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Hybrid Deep Learning and Machine Learning Models for Accurate Day-Ahead Solar Power Forecasting

Ranjit Kumar
M.Tech Scholar
Department of Electrical Engineering
Jaipur Institute of Tech. - Group of Institutions, Jaipur

Ravi Kumar Bairwa
Assistant Professor
Department of Electrical Engineering
Jaipur Institute of Tech. - Group of Institutions, Jaipur

ABSTRACT: Solar energy is one of the most economical and clean renewable energy sources in the world. Therefore, solar forecasts are an inevitable requirement to achieve the maximum solar energy during the day and increase the efficiency of the solar system. The core of solar energy forecasts is a weather forecast problem. This article has the information related to hybrid SVM and KNN machine learning and LSTM machine learning classification technique used to predict the solar energy. It first explain the position of the sun relative to a given position on the earth's surface and then the transmission of solar radiation through the earth's atmosphere. The study emphasizes the importance of AI-controlled approaches to improve the efficiency of photovoltaic systems. In addition, the use of sensor -based weather data and advanced classification techniques contributes to more accurate predictions. Comparison of regression and classification methods shows the strength of the hybrid model in handling non-led sun radiation variations.

Keywords: Artificial Intelligence, Machine Learning, SVM, KNN and LSTM

1. Introduction

Overuse of fossil fuels has had a significant impact on global economic policy, the environment, and energy security. It has also contributed to global warming and the energy crises of the last several decades. As a result, there has been an attempt to develop and deploy environmentally friendly renewable energy sources [1]. Solar power is rapidly expanding due to its merits as a sustainable and environmentally friendly energy source. This energy is safe for the environment since it produces no pollution. In 2014, the European Photovoltaic Industry Association (EPIA) found that 177 GW of solar generating capacity was under construction, proving the technology's increasing popularity [2]. Photovoltaic (PV) energy systems provide a danger to power generation because of the erratic and unpredictable nature of the weather. Considering solar energy's intermittent nature and inability to be reliably forecasted, grid operators and solar electric power supply companies place a premium on reliable projections of solar power production. It is necessary to develop an algorithm to forecast the output power of a PV system in order to maximise the system's potential return on investment. Environmental variables such as temperature, humidity, wind speed, and dust buildup all have an effect on power production [3]. A simple use of power prediction algorithms and the accompanying assurance of roughly future production is all that is needed to maintain peace and order. This knowledge might be used by electricity suppliers to create a controller for a hybrid power plant that can make seamless transitions between its various energy sources. Solar power, very simply, is the process of turning solar energy into usable electricity. Numerous methods, such as directly using photovoltaics (PV), indirectly using concentrated solar power (CSP), etc., may be used to achieve this. Lenses, mirrors, and solar tracking technologies are used in focused solar power systems to concentrate sunlight from a wide area of the sky into a beam. Solar cells may convert light into electricity owing to the photovoltaic effect. From a solar-powered calculator to rooftop PV systems for homes in remote areas, photovoltaics were first used for very small and medium-sized projects.

Photovoltaic System

Power-generating PV modules are collections of solar cells that have been wired together. The cells are protected from the environment and electrical shock while in transit. There are a few major influences on photovoltaic (PV) modules and arrays, and they include

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- electricity is lost because to misconnected solar cells
- temperature module
- Causes of failure in photovoltaic modules

Multiple PV modules and strings are what make up a PV array. Multiple PV cells come together to form a module that generates PV power. Multiple PV arrays are linked to one another and then to an electrical infrastructure, such as a building or the public power grid. A simple grid-connected PV-system is seen in Figure1.

