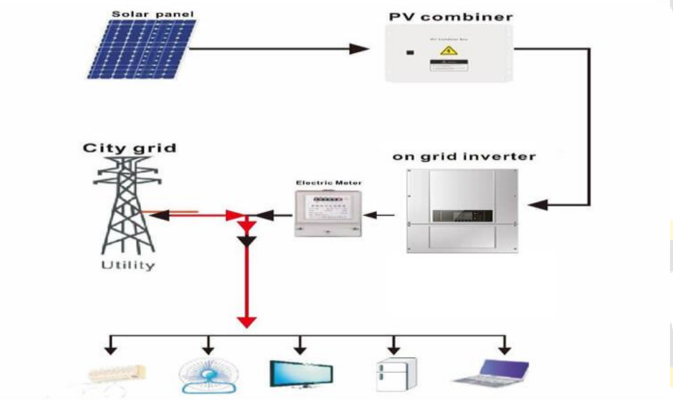

Figure. 1 Grid Connected Solar Photovoltaic System

There are different forecasting segments for renewable Energy.However, academics have devised a variety of methods for forecasting these variables in the literature, and these methods differ from one another. Here are a few of the most important renewable energy topics to consider when making forecasts predicting the output of solar energy.

Wind and solar power forecasting, due to its unique characteristics, has become increasingly important as renewable energy sources have expanded their penetration into the power system. A large number of scientists have therefore focused in recent years on developing new reliable forecasting models. Exogenous variables play an important role in the implementation and analysis of new forecasting models that have recently been published in the literature. Predicting renewable energy resources requires an intelligent approach. The most accurate forecasting of these variables with the least amount of computer effort is still a work in progress due to the increasing complexity of the power system. To address these concerns, this research will focus on solar power forecasting as well as wind power forecasting and its variability. There will be a variety of forecasting models based on the time frame, specific application areas, and the forecasting technique. As a final check, we'll look at how these results compare to other models that have been published before. [39] [40]

II. LITERATURE SURVEY

The key component of the study method is the classification analysis. It should be included in the literature survey after a detailed review of the study paper and completed after the five-stage analysis process mentioned in the previous chapter is complete. To cover the solar photovoltaic system area and the charging controller including the description and analysis of research articles.

(Pedro and Coimbra 2012) [1] Five forecasting models with non-exogenous inputs were tested by (Pedro and Coimbra 2012) [15]. For eight months, they contrasted ARIMA with a persistent model, standard k-NNN, standard Nn, and a NN optimised by Genetic Algorithms (GA-NN). After comparing GA-NN with ARIMA, data showed that GA-NN outperformed the other two approaches.

(Agoua et al. 2018)[2] The power output can be predicted using a statistical spatial-temporal technique up to six hours in the future. They devised a brand-new method of stationarization to deal with the problem of the time series not being stationary. When compared to using raw data, the results suggest that this pre-processing was useful and resulted in greater performance. A better spatio-temporal model can be achieved by integrating meteorological factors, such as wind power. The proposed approach outperformed random forest and AR by a factor of 20% when compared to a persistent model.

(Li et al. 2014) [3] ARIMA for solar power forecasting solely evaluates solar power data and does not take into consideration meteorological information. A generalised model for forecasting power production has been suggested as ARIMAX, which allows for exogenous inputs. Temperature, precipitation, insolation length, and humidity are all readily available as exogenous inputs to the model. The experiment findings also demonstrated that the proposed model is more generic and adaptable for practical usage than the traditional ARIMA and improves the ARIMA's performance. Weather information improved ARIMA's solar power predicting performance by 36.46 percent, according to the researchers' findings

(Gihan Amarasinghe et al 2018)[4] There is an artificial neural network that uses weather information to estimate solar power generation. Author explained this. Solar power generation may be predicted using weather data using an Artificial Neural Network (ANN). These weather conditions, such as cloud cover and wind speed, affect the output of solar panels. The Buruthakanda solar park is used in an application study. An Artificial Neural Network (ANN) could be used to anticipate solar power generation based on meteorological conditions (ANN). Factors like sun radiation, cloud cover, and wind speed influence a PV panel's ability to generate solar power.

