Long-term power prediction of photovoltaic panels based on meteorological parameters and support vector machine

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Article Info

Article history:

Received Oct 30, 2023
Revised Nov 18, 2023
Accepted Dec 4, 2023

Keywords:

Internet of things
Meteorological system
Photovoltaic system
Solar energy
Support vector machine

ABSTRACT

Solar energy is the most generally accessible energy in the entire globe. Proper solar panel maintenance is necessary to reduce reliance on imported energy. Continuous monitoring of the solar panel's power output is required. The deployment of internet of things (IoT) monitoring of solar panels for maintenance is the basis for the current research. A multi-variable long-term photovoltaic (PV) power production prediction approach based on support vector machine (SVM) is developed in this study with the aim of completely evaluating the influence of PV panels performance and actual operational state factors on the power generation efficiency. This study examines the use of SVM and climatic factors to forecast the long-term output of power from solar panels. A solar power facility in a semi-arid area provided the data utilized in this investigation. Temperature, humidity, wind speed, and sun radiation are some of the meteorological variables that were considered in the study. To anticipate the power generation of the panels, the SVM is trained using the climatic factors and the power generation data. The findings demonstrate that the SVM model consistently predicts the panels' long-term power generation with a high degree of accuracy.

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1. INTRODUCTION

With global warming and reducing carbon emissions, solar energy as a new type of renewable energy is undoubtedly one of the most ideal clean energy in the future world [1]–[3]. But the volatility and discontinuity of solar energy cause huge problems for large-scale grid connection. The output of photovoltaic (PV) system is often affected by solar radiation intensity and weather, and the change in power generation is a non stationary stochastic process [4]–[6]. Long-term PV power output prediction will help the power dispatching department to plan the relationship between conventional energy and PV power generation, which can accurately and timely adjust the power generation plan to provide a basis for scientific power generation [7]. The output of PV power generation is affected by factors that cannot be accurately measured. Therefore, how to accurately predict the output of PV power has become a problem worth discussing [8]–[11]. Temperature and humidity are in positive correlation with solar power generated by a PV panel that means if we use huge amount of data including independent variables such as temperature and humidity we can predict power generated by panel at certain temperature and humidity but the problem here is that the correlation of temperature and humidity is nearer to zero so a highly efficient regression algorithm and huge data set should be used to give correct predictions [12]‒[14]. As solar energy is readily accessible worldwide, it can help reduce reliance on imported energy [15]. The world receives enough sunshine in 90 minutes to provide all of the planet's energy needs for a year. While operation, solar PV produces no greenhouse gases and no other pollutants. But the need for energy continues to rise globally. According to the most recent IE a medium-term renewable market study, renewable energy would expand 13% faster between 2015 and 2021 than was predicted last year. By 2021, about 28% of total power will be generated using renewable sources, up from over 23% in 2015 [16]‒[18].

The internet of things (IoT) is a network of interconnected computing devices, mechanical and digital machinery, items, people, and animals that have the ability to exchange data across a network without the need for computer or human-to-computer or human-to-human contact [19]. Real objects may now be controlled remotely using internet connections, allowing for constant monitoring of solar panels to meet the rising need for electricity. Compared to nuclear power facilities, solar panels produce 300 times more hazardous waste per unit of electricity [20].

2. STATE OF ART

The fluctuation of PV power output has become more noticeable with the growth of solar power generation that is linked to the grid. To guarantee the stability of the power system, precise PV output forecasts are required. In this study, the moth-flame optimization technique for support vector machine (SVM) prediction of solar power generation is improved. The inertia weighting approach and the Cauchy mutation operator are also introduced [21].

One of the primary causes of erratic fluctuations in the PV output power is cloud shadowing on the PV power station, which has a significant impact on an ultra-short-term PV power forecast. The motion vector is used in the first stage to anticipate the cloud's travelling trajectory, and the cloud that will block the sun is chosen [22]. A contemporary power system's ability to operate dependably and economically depends on an accurate estimate of solar PV production. This model is based on a recursive long short-term memory network (Rec-LSTM), which may give multi-step forward forecasting of the probability distribution of PV production. It takes past PV generations as input [23].

