# Unconventional Entreats for the Anticipation of Solar Irradiance

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**Abstract:** At present, the world is putting a pioneering whack to escalate their energy generation capacity to meet the global demand in increase in electricity requirement. The solar energy provides a sustainable model for energy production, when the world is shifting to renewable energy from fossils. The installation of solar photovoltaic panels has increased in recent years to a significant percentages upgrade as the Sun is most viable form of alternate energy that can be harnessed easily and most efficiently. But, the efficiency of the power output via solar modules is still a big challenge to be worked upon. A large number of external and climatic conditions to affect the generation and prediction of output power from the PV cell module. The emitting challenge that are being faced by operators of alternate energy producers as in for operation, planning and power scheduling can be minimized to a certain level by predicting or forecasting the photovoltaic module output on the basis of short term and long-term basis. The anticipation of the yield of the PV module can play a major key role for the execution and weighing of the fiscal and monetarily consummation of the power system. The solar irradiance anticipation is one major step for solar power yield anticipation which is dependent on various factors such as cloud and climatic condition over the region. The meteorological transcript of the suburb for a prolongated span of term is imperative precondition of anticipation of PV module power yield as time series problem. The appositeness of Machine Learning Algorithm complies as a momentous factor in this field. Here in the chapter disparate Machine Learning algorithms are implied for the study of prediction of solar irradiance.

**Keywords:** Machine Learning Algorithms, Photovoltaic Module, Prediction, Renewable Energy, Solar Forecasting, Solar Irradiance, Solar radiation.

## 1. INTRODUCTION:

The increase in electricity demand and depleting reserve of fossil fuels has tend to shift the world for a search of alternate source of energy. The emission of carbon content during the process and as by product of converting the depleting fossil fuels into energy to be consumed by human has resulted in the global rise of temperature and devastation of Earth's environment and also its atmosphere[1]. The result of which is what has turned different cities of the various countries like New Delhi in India, Shouguang in China, Bamenda in Cameroon, Peshawar in Pakistan, Kampala in Uganda, etc are a few examples, into a whole lot of gas chamber, causing serious health injuries and fatal life threatening diseases and just by inhaling the atmospheric air. Leaders from the different countries and many players in the field of energy sector are thus switching to Renewable Energy Power Generation Capacity (RC).

For the future generation, offspring to sustain, the need for sustainable energy raised that would be available for span of centuries to come and also be cleaner form i.e. causing minimum degradation for the quality of life standards of human and as well as another living organism. The potential for sustainable energy demand is depicted by renewable energy sources even for the long term which the current depending on the energy sources fails terribly for the long term.

The Sun has been preeminent superlative point of supply for all the living entity and physical, alchemical or organic activities being borne on this planet [2]. Harnessing of solar energy and converting it directly into the electricity be possible by the help of photovoltaic cell module. The large-scale world-wide veering towards solar has resulted into the competition for development of PV modules. The competition for development of progressively in large number of solar PV modules resulted in lower cost of production and also significant intensification in the energy transformation performance of the PV chunk.

The energy obtained from solar radiation through the solar PV module stands to be most promising and rapid growing industry. Worldwide share of Renewable Energy Power Generation Capacity (RC) has elevated briskly in latter years. The share of RC in the total generation capacity is estimated to go up to 30% by the year 2040 as expected by International Energy Association (IEA) which accounts for merely 14% as of date. Another research study conducted by IEA as put by Sustainable Development

Scenario (SDS), the demand for electricity will increase by double in next two decades compared for energy demand as a whole.

The distributed solar PV system at stand alone or individual/society level such as homes, commercial buildings or complexes or as in industry is to accelerate, lead feasible shift in power system. This might be leading for self-power dependence of consumers and/or net zero buildings, producing their own electricity to full fill their energy obligations. Thus, providing challenges for electricity producers or operators and policy makers world-wide. The various research case studies forecast the increase in budgeted PV module capacity to an upsurge by virtually one half of the fraction of total PV growth.