(Voyant et al. 2016) [5] The 5-minute time-step data of slanted sun worldwide irradiation was estimated using an ANN (Artificial Neural Network) model. The NN predicts the clear sky index for the following day based on the NWP data. Final predictions are made by combining the training neural network (NN) and ARMA models. For each of the five Mediterranean test locations, the hybrid system beat the single neural network and the persistence model.

(Waqas Khan et al 2022) [6] argued that accurate solar energy forecasts are essential to enable for a higher level of renewable energy integration into the existing electrical system. DSE-XGB approach has the best mix of consistency, stability, regardless of the weather conditions in diverse case studies. With the suggested DSE-XGB technique, consistency and stability are demonstrated optimally regardless of weather conditions on several case studies to date.

(Ramli et al 2018)[7] Data from Jeddah and Qassim in Saudi Arabia were used in a study by Ramli et al. (2018)[7] to compare SVM and NN for solar irradiance projections. SVM models were shown to be more accurate and resilient, with MRE values of 0.33 and 0.51 for the two cities

(Chen et al. 2015)[8] According to (Chen et al. 2015)[6], there are seven SVM models with different inputs that can forecast the daily sun irradiation levels. Using data collected from three Chinese stations, they compared the newly developed models to five empirical sunshine-based models (linears, exponentials, linear exponentials, quadratics, and cubics). When compared to empirical models, SVM models had a 10% lower root mean square error (RMSE).

(Ekici et al 2014)[9] When predicting the next day's solar insolation, a least squares support vector machine model has been presented by (Ekici et al 2014)[7] to ensure that photovoltaic systems can be utilised to their full potential. The daily mean and maximum temperatures, sunshine length, and historical daytime solar radiation were all utilised as inputs to build the model's predictions. Using the proposed model, the results revealed that it was both successful and feasible for the task at hand. An RBF kernel-based LS-SVM model was proposed by the author to predict the next day's solar radiation values.

(Emmanuel, et al., 2009) [10] proposed comprehensive monitoring of the PV park system was conducted to assess the system performance of the local grid. The measurement of final yield (YF),

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referential output (YR), performance ratio (PR) and capability factor (CF) in order to evaluate photovoltaic efficiency, as specified by the IEC 61724 standard. The PV system has a maximum capacity of 171,36 kW p, and has been in operation since 2002. Since 2002. The output ratio and varied power losses (temperature, pollution, internal and network power and interconnect capacity available) for 1 year parks have been accurately tracked and measured. The photovoltaic plant supplied 229 MW grid power during 2007, from 335.48 MW to 869.68 KWh. This is a large-scale system incorporation producing a 13% wind energy supply next year, which shows how clean energy and distributed output is implemented in the system's basic phases. The simulation results indicate that in the 1.96 ~ 5.07 h / d, the final yield (YF) is 58 to 73%, with an average tolerance of 6.736%.

(Brent Fisher ,et al.,2014) [11] proposed performance modelling field Semprius company CPV systems. Semprius SPM by using model sand PV syst two properties, having a high concentration of world record efficiency photovoltaic (CPV) module manufacturer. The authors find that, SPM and PVSS are able to trade annual generating capacity for a precise estimate of 1–3 percent. Over the hours, two models may monitor the actual generation, while accuracy could be the result of SPM. SPM is software associated with Sandia National Laboratories for designing applications that can precisely approximate the effects of the CPV method. Finally, it appears that the model is reasonably robust to allow a accurate estimation of energy costs in a split era. The inverter simulation actions to boost insulation and solar forecasts would strengthen the accuracy of the CPV efficiency forecast.

(Fatehi et al., 2014) [12] proposed a reliable model to describe the use of photovoltaic modules PV syst incidence angle dependence .Experimental results are shown wave (one-parameter) optimized values single solar module . The PV system helps to realize the variations between various device configurations and the standardized parameter file locations in the PV syst version 6.23 are defined as a 1000 decimal PAN register. This optimization approach is not limited to adding the function PV system, and can be implemented for any incidence angle correction model in future for any simulation programmer from AHSRAE.