Users may learn a great deal from historical data. However, the data is frequently so large that it cannot be entirely retrieved, synthesized, and quickly processed for an application like anticipating variable generator outputs. For the output prediction of solar PV systems (i.e., proposed PV system) in Australia, a hybrid deep learning-based technique is suggested in order to acquire the trade-off between accuracy and effectiveness [23], [24].

By developing a SVM energy consumption prediction model, this research investigates and examines the energy consumption of hotel structures. The hotel air conditioning system operating parameters and weather parameters are input variables used by the SVM model to establish the critical value of the input parameters and to prevent the impact of outliers on the predictability of the mode [25]‒[27]. The radial basis function (RBF) kernel function is chosen as the SVM's kernel function, and by optimising the kernel parameters, the model's prediction accuracy is increased. The final model prediction's mean squared error (MSE) score was 2.22%, and R2 was 0.94. Inference from the literature survey: thus from the literature survey, it has understood that SVM has good potential for power prediction and it is an active area of research. This is the motivation to carry out project in this area.

3. ALGORITHMS TO PREDICT

3.1. Random forest

Every decision tree has a significant variance, but when we mix them all in parallel, the variance is reduced since each decision tree is correctly trained using that specific sample of data, thus the outcome is dependent on numerous decision trees rather than just one as shown in Figure 1. With the aid of several decision trees and a method known as bootstrap and aggregation, sometimes referred to as bagging, random forest is an ensemble methodology capable of handling both regression and classification tasks. This method's fundamental principle is to integrate several decision trees to get the final result rather than depending just on one decision tree. Multiple decision trees serve as the fundamental learning models in random forest.

3.2. Support vector machine

SVM are supervised learning models with related learning algorithms used in machine learning (ML) that examine data used for regression and classification analysis. The straight line needed to fit the data is referred to as the hyperplane in support vector regression (SVR). The SVR seeks to match the best line within a threshold value, in contrast to other regression models that aim to reduce the error between the real and projected value Figure 2. The distance between the boundary line and the hyperplane is the threshold value. SVR is difficult to scale to datasets with more than a few ten thousand samples since its fit time complexity is more than quadratic with the number of samples.

Because SVM can handle nonlinear interactions between the input variables and output variables, which are frequently the case in solar power production prediction, it has been widely employed in predicting solar power generation. The hyperplane discovered by the SVM algorithm divides the data into several groups according to their attributes. In the instance of predicting solar power generation, the SVM algorithm discovers a hyperplane that divides the data points with high power generation from those with low power generation by learning the association between climatic conditions and solar panel power generation. SVM works relatively well when there is a clear margin of separation between classes. SVM is more efficient in high dimensional spaces. SVM is effective in the case when the number of dimensions is greater than the number of samples. SVM is relatively more efficient. Proposed objectives:
i) To propose SVM for power prediction.
ii) To investigate various types of algorithms for power prediction.
iii) To compare their performance in terms of accuracy, compactness and complexity.
iv) To identify suitable ML algorithm.
v) To validate results extensively using ML.