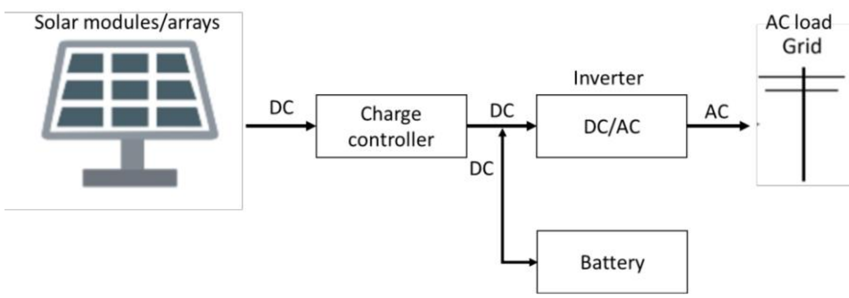

Figure 1: Simple Grid-Connected PV System Schematic

2. Data and Model Structure

The trained models were then evaluated using historical on-site data and historical weather prediction data after they had been preprocessed, implemented, and optimised. In the sections that follow, we'll go into further depth about each of these measures.

Figure 2: Flowchart of Work Approach

2.1 Artificial Intelligence (AI)

Without a shadow of a doubt, studying intelligence and creating intelligent machines are two of the primary goals of AI research (AI). But the phrase is very controversial, and defining it precisely is challenging. No one has been able to provide a definition that fully accounts for all of the essential considerations thus far. The phrase "artificial intelligence" was used by Elain Rich to characterise research into how to train computers to do activities at which humans excel. [24]

Ertel [25] asserts that this idea, which encapsulates the spirit of AI study over the last half-century, will remain current and useful in the year 2050.

The goal of AI, a vast field of computer science, is to develop autonomous, intelligent software. It has two primary subfields, symbolic learning and statistical learning. Technologies like computer vision and robotics that rely on image processing are part of symbolic learning. Pattern recognition is at the heart of machine learning, which may then be used for statistical or deep learning. Speech recognition and NLP are two of the primary areas of study within statistical learning. Machines may use a variety of "deep learning" techniques, which are essentially various ways to imitate the functioning of the human brain. Since data enables the system to learn, it is essential in the area of machine learning. Figure 3 provides an overview of the relationships between these three subfields of proving that deep learning is a branch of machine learning will help advance AI.

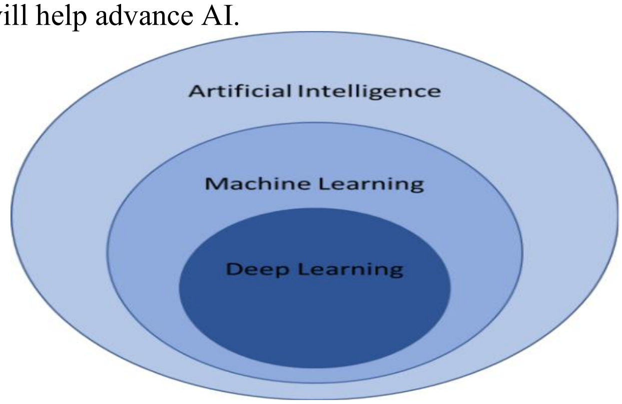

Figure 3: Subsets of Artificial Intelligence (AI)

2.2 Machine Learning

Figure 4 shows that Artificial intelligence (AI) is a kind of machine learning (ML). The optimization of a performance measure is made possible by machine learning (ML) via the application of computational methods, training data, and prior knowledge. These sorts of algorithms are essential for transforming unprocessed data into useful models. With the advent of big data, researchers in the area of machine learning have developed a renewed interest in creating effective algorithms for model development, data mining, and forecasting. Since enormous datasets often include noise and missing information, algorithms for processing them must be computationally efficient and durable in performance.