III. SOLAR PV ENERGY FORECASTING

Solar photovoltaic displays (PV system), which is the array for many of photovoltaic modules that are interconnected. By means of a single photovoltaic module that is produced, the modules are arranged in such a way that a number of capacities can be realized. The associated cluster module is like the cells of the module.The solar cell collectively forms a photovoltaic panel. They are manufactured from a semiconductor, for example silicon, and a thin semiconductor wafer of gallium arsenide has not been typically recompensed to form a negative electric field on the opposite side. If a circuit from both sides of the conductor is connected with the semiconductor which has been thumped clear of semiconductor material molecules, electrons will continue to stream up, as described in the figure 2.[12]

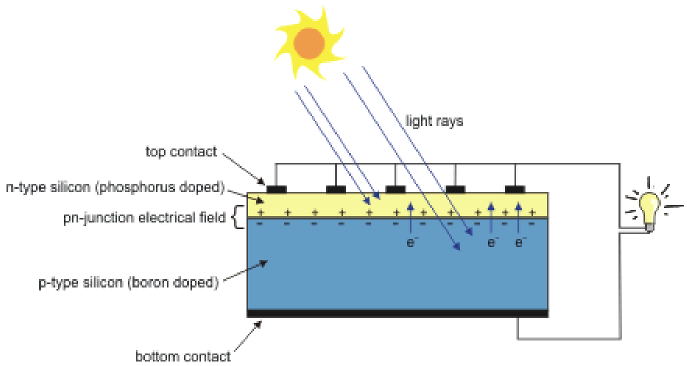

Figure. 2 Structure of a PV cell

In terms of electricity generation for residential, commercial, and industrial uses alike [1–5], solar energy holds a lot of promise. Using PV systems, photovoltaic solar energy has expanded in recent years due to its advantages of being abundant, non-exhaustible, clean, and ecologically benign [6–8].When it comes to making informed decisions, accurate projections are essential enhancing PV solar power plants The most important in solar energy production, there is a major challenge the intermittent generation of power from solar panels because of the weather. a shift in the weather and the sun's rays can have a significant impact on the environmenta decline in the quality of electricity output more than a quarter of the PV power generated.By means of actual solar power plants. As a result, PV cannot be fully integrated systems into the power grid. As a result, a precise short-term forecast. Photovoltaic energy forecasts are extremely helpful in managing electricity generation on a daily/hourly basis and grid storage [13]. PV requires accurate solar energy predictions for the benefit of plants in order to promote their involvement in the generation of renewable energy market and for a more effective allocation of resources [1–3]. Various methodological approaches to forecasting have been described in the literature [2–12] of PV energy It is possible to categorise these techniques into four distinct categories.

(i) Time series forecasting
(ii) Statistical methods ARIMA
(iii) Machine learning
(iv) Artificial Neural Networks (ANNs) and other learning methods which is based on machine learning methods numerical weather prediction-based physical models and hybrid approaches that combine the first three strategies.

The simplicity and elegance of the ARIMA model are its greatest assets. Only stationary time series can be used [14, 18, 19]. Therefore, we use data from seasonal time series. as well as non-stationary data becoming fixed data for the ARIMA model's applicability. An example of a model This product was created by utilising cutting-edge statistical methods [20]. The best method is chosen and tested using this method. Using seasonal analysis of the ARIMA time series (SARIMA), yet another statistical model can be constructed. Improved by using NWP (numerical weather prediction) model forecasts for short-term solar radiation [19]. For the successful integration of solar power into the energy grid, accurate forecasting of the power supplied by PV systems is required.

Table 1: Details of Variables of Weather Data

Weather Features	Unit	Weather Features	Unit
Cloud Coverage	So range	Relative Humidity	%
Visibility	Miles	Wind Speed	Mph
Temperature	*C	Station Pressure	inchIg
Dew Point	*C	Altimeter	inch Hg

IV. PROPOSED METHODOLOGY

The Improved forecasting models for solar and wind energy are constantly being developed.