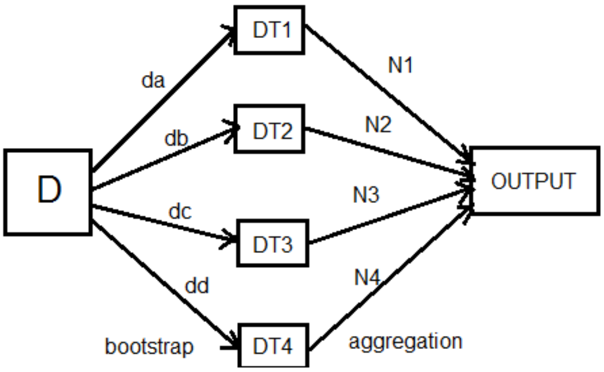

Figure 1. Random forest regression working

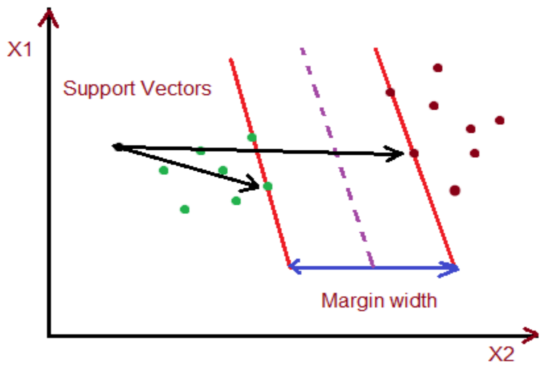

Figure 2. SVM regression

4. HARDWARE REQUIREMENTS
4.1. Arduino Uno
Based on the ATmega328 (datasheet), the Arduino Uno microcontroller board is used. It has a universal serial bus (USB) port, a power connection, an in-circuit serial programming (ICSP) header, a reset button, a 16 MHz ceramic resonator, 6 analogue inputs, 14 digital input/output pins, and 6 of these may be used as pulse width modulation (PWM) outputs. Everything required to support the microcontroller is included; all that is required to get going is the insertion of a USB cable, an AC-to-DC converter, or a battery. The Uno differs from all preceding boards in that it does not make use of the FTDI USB-to-serial driver chip. A USB-to-serial converter constructed with the Atmega16U2 (or Atmega8U2 up to version R2) is used in its stead. It is easy to enter device firmware update (DFU) mode with the revision 2 of the Uno board thanks to a resistor that pulls the 8U2 HWB line to ground.

4.2. ESP8266
A low-cost Wi-Fi microcontroller called the ESP8266 is produced in Shanghai by the Chinese firm espressif systems. It is equipped with a microcontroller and a complete transmission control protocol/internet protocol (TCP/IP) stack. The ESP-01 module, developed by a third-party firm AI-Thinker, first brought the chip to the attention of western manufacturers in August 2014. The module was incredibly cheap, and the fact that it had so few external parts suggested that it may be relatively robust, made it even more so. The module, chip, and software on it were attractive to several hackers since they were inexpensive in large quantities and took the effort to translate the Chinese documentation Figure 3.

4.3. Current sensor
A device known as a current sensor senses current and adjusts it so that output voltage may be measured. This output voltage and the current flowing via the measured path have a straightforward

proportionality. A data collection system is then used to control, display, or just store this output voltage signal in order to further examine the current measured by an ammeter. This is accomplished by adding a resistor to the current path, which linearly transforms the current into voltage. The technology behind this sensor is crucial since various types of sensors could have unique characteristics for various uses.

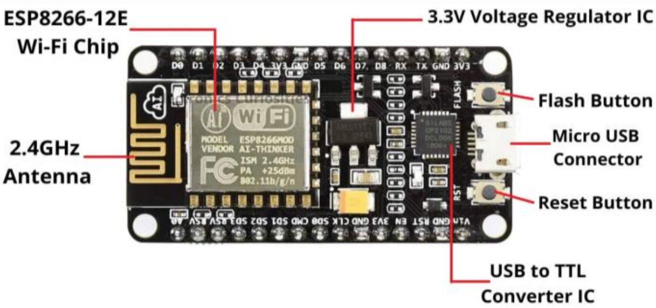

Figure 3. ESP8266 WiFi module

4.4. Voltage sensor

A voltage sensor is a sensor that measures and records the voltage level of an item. Voltage sensors may measure either AC or DC voltage levels. The sensor receives voltage as its input, and it can provide switches, analogue voltage signals, current signals, or aural signals as its outputs. Sensors are devices that are able to recognise and react to certain electrical or optical signalsFacilities may monitor vital assets around-the-clock with the use of reasonably priced voltage detectors.

4.5. Solar panel

A solar panel, usually referred to as a solar module, is a component of a PV system. They consist of a solar cell panel comprised of several solar cells. They come in a variety of rectangular shapes and are combined to generate electricity is shown Figure 4. Solar panels, commonly referred to as PVs, collect solar energy and convert it into electricity that may be used to power homes or structures.