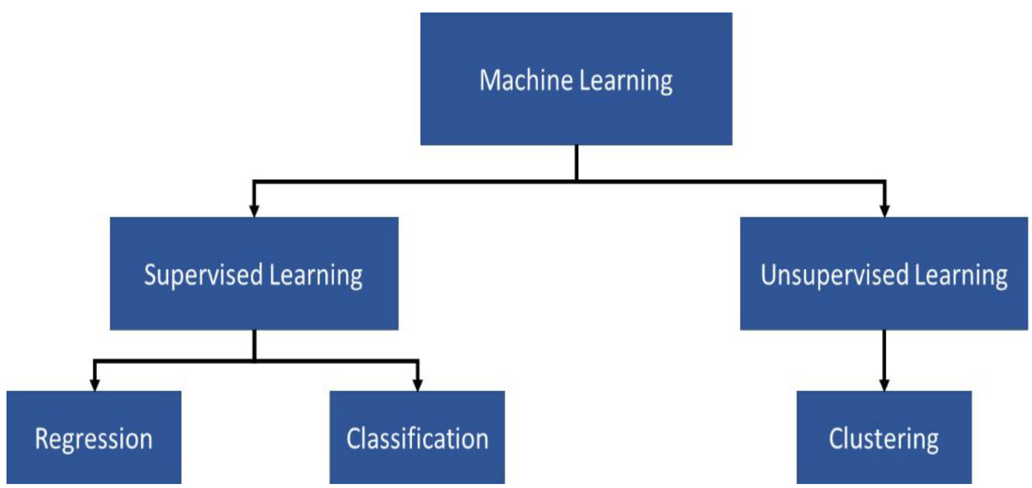

Figure 4: Scheme for Machine Learning

Supervised learning yields a learning process that fine-tunes the prediction model until it achieves the required performance by comparing predicted and actual results on a continuous basis. Even when the link between the variables in a supervised model cannot be determined, the input and output data are known. Typically, the aim of supervised neural network training is to identify weights that lead to lower model error rates. Supervised learning encompasses both classification and regression.

2.3 Classification

The method of classification is used to categorise the input data and predict the categorical replies. To classify anything is to place it into a category that has already been established. If a rule can be found that is consistent with both old and new data, it may be used to make predictions about future situations.

2.4 Regression

The task of regression may be seen as a curve fitting problem when the dependent variable is continuous and can take on any value in the real or complex number domains. With a training set of points yi and xi, where I is a real integer bigger than 1, If the graph of a function f is consistent with the data, we can estimate it.A function learned from a trained model may be used to generate an informed prediction when faced with a fresh data point whose output value is unknown. A simple use of linear regression is shown in Figure 5, where a new point is predicted using a function that has been tuned for the training data set given [26].

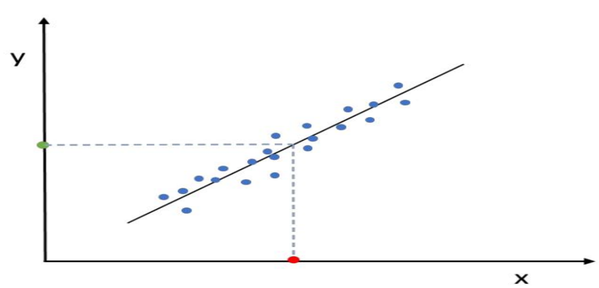

Figure 5: Example of a Linear Regression

The green dot represents the updated output value that was anticipated using the trained model and the equation (1).

$$\hat{y} = f(x) \tag{1}$$

Where represents the values produced and f(x) is a mode-trained function.

3. Solar radiation prediction

For Iran, solar power has the most potential of any renewable energy source. This nation is perfect for the building of solar power plants since it receives 2200 kWh/m2 of solar radiation annually. It's possible that there are a few islands off the coast of southern Iran. Given the abundance of solar energy in these areas, solar power is often advocated as a viable option for generating electricity. It has been suggested that projections of solar radiation might be very useful to grid operators and power market operators in making operational decisions. The forecast from the sun is utilised by energy companies when negotiating contracts with banks and utility companies that would be responsible for distributing their product.