4.1.1 The Physical Approach Model

For example, the plant's output of solar electricity can be explained in terms of the physical correlations between various weather conditions, topography, and solar irradiation. Local meteorological measures like sky imagers and SCADA (the user) data for output power, as well as extra information about adjacent terrain and topography are all inputs to the NWP model, as are numerical weather predictions (NWP). Up to three hours in advance, satellites and sky imagers track clouds and anticipate solar irradiance; beyond that, NWP is typically employed to project irradiance [7].

4.1.2 The Statistical Approach Model

An study of historical data series using only statistical methods without reference to system physics reveals a link between expected solar irradiance from NWP and solar power generation. This link can be used to predict the future of the plant.

4.1.3 The Learning Model

AI approaches are utilised to learn the relationship between projected weather conditions and electricity output created as a time series from the past. Nonlinear and complex relationships between input data (NWP forecasts and output power) can be intuitively described using AI methods, rather than an explicit statistical analysis. Temperature forecasts

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and power output data from the past are critical for both the statistical and AI approaches.

4.2 The Combined Approach

Physical and statistical models are commonly used in modern realistic renewable power forecasting models. In order to make more accurate projections, the physical approach requires statistics, while the statistical approach requires the physical relations of output power production. The ideal weighting between physical approach-based forecasts and statistical forecasts is obtained by changing the combined models' weights optimally [8, 9].

4.3 Building Forecasting Model

The framework for this paper's technique and theoretical underpinnings comes from reference [11], which use multiple linear regression (MLR) analysis for short-term load forecasting. Figure 4.1 depicts the process of creating a solar forecasting model.

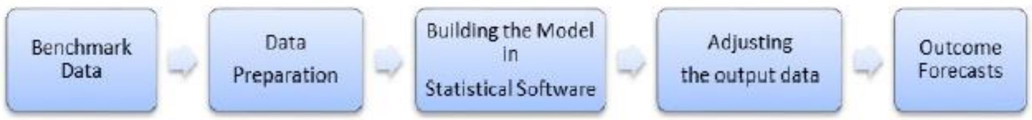

Figure 4.1 General Structure of Forecasting System

Before creating a forecasting model, it's a good idea to run some historical data analysis. All 12 weather variables, including solar power, are included in the historical data. In order to get the data ready for analysis and modelling, the data preparation is critical. Figure 4.2 depicts the many stages of data preparation. It is important to note, however, that the order of months shown in the box plot does not necessarily correspond to the calendar year. between the two sources of information (NWP predictions and output power). Time series o,f weather forecasts and electricity outputs from the past are critical for both the statistical and AI approaches.

Figure 4.2 Steps for Data Analysis in Solar Forecasting

Physical and statistical models are commonly used in modern realistic renewable power forecasting models. Because the physical approach requires the statistics to modify for more accurate forecasts, while the statistical approach requires the physical relations of output power production for more accurate forecasts. Physical approach forecasts and statistical forecasts can be integrated in a way that maximises their performance [8–9].

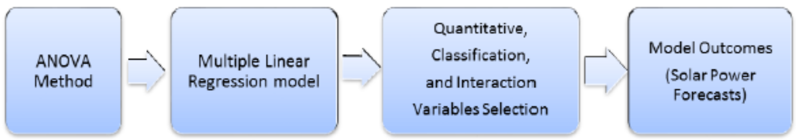

Figure 4.3 Steps for Machine Learning Based Generation Forecasting

Short-term load forecasting is accomplished using MLR analysis, which is outlined in reference [11] as a foundation for this paper's methodology and theoretical underpinnings for the proposed solar power forecasting model. Figure 4.4 depicts the process of creating a solar forecasting model.

In the scatter plots, it is clear that the outliers do not alter the general trend of the data. The vast bulk of the data's extreme points occur at the times when the sun

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rises and sets, whenThe solar panel's lifespan is unpredictable. Experimentation with data purification resulted in somewhat better forecasts. Outliers may be formed by incorrectly entered data, however this does not indicate that data preparation before the modelling step should be overlooked because of this.