The balance in between the energy consumption and production of SEG be precise at any instantaneous moment of the time that must be ensured by the energy operator. This is often be difficult to ensure by the energy with conventional and controllable energy production system such as an isolate or off-grid system. Major portion of the world is switching to RC, which also makes the task a bit more difficult, as the RC is often controlled by the solar irradiance and external scenarios such as weather condition over other region and for a given phase or time period. The successful and efficient integration of Solar Energy Generation (SEG) with National Electricity Grid (NEG), thus requires the meticulous forecasting of the solar power output (SPO).

SEG is dependent on intro-hour variability, technology used, seasonal and/or weather parameters etc. The problem this can be eased by the application of new inventive and ingenious techniques. The machine Learning Techniques (MLT) is the recent and advanced system that has employed by various researchers to calculate or the solve the problem like this which are dependent on time duration and over the history of the region for the time duration [3,4]. The parameters such as direct and diffused irradiance, cloud cover, warmth, moisture, air current speed etc which can be asset for developing the model for forecasting SEG. The refined configuration thus yet be used to retrieve further SEG forecasting.

The prediction of SEG by means of MLT been preferred in recent years in accordance with the growth in the demand of PV module when compared to conventional Time-Series Method (TSM) for predictive modelling. Artificial Intelligence by means of

MLT isn't unfamiliar and contemporary concept [5], the advanced computational capacity and greater availability of data trait made the technique fruitful for SEG forecasting.

## 2. SOLAR FORECASTING:

Solar Power forecasting (SPF) embroils the insight for the cosmic shift inn the path of the Sun, meteorological conditions and proficiency over scattering and irradiance of solar flare. The modelling of Sun's spot with respect to time and climatic conditions such as wind speed, presence of cloud is the initial steps for SPF. The above said model can be then further be used for observing and predicting the intensity of solar rays, Solar Radiations (SR) which can be then used for insights for SPF.

### 2.1 The urgency for prevision of Solar Radiations and Solar Power Output:

The assimilation of sustainable energy sources (all those which are predictable and those too dependent on weather and other physical conditions being unpredictable) with that of conventional or prospective future structure for energy supply would be the most significant task to be imposed on the prospective comprehensive energy supply. At any particular instant of the time during of the operation of the system, the grid operators or the engineers must maintain the proper harmonics between the utilization and procreation of the energy. Often, it's tough for the operators to maintain harmonics for the smaller grids and for those secluded grids which are not yet akin with the nervous grid system [6,7]. The dependency of the electrical grid structure escalates when it comes to reliability of the aforesaid grid over its competence to entertain the anticipated and fortuitous transition (for generation and utilization) a turmoil efficiently to sustain the quality and constancy of utility to the end users. Numerous materialistic perspectives are then taken by the SEG suppliers so as to maintain the structure.

The perplexing nature of electrical network grid (ENG) exacerbate for the continuous weigh of the generation - utilization and the grid operations when the RES is assimilated to the ENG [8,9]. Conglomeration of complications arises when SEG is applied in as solar produces intractable temperament that diverges on time and that complicates the situation as it leads to inconstancy in voltage, trait of the power generated and also brings cohesion concern for the system. Thus, augur of the SPO is prerequisite for the

compelling operation of the electrical grid. To curtail the overall expense for energy production assessment of the energy reserves is requisite so as to slate the power and also for commercializing the energy into the market. With the widening of the share of the SEG to overall power generation the portend of the power also became a necessity. The conclusive anticipation od operation of the grid system and repository is obligatory so as to dodge the hefty abnormality in the SEG. Sundry repository systems are devised for captivating the exuberant power (and discharging it at the crest of the demand during utilization). Basically, three categories of such storage are diversified into:

- Bulk Energy Storage
- Distributed Generation
- Power quality storage

| Diversification | Discharge Power | Discharge Time | Stored Energy | Application |
|---|---|---|---|---|
| **Bulk Energy** | 10-1000 MW | 1-8 hr | 10-8000 MWh | Load levelling, generation capacity |
| **Distributed Generation** | 0.1 -2 MW | 30min – 4 hr | 50 – 8000 kWh | Peak Shaving, transmission deferral |
| **Power Quality** | 0.1 – 2 MW | 10sec -30 sec | 0.03 – 16.7 kWh | End use power quality/reliability |

Table 1: Diversification of energy storage and technical specifications

The study from the above tell its conclusive that the energy repository can be extensively used for various crisis and pertinence as a time dependent variable. The table also tells about energy repository occurs asserted time intervals and expert operators are required having insight for the cosmic radiation produced energy at distinct prospective horizons [10-13].

### 2.2 Types of Forecasting:

The rising demand for the energy and several environmental issues due to the use of conventional fossil fuels for generation of energy and also the recent & improved constitutional amendment in the energy sector has widened the path for the private players and the government sectors as well to peep into the RES to meet substantial escalation in the insistence of the energy. The forecasting of total SPO for a given territory in ENG for compelling and dynamic transmission of power from ENG to the end user. The proposition generally followed by solar forecasting are : (a) Direct Forecasting (DF), where the SPO for the PV module is forecasted; and, (b) Indirect Forecasting, when the data from the meteorological department is used [14, 15] which later is implied to calculate the forecasting of SPO on the basis of traits of the SPG plants as in their overall area and effective overall efficiency of the plant.

**2.2.1. Direct Forecasting:** Few methods for prediction by DF method for a SPO as yield by PV plant which is calculated on the basis of preceding statistical inputs solar power. Neural Network (NN) bred with back propagation algorithm, k – nearest neighbour, NN bred with genetic algorithm and ARIMA. An experiment carried out for predicting the SPO by DF method which suggested NN methodology for prediction of output for the plant for short duration has the best scenario than the other two methodologies.

For the application of DF methodology for the prediction of solar PV output there are several approaches as well. Different researchers follow different approach for prediction methodology. A suggestion says classification of days into four categories on the basis of solar light and cloud visibility (as clear sky, fogged weather condition, cloud filled, rain poured). Individual model for prediction by the support of vector machine technique, which when disciplined with archival data. The data collected from meteorological department, parameters such as gale agility, warmth, humidity etc. to prepare different NN (Self organised Map (SOM)) which then proved helpful to determine traits for the day and further classify it into four categories, the first classification of ours in initial steps. This then was used for designing and forecasting model/simulation for the predict solar PV output.

**2.2.2 Indirect Forecasting:** Different individual researchers and scientists designed different approach to predict the total solar PV output in terms of power of any SEG plant. To predict the power generation output filtering of the data by polynomial method and averaging by applied spatial method to forecast for weather condition, which then used to reckon solar irradiance. Kalman filter method and spatial averaging method for prediction enhances the certainty by a significant number which was optimized on the basis of specified region or a site.

Another approach in innovative manner designed by Mellit & Pavan was the hourly predictions of solar irradiance in accordance with the data from the preceding day [19], then the back-propagation approach to NN was considered for prediction algorithm. The PV characteristics coefficient when multiplied with the solar irradiance predicted by NN algorithm output yielded the SPO in terms of power [20].

Lasso Linear Regression Model was another approach applied for the prediction which turned to be very effective when prediction for the solar irradiation on the horizon was for the very small durations. Various results confirmed the ARIMA model lags in various manners [21] to the above said model.

## 3. Problem in Prediction:

When 'n' numbers of weather criteria are present in a time - series pattern as classical weather report in the set as ($x_1$, $x_2$, $x_3$, …., $x_n$), the prediction of PV power output be represented as:

$$Y = f\ (x_1, x_2, x_3, \ldots., x_n),$$

Where, '$f$' is a mapping function amid classical weather report and impending SPO.

The following figure (figure 2) depicts the diverse (where, n = 6) weather criteria for SPO.