Figure 4. Solar panel

4.6. DHT11 sensor

The DHT11 sensor is an inexpensive, digital temperature and humidity sensor that can deliver precise readings of temperature and relative humidity (RH). A polymer sheet that absorbs water molecules serves as the capacitive type humidity sensor, which detects changes in capacitance to determine how much moisture is in the air. The DHT11 sensor also includes a temperature sensor that is thermistor-based and monitors the ambient temperature. The calibration and integration of the DHT11 sensor on a single chip streamlines the integration process and lowers the sensor's cost.

4.7. Project design

Gathered past meteorological information for the area where the solar panels are located, such as solar irradiance, temperature, humidity, and wind speed. This information may be acquired from resources like the National Renewable Energy Laboratory (NREL) or other suppliers of meteorological data. The day of the week, the season, and other pertinent details were extracted from the meteorological data is shown in Figure 5.

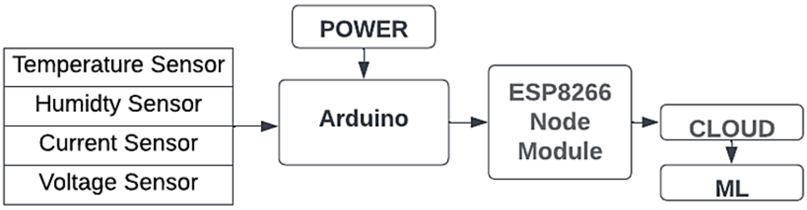

Figure 5. Working model of proposed system

4.8. Equations

Solar power output is affected by several meteorological parameters such as solar irradiance, temperature, humidity, and wind speed. The equations for estimating the solar power output based on these parameters are as follows:

– Solar irradiance (G): solar irradiance is the amount of solar energy that falls on a surface per unit area. The equation for calculating solar irradiance is given by:

$$G = G0 * cos(\theta z)$$

where G0 is the extraterrestrial solar irradiance (1,367 W/m^2), θz is the solar zenith angle, which is the angle between the sun and the vertical axis of the solar panel.

– Temperature (T): the temperature of the solar panel affects its efficiency and power output. The equation for estimating the temperature of a solar panel is given by:

$$T = Ta + (NOCT - 20) * (G / Gref)\text{^}0.5 * \alpha$$

where Ta is the ambient temperature, nominal operating cell temperature (NOCT) is the temperature at which the solar panel is rated (usually around 45 °C), Gref is the reference solar irradiance (usually 1,000 W/ m^2), α is the temperature coefficient of the solar panel.

– Humidity (RH): the humidity of the air affects the cooling of the solar panel. The equation for estimating the humidity of the air is given by:

$$RH = 100 * (Pw / Ps)$$

where Pw is the partial pressure of water vapor, Ps is the saturation pressure of water vapor at the air temperature.

– Wind speed (v): wind speed affects the convective cooling of the solar panel. The equation for estimating the wind speed is given by:

$$v = (4 * G / \rho * Cd * A)\text{^}0.5$$

where ρ is the air density, Cd is the drag coefficient of the solar panel, A is the surface area of the solar panel.

4.9. Data collection

Data should be gathered on a number of important aspects, including solar irradiance, temperature, humidity, and the angle of incidence of sunlight, in order to precisely anticipate the power output from solar panels. Designing and executing an effective solar energy system requires the collection of data to forecast solar panel power output for that use sensors such as DHT11 to collect real time data of meteorological parameters and ARDUINO UNO to aggregate all the data from sensors as well as power generation by PV panel at that instance. Now ESP8266 wifi module which is coded in embedded C will send that whole data to the cloud storage where it will get stored and can be used in ML algorithms to predict the power generation is shown in Figure 6.