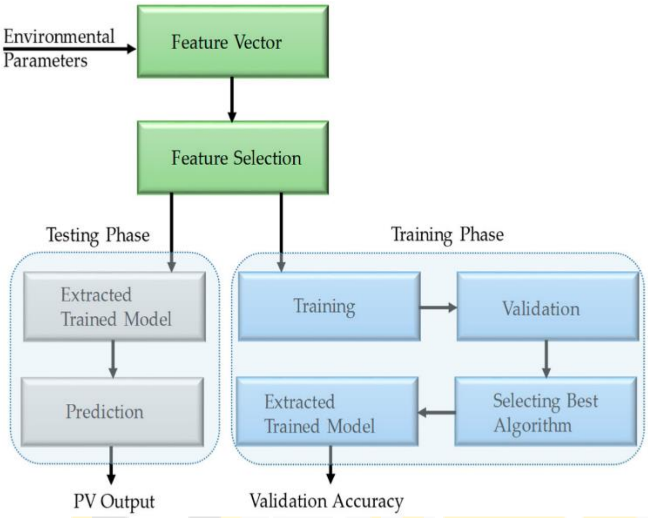

Figure 4.4 Flowchart of Training and Testing Phases of Solar PV Energy Forecasting

You may also use a scatter plot to figure out how one variable (the weather variables) relates to another (the solar power). For the measured power with regard to the solar irradiance, or surface solar radiation down, the advantage of plotting the data in scatter plots (SSRD). Right-hand plots show clearer correlations between variables, and the correlation coefficients between them are higher than the correlation coefficients between the variables on the left. There are no average values for the previous four specified meteorological variables (i.e. solar and thermal radiations, as well as precipitation). Until the end of the day, they increase hourly and then re-start accumulation [12]. The formula in Eq. is used to calculate the average values for these data (4.1).

$$Avg(t) = \frac{Ac(t+1)-Aco(t)}{3600} \qquad (4.1)$$

The essential processes in the development of the forecasting model. The multiple linear regression analysis makes use of the analysis of variance (ANOVA).There are twelve predictor variables to pick from, making it difficult to select one as an independent or explanatory variable by graphing. In order to find the most impactful variables, we do a correlation and sensitivity analysis on the historical data. The results of the correlation study are shown in Fig. 6. One may easily see that the strongest association between solar power and irradiance, time (hours), surface irradiance, and net top irradiance, as well as their second-order polynomial or quadratic terms. The amount of water vapour in the air acts as a little mirror, increasing the amount of solar power created by reflecting more of the sun's rays. As compared to other variables, the variable of temperature at 2" " m has a noticeable effect. It makes sense, given that solar panel performance is influenced by temperature. Actually, physical-approach models choose the temperature and sun irradiance for forecasting PV power [13].

The multiple linear regression (MLR) model can be represented as shown in Eq. (4.2).

$$Y = \beta_o + \beta_1 X_1 + \cdots . + \beta_k X_k + \epsilon \qquad (4.2)$$

Here, Y is the outcome variable, and X k is the k-predictor variable. These are the variables, and the error or fluctuations in Y are represented by k. The solar power is the response variable, and the most effective meteorological variables are used to determine the predictor variables [11].With the use of multiple linear regression analysis, the ability to take into account interactions between variables increases the model's predictive strength. As we know that the solar azimuth angle changes during the day, and the sun's elevation rises and falls with the seasons, therefore the selected predictor variables interact with the hours and days and months.Variable selection is done based on each individual variable, however when the variables interact in the MLR analysis model, they may lose some of their correlation power. As a result, the best candidate model must be included in the final mix of variables. This is done manually by completing the three primary phases of model construction, training, validation and testing to find the best candidate model for the most efficient performance.

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V. RESULTS

The The position of a solar photovoltaic module and the characteristics of the surrounding area have a significant impact on the system's efficiency and profitability. The solar photovoltaic system's complex network-connected mathematical modelling and simulation is relevant to this. We employed mathematical modelling for generation forecasting and accuracy assessment utilising deep convolutional neural networks in order to address the issue of linked network and independent photovoltaic solar system architecture and construction. Results of the proposed work can be classified into following broad categories.