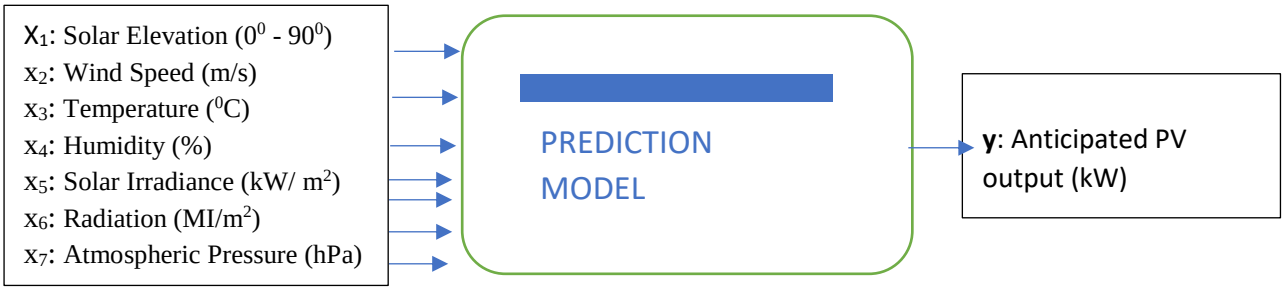


Figure 1. Solar PV Power prediction model

ML algorithms such as Support Vector Machine (SVM) [17], k-NN & Long Short Term Memory (LSTM) been introduced by various researcher and scientists as in for initial phase in as predicting solar irradiance, which is then, later to predict SPO forecasting. Researchers sometimes also takes help of Gradient Boosted Regression Tree (GRBT) mode [18] whenever forecasting at multiple sites of SEG is to be done in lieu of several hours ahead of time. Regression is the extended version of GRBT, which was originally designed for classification of the data only; In later time frame, it developed into a ML model which was able to read the outcome of many small sized regression tree and then to generate the superior output combing all the preceding data [24]. The limitation that been pulled on the aforesaid model is that, it doesn't enjoy luxury of updating procedure as contemporary data set of observations land.

The LSTM NN model and Auto Encoder (AE) methods model has presented impressive development when compared with that of Deep Belief Network (DBN), AE Multilayer Perceptrons (MLP) or LSTM when worked alone. The researcher's models used the AE method for observing the most potent mien for learning by that of encoding side of that which was then fed to LSTM network which then predicted the SPO for PV plant at SEG farm [23].

## 4. Pre - Processing & Data Collection:

The variables required for prediction model in the data set be divided in the categories as shown as in the given table.

The data for the sundry variables as in table such as power generation on regular fixed time intervals, and data for all the variables for the weather forecast for the same time period and interval as of power generation were to be observed. Later on, solar elevation dossier, which conforms that solar radiation energy, density of the air at the location and the other weather and cloud behaviour for the location. Auxiliary variables such as vapour pressures, atmospheric pressures, surface temperatures etc. are predicted by the weather forecast model.

| | Source | Variable | Descriptions |
|---|---|---|---|
| **Dependent Variables** | Power Plant (y) | Generation | Solar Power Generation (kWh) |
| **Independent Variables** | Weather Forecast (F) | Rainfall Type | 0: none; 1: rain; 2: rain/snow; 3: snow |
| | | Sky Type | 0: sunny; 1: little cloudy; 2: cloudy; 3: overcast |
| | | Wind Direction | 0: East; 1: West; 2: North; 3: South |
| | | Wind Speed | Wind Speed (m/s) |
| | | Humidity | Humidity (%) |
| | | Temperature | Temperature ($^0$C) |
| | | Elevation | Solar Elevation ($0^0$ - $90^0$) |
| | Weather Observations (O) | Radiation | Radiation (MI/m$^2$) |
| | | Vapour Pressure | Vapour Pressure (hPa) |
| | | Surface Temperature | Surface Temperature ($^0$C) |
| | | Atmospheric Pressure | Atmospheric Pressure (hPa) |
| | Derived variables | WeekNum | Weekly Index (1-53) |
| | | TimeZone | 0: 0900-1200; 1: 1200-1500; 2: 1500-1800; 3: 1800-2100 |