Specifically, this research intends to:

1. In order to predict future solar radiation in the study region, we will develop a Multilayer Feed-Forward Neural Network (MLFFNN).
2. RBFNN-based hourly solar radiation forecast (RBFNN).
3. Third, we'd want to build a model that forecast solar radiation by the hour using support vector regression (SVR).
4. Using a fuzzy inference system to predict solar radiation (FIS).
5. For predicting solar radiation, an adaptive neuro-fuzzy system (ANFIS) is presently being developed.

4. Weather Data and Sensors

Predicting solar radiation via machine learning requires a vast amount of meteorological data.

The Sun's Radiation and Its Constituents Since solar radiation changes with latitude, latitude band, and time of year, trying to estimate it is a challenging challenge. Solar radiation [17] refers to the total amount of the sun's energy that reaches Earth's surface at any one moment. Given the sun's specified characteristics, it's essential to have a thorough understanding of the phenomenon. The sun goes through a variety of processes, all of which result in the loss of mass that is then turned into energy. Solar energy is transferred from the sun to Earth via a process known as solar radiation [18]. Diffuse solar radiation, direct solar radiation, and global

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solar radiation are the three most common kinds of solar energy. Electromagnetic radiation that is collected by the Earth's atmosphere and redirected back toward its source is referred to as diffuse radiation [19]. The ability of clouds to absorb and reradiate solar energy is exceptional [20]. This disrupts the efficiency of electricity generation by solar systems. Light from the sun travels in a straight path from the solar disc to Earth, however it may be concentrated or reflected. Concentrating solar power requires this specific wavelength of light for optimal performance [21]. Diffuse and direct sun irradiation may be used together to determine the total amount of solar radiation reaching a certain region. Solar radiation at any given point may be extrapolated to the whole planet using the total pyranometer [22].

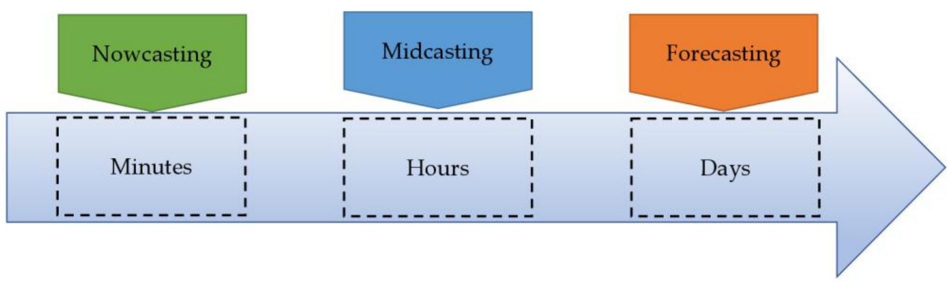

Figure 6. Prediction Scale According to Time Horizon Methods

5. Forecast Models

We explain how the different models arrived at their distinct forecasts.

ML Forecasting Algorithms

Below, we explain how these distinct models arrived at their respective projections.

- Depending on the time horizon of your prediction,
- data availability filtering;
- Take out the late-night checks;
- Separate the data into a training and a test set; divide the training data into k folds, each representing half a year;

- Define a collection of parameters (K = (1,..., 10) for KNN, for example); for each parameter p in the list, perform
- Specifically, execute the following for each fold I in the set of K folds: Use fold I as validation set;
- [Optional] data processing ahead of time;
- Alter the model to include the remaining K 1 folds;
- Infer numbers to use in the validation set;
- end

K-Nearest Neighbours Algorithm

In order to decide which category of Y best matches a given instance of X, the K-nearest neighbour classifier employs probabilistic inference. Evaluate the N0 closest points in the training data in terms of Euclidean distance from the value x0 of a test observation. In order to estimate the conditional empirical distribution of class j, KNN uses the score for the K nearest points that are classified as j.