- Weighted Linear Regression Machine Learning Based Forecasting Model
- Yield Forecasting and Loss Simulation.
- Classification of yield of generation and comparison with real generated data.
- Error and Performance Analysis

The first step is to design the dataset for the input of machine learning. The important featres of the dataset are as follows-

- In radians, the distance from the sun to the equator.
- The average daily temperature in Celsius degrees.
- The average wind direction for the day, expressed in degrees (0-360). 1 Meters per second is the unit used to measure the average daily wind speed.
- Scale from 0 to 4 indicating how much of the sky is obscured; zero means the sky is completely clear, and four means the sky is completely obscured.
- Kilometers of visibility Percentage of humidity.
- In metres per second, the average wind speed over a three-hour period was calculated.
- The average barometric pressure during the three-hour period in which the measurement was obtained, expressed in mercury inches, is referred to as average-pressure.

Plots and graphs, Root Mean Square Error (RMSE), the correlation coefficient (R) between the forecasts and the actual measured solar output, and a comparison with a real dataset are used to assess the accuracy of the forecasts and model performance.

The persistence model obtains the actual solar power output at the present hour and uses it as a solar power projection for the following future hour, as its name implies. The RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2} \qquad (5.1)$$

Where Y represents the solar power projected value and Y represents the solar power observed value. Y and Y are normalised values of the solar power system's nominal power capacity. To produce more accurate forecasts, the RMSE for all forecasting hours should be decreased. If the model is trained and tested only during daylight hours, ignoring the night hours (when there is no solar power generation), the RMSE and the correlation coefficient R should be calculated solely for these day hours, ignoring the night hours.The persistence model and the multiple linear regression analysis MLR model are outperformed by the convolutional artificial neural networks model. The performance is determined on how well it is trained and the quality of the data it uses. The model's performance isn't improved by normalising the input data, however deleting the night hours improves it marginally. Before developing the forecasting model, plotting the data, evaluating the correlation and sensitivity analysis between the variables, as well as data cleansing of outliers, are all necessary data preparation processes. The model delivers more accurate forecasts during clear sky hours than during cloudy hours.

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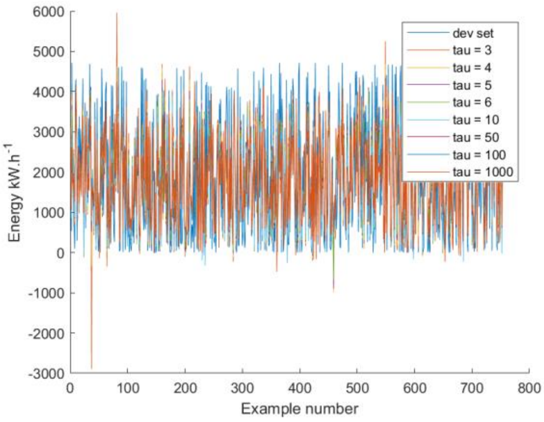

Figure. 5.1 Analysis of Parametric Variation of Linear Regression

Using local weather data, we investigated and implemented machine learning techniques for solar energy forecasting. Temperature, cloud cover, and relative humidity were found to be the most important factors for predicting solar output using dimension reduction-based regression and GBM. There is a very minor difference between the training and testing errors. The challenge of learning itself. In addition, we haven't yet looked into the possibility of taking advantage of the Internet to conduct study.Instead of randomising, short-term weather dependence.