Table 2: Different variables

The data thus collected were structured as per the categorical variables for the respective category for the quantitative modelling. One hot coding method were then implied to the categorical variables for which were then indoctrinated to multiple-binary variables. The task for pre processing structured all the data and then were further assigned to create week index variables which then used to reflect change in season as per data collection. And also, in the similar fashion, to create impression about the time of the day, the corresponding variables was then further used to reveal the time intervals.

## 5. Conclusion & Outlook:

The uneven productivity from the SEG farms causes serious challenges while assimilating them with ENGs. The uncertainty of the output from SEG farm is mostly

because of the natural and meteorological condition(s) which then controls the solar radiations and thus output power. The factors on which solar radiation depends are natural and aren't in control of human beings. This inconsistency in the output is nightmare for the operators and/or engineers at the SEG farms and ENG to maintain homogeneity between the power at generation and consumption end.

An effective measure thus, was very much needed which when implemented would help in predicting the approximate SPO in advance in such a manner that be helpful for the operators and/or engineers at the SEG farm and ENG for them to maintain consistency and quality of the power to be delivered to the end users.

The research area in this field isn't very old, rather popped in recent years and yields the absolutely wonderful results and outplayed the prediction data with that of old-fashioned conventional methodology. The prediction output in power at SEG farm can be calculated by different approaches as per the demand of the situation.

## 6. References:

[1] B. Espinar, J.-L. Aznarte, R. Girard, A.M. Moussa, G. Kariniotakis, Photovoltaic Forecasting: A state of the art, in: OTTI - Ostbayerisches Technologie-Transfer-Institut, 2010: p. Pages 250-255- ISBN 978-3-941785-15-1. https://hal-mines-paristech.archives-ouvertes.fr/hal-00771465/document (accessed March 4, 2015).

[2] V. Lara-Fanego, J.A. Ruiz-Arias, D. Pozo-Vázquez, F.J. Santos-Alamillos, J. Tovar-Pescador, Evaluation of the WRF model solar irradiance forecasts in Andalusia (southern Spain), Sol. Energy. 86 (2012) 2200–2217. doi:10.1016/j.solener.2011.02.014.

[3] A. Moreno-Munoz, J.J.G. De la Rosa, R. Posadillo, F. Bellido, Very short term forecasting of solar radiation, in: 33rd IEEE Photovolt. Spec. Conf. 2008 PVSC 08, 2008: pp. 1–5. doi:10.1109/PVSC.2008.4922587.

[4] D. Anderson, M. Leach, Harvesting and redistributing renewable energy: on the role of gas and electricity grids to overcome intermittency through the generation and storage of hydrogen, Energy Policy. 32 (2004) 1603–1614. doi:10.1016/S0301-4215(03)00131-9.

[5] M. Paulescu, E. Paulescu, P. Gravila, V. Badescu, Weather Modeling and Forecasting of PV Systems Operation, Springer London, London, 2013. http://link.springer.com/10.1007/978-1- 471-4649-0 (accessed March 4, 2015).

[6] H.M. Diagne, P. Lauret, M. David, Solar irradiation forecasting: state-of-the-art and proposition for future developments for small-scale insular grids, in: n.d. https://hal.archives742 ouvertes.fr/hal-00918150/document (accessed March 4, 2015).

[7] A. Hammer, D. Heinemann, E. Lorenz, B. Lückehe, Short-term forecasting of solar radiation: a statistical approach using satellite data, Sol. Energy. 67 (1999) 139–150. doi:10.1016/S0038- 092X(00)00038-4.