$$\Pr(Y=j \mid X=x_0)=\frac{1}{K}\sum_{i\in N0} I(y_i=j) \quad (2)$$

Last but not least, the j-class with the greatest estimated probability receives the assignment of x0. K will inevitably have a significant impact on the KNN classifier's performance. For instance, the decision limit will overfit the training set if K is equal to 1, resulting in a classifier with a low bias and a large variance. But as K increases, the choice limit moves more and more in the direction of linearity, with small standard deviations but enormous absolute values. Because the bias-variance trade-off is altered when K's value is changed, the identification procedure is crucial. Cross-validation is a technique that may be used to get a reliable K value; this technique will be covered in more detail later. [15]

Regression issues are a perfect match for KNN's advantages. Here, KNN uses distance measures to determine the K closest neighbours, and then it averages those values to get an

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appropriate number to give the whole collection. This prognosis allows us to deduce the following:

$$\hat{y}=\frac{1}{K}\sum_{i\in N0} y_i \quad (3)$$

LSTM

We discuss some modifications that may be made to solar PV power forecast systems in this part in order to improve their accuracy and reliability. An example of an artificial neural network (ANN) subtype is the long short-term memory network (LSTM). They are a special kind of recurrent neural network (RNN). Recurrent neural networks (RNNs) are useful for tackling issues requiring sequential data, such as time series forecasting, voice recognition, translation, etc. [16], because of their loop structure.

Figure 7 show the RNN's rolling and unfolding structure. As can be seen, RNN uses information from previous calculations to apply the same operation to each member of the sequence.

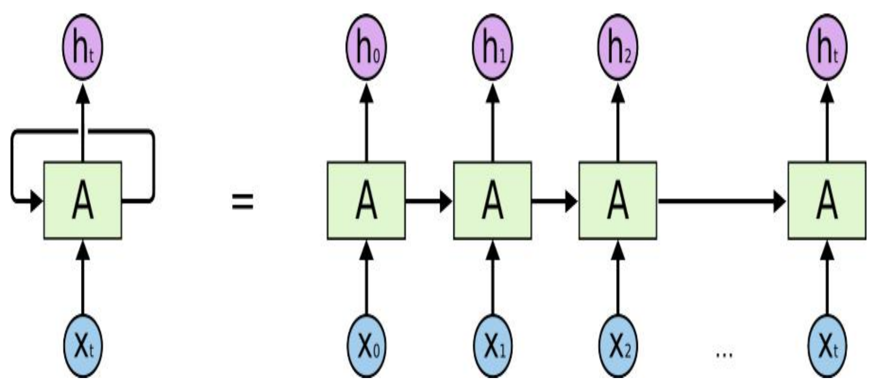

Figure 7: Network of Recurrent Neurons that Can Be Rolled and Unrolled [16]

6. Conclusion &Future Scope

This review emphasizes the importance of hybrid deep learning and machine learning models in accurate daily solar prognoses. Integration of LSTM with SVM-NN increases the accuracy of the prediction by effectively capturing temporary dependence on weather figures and complex patterns. By assessing factors such as sunshine, atmospheric transmission and meteorological variables, these models provide reliable solar groginos. Conclusions suggest that a combination of deep learning with machine learning can significantly increase the accuracy of solar energy, which can make the integration of renewable energy more efficient. Future research should detect further adaptation techniques and implementation of real -time for practical applications.

The overall cost of solar power generation is decreasing as the worldwide price of photovoltaic modules (PV) decreases. The number of successful bids for the JNNSM project in India plummeted as a result. India's solar energy prices are already among the lowest in the world, at about 15–17 cents per kilowatt hour (kWh) on average. For the next four years, costs may continue to decline due to component sector overcapacity before levelling out. Depending on the location, solar energy might be 15% cheaper than the costliest grid-connected, conventional energy source in 2016. According to traditional figures, these providers have a combined output capacity of close to 8 GW, which is comparable to 25-30 GW of solar equivalent. However, it is very improbable that all of these possibilities will be fulfilled by 2016. This is because of implementation difficulties. When we reach net parity, two fundamental shifts will occur in the solar industry.

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