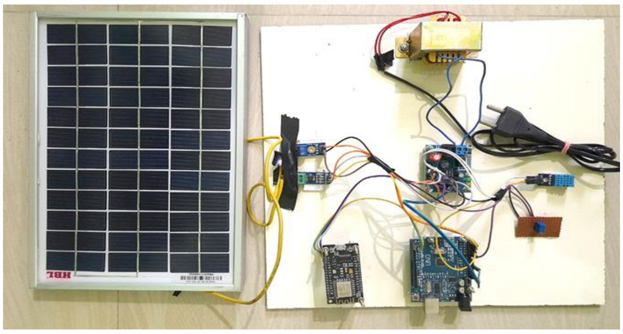

Figure 6. Hardware setup

4.10. Amount of data required

Several variables, such as the precision and complexity of the prediction model, the number of variables taken into account, and the length of the prediction horizon, affect how much data is needed to forecast solar panel power output. Predictions are often more accurate the more data there is. Nevertheless, gathering excessive amounts of data can also be detrimental since it may increase the computing time and memory needed to train the prediction model. To give a preliminary approximation, one year of data collection at a resolution of one data point per minute on solar irradiance, temperature, shade, and the angle of incidence of sunlight can yield around 25,600 data points Figure 7.

	count	mean	std	min
year	35064.0	2020.499658	1.117744	2019.0
month	35064.0	6.522930	3.448752	1.0
date	35064.0	15.729637	8.800218	1.0
time	35064.0	11.500000	6.922285	0.0
temperature	35064.0	27.858687	2.564046	19.7
relativehumidity	35064.0	76.082307	10.389135	37.0
direct_radiation	35064.0	146.404603	225.051671	0.0
diffuse_radiation	35064.0	73.537303	93.754859	0.0
direct_normal_irradiance	35064.0	204.725117	274.472361	0.0
windspeed	35064.0	13.060544	4.954938	0.0
power	35064.0	104.469627	157.712648	0.0

Figure 7. Data analysis

5. RESULTS AND DISCUSSION

Observations explained that power generation by solar panel is directly linked with meteorological parameters. And after analyzing various ML models it was clear that SVM and random forest are best for predictions. Huge data collection problem was solved by using cloud. The performance and utility of the prediction model may be impacted by its complexity. A straightforward model with fewer variables could be more reliable and simpler to use, but accuracy might suffer. On the other side, a more complicated model with more variables and interactions could provide estimates that are more accurate but might be harder to build and keep up. A balance between model complexity and accuracy is therefore crucial. For example, whereas a more complicated ML model may be required for some applications, a linear regression model with only a few variables could be adequate in others. Validating prediction models is important to guarantee their accuracy and dependability. This could entail comparing projected values to measured values, testing the model under various circumstances, or evaluating model performance using statistical techniques. Assessing the effect of prediction models on government policies and regulations connected to renewable energy, such as feed-in tariffs or net metering, is one potential regulatory use of prediction models for solar panel power generation. The quality of the data gathered, which includes different weather conditions, panel orientation and tilt, as well as other aspects, has a significant impact on the accuracy of prediction models shown in Figure 8.

```
from sklearn.svm import SVR
rf = SVR(kernel='poly')
rf.fit(X_train, y_train)
print("SVM : ", rf.score(X_test, y_test)*100)
d_score= rf.score(X_test, y_test)
[26]
... SVM : 98.07288402796895
```

Figure 8. Accuracy of the model

6. CONCLUSION

In conclusion, a prediction model for solar panel power generation based on meteorological conditions offers precise and trustworthy predictions of solar panel power generation. For optimal energy production and efficiency, the design, operation, and administration of solar panel systems may be optimized by taking into account the model's accuracy, power generation factors, prediction horizon, model complexity, and uncertainty and error analysis. By employing this method and applying ML to a dataset, projections of the amount of electricity a panel would produce can be made, and they may be utilized before starting up projects anywhere. To discover relationships between solar power and other climatic characteristics, more research may be done. For the purpose of maximizing the performance of solar panel systems and encouraging the use of renewable energy sources, the development of precise and trustworthy prediction models for solar panel power generation is crucial.

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