[8] E. Lorenz, J. Remund, S.C. Müller, W. Traunmüller, G. Steinmaurer, D. Pozo, J.A. Ruiz-Arias, V.L. Fanego, L. Ramirez, M.G. Romeo, others, Benchmarking of different approaches to forecast 748 solar irradiance, in: 24th Eur. Photovolt. Sol. Energy Conf. Hambg. Ger., 2009: p. 25. http://task3.ieashc.org/data/sites/1/publications/24th_EU_PVSEC_5BV.2.50_lorenz_final.pdf (accessed March 4, 2015).

[9] Lorenz E, Scheidsteger T, Hurka J, Heinemann D, Kurz C. Regional PV power prediction for improved grid integration. Progr Photovolt: Res Appl 2011;19:757–71.

[10] Yang D, Ye Z, Lim LHI, Dong Z. Very short term irradiance forecasting using the lasso. Sol Energy 2015;114:314–26.

[11] Alonso-Montesinos J, Batles FJ. Solar radiation forecasting in the short- and medium-term under all sky conditions. Energy 2015;83:387–93.

[12] Rigollier C, Bauer O, Wald L. On the clear sky model of the ESRA — European Solar Radiation Atlas — with respect to the heliosat method. Sol Energy 2000;68:33–48.

[13] Rigollier C, Lefevre M, Wald L. The method Heliosat-2 for deriving shortwave solar radiation from satellite images. Sol Energy 2004;77:159169.

[14] Alonso-Montesinos J, Batlles FJ, Portillo C. Solar irradiance forecasting at one minute intervals for different sky conditions using sky camera images. Energy Convers Manage 2015;105:1166–77.

[15] Urraca R, Antonanzas J, Alia-Martinez M, Martinez-de-Pison FJ, Antonanzas- Torres F. Smart baseline models for solar irradiation forecasting. Energy Convers Manage 2016;108:539–48. [16] Mellit A, Pavan AM. A 24-h forecast of solar irradiance using artificial neural network: application for performance prediction of a grid-connected PV plant at Trieste, Italy. Sol Energy 2010;84:807–21.

[16] D. Yang, Z. Dong, Operational photovoltaics power forecasting using seasonal time series ensemble, Sol. Energy 166 (2018) 529–541.

[17] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Comput. 9 (8) (1997) 1735–1780.

[18] C. Persson, P. Bacher, T. Shiga, H. Madsen, Multi-site solar power forecasting using gradient boosted regression trees, Sol. Energy 150 (2017) (2017) 423– 436.

[19] A. Alzahrani, P. Shamsi, M. Ferdowsi, C. Dagli, Solar irradiance forecasting using deep recurrent neural networks, Renewable Energy Research and Applications (ICRERA), 2017 IEEE 6th International Conference on, IEEE (2017) 988–994.

[20] F. Jawaid, K. NazirJunejo, Predicting daily mean solar power using machine learning regression techniques, in: 2016 Sixth International Conference on Innovative Computing Technology (INTECH), 2016, pp. 355–360.

[21] A. Mosavi, M. Salimi, S. Faizollahzadeh Ardabili, T. Rabczuk, S. Shamshirband, A.R. Varkonyi-Koczy, State of the art of machine learning models in energy systems, a systematic review, Energies 12 (7) (2019) 1301.

[22] M. Rana, A. Rahman, L. Liyanage, M.N. Uddin, Comparison and sensitivity analysis of methods for solar pv power prediction, in: Pacific-Asia Conference on Knowledge Discovery and Data Mining, Springer, 2018, pp. 333–344.

[23] Y. Ren, P. Suganthan, N. Srikanth, Ensemble methods for wind and solar power forecasting—a state-of-the-art review, Renew. Sustain. Energy Rev. 50 (2015) 82–91.

[24] L. Gigoni, A. Betti, E. Crisostomi, A. Franco, M. Tucci, F. Bizzarri, D. Mucci, Dayahead hourly forecasting of power generation from photovoltaic plants, IEEE Trans. Sustain. Energy 9 (2) (2018) 831–842.