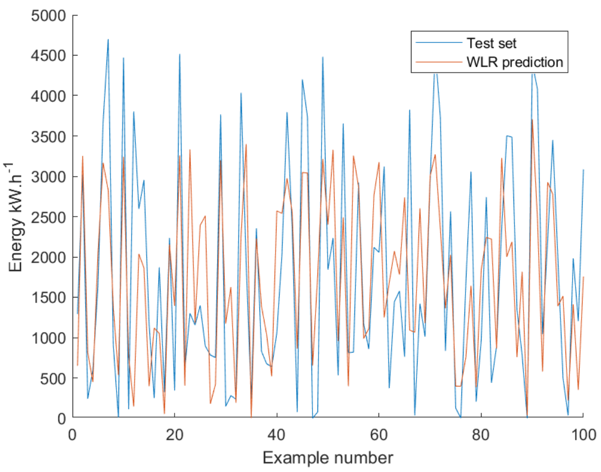

Figure. 5.2 Analysis of Predicted and Forecasted Value for Samples of Dataset

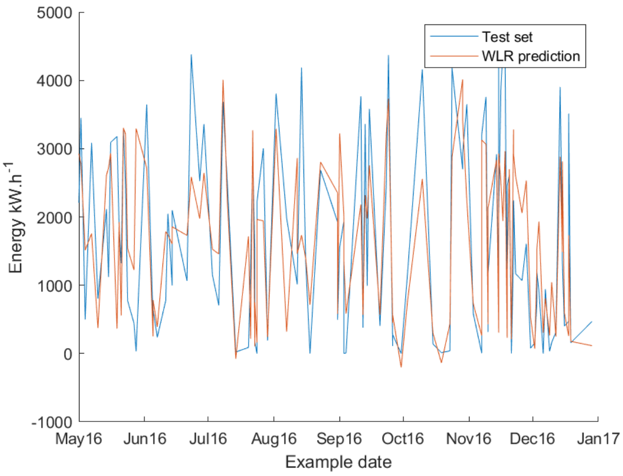

Figure. 5.2 Comparative Analysis of Predicted and Actual Generation

For solar power estimates, the multiple linear regression analysis model was very accurate. If the forecasting hours were longer, model performance for nearer predicting horizon than farther horizon is better with clear sky, however this is as a result of overcast conditions, the overall performance of the template. Correlations and sensitivities are shown by plotting the data study of the relationships between the variables and the cleanup of the identifying and removing outliers is a critical step in data preparation before creating the forecasting model whereas additional data from the past helps the model.Therefore improved performance is expected.

Table 5.1 Comparative Analysis of Peformance of Forecasting

Model	No. Parameters	Training Error	Test Error

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PCA-based Weighted Regression[36]	5	0.866*10^6	1.077*10^6
Generalized Boosting Method (Random Forest)[36]	3	0.824*10^6	1.230*10^6
Standard Weighted Regression (Proposed)	8	0.79*10^6	1.0*10^6

Figure 5.1 indicates the performance impact of parametric variation on the performance of linear regression. Figure 5.2 indicates the performance of linear regression on the error and performance parameters.Table 5.1 indicates the comparative performance of proposed system with respect to other machine learning techniques and generated data. Solar power estimates will be more accurate if we use more accurate weather forecasts. The MLR model's performance is considerably improved when classification variables and interactions between factors are used, although this is not the case with the given model. The model's performance will increase with more historical data.

VI. Conclusion

The major goal of this study is to look at solar power generation forecast and evaluation methodologies. As a result, in this study, we conducted extensive experiments utilising deep learning models to accurately anticipate power generation based on the outcomes of our trials. The ability to construct an accurate prediction model utilising only the monitoring system data on-site installed in the solar power plant has been validated through experiment prediction. The real applications will still require the collection of other potentially associated feature data, and the solar power prediction model may be steadily refined to optimal by various model tests. The performance indicator predicted by the model can only be enhanced since it only uses the associated feature values and data set of a single inverter that were obtained in the aforementioned experiment. These feature variables, which are employed in the best prediction findings, will boost the power generation forecast effect. The connection between the greenhouse effect and solar thermal radiation is the most likely explanation. In order to improve the prediction accuracy in the future, it is recommended to gather the important characteristic variables of the solar irradiance or the greenhouse. There are numerous new and improved neural networks that can be used in the study right now. In future work, strategies based on a hybrid deep learning model could be incorporated into the system to continuously improve solar power generation forecast performanc.

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