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Sky Image Analysis and Solar Power Forecasting: A Convolutional Neural Network Approach

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Abstract. Recently, the share of renewable sources in the energy mix of production units has been steadily increasing. The unpredictability of renewable sources leads to difficulties in planning, managing and controlling the electric energy system (EES). One of the ways to reduce the negative impact of unpredictable renewable sources is to predict the availability of these energy sources. Short-term forecasting of photovoltaic power plant production is one of the tools that enable greater integration of renewable energy sources into the EES. One way to gather information for the short-term forecast production model is to continuously photograph the hemisphere above the photovoltaic power plant. By processing the data contained within the images, parameters related to the current output power of the observed power plant are obtained.

This paper presents a model that utilises a convolutional neural network to analyse images of the hemispherical sky above a power plant to predict the current output power of the power plant. Estimating current production is a crucial step in developing models for short-term solar forecasts. The model was specifically developed for photovoltaic power plants and is capable of achieving high accuracy in power prediction. The estimation of power production from photovoltaic power plants enables the use of next-frame prediction for short-term forecasting.

Key words. Sky Image Analysis, Solar Power Forecasting, Convolutional Neural Network (CNN), Renewable Energy Integration, Power system stability.

1. Introduction

Photovoltaic power plants are among the most represented power plants based on renewable energy sources[1]. Due to their lower negative impact on the environment, recent research has focused on further improving solar cells in terms of efficiency, manufacturing costs and durability. For this reason, the number of photovoltaic power plants is increasing with time.

The unpredictability of power generation from renewable energy sources, including solar energy, leads to voltage and frequency instabilities in the power grid, causing difficulties in power grid operation. Changes in the availability of energy from renewable sources occur within a short period of time, in which other, traditional power plants do not have time to adjust their output. The slow response of traditional energy sources results in a loss of balance between generated energy and consumer demand. At times when the balance between generated and consumed electricity is not ensured, the voltage and frequency deviate from their nominal values, resulting in a deterioration of power quality.

To reduce the negative impact of renewable energy sources on the power grid, it is necessary to predict changes in the availability of these energy sources with some accuracy. Due to the dynamic nature of meteorological conditions, it is difficult to accurately predict cloud cover at a given location [2]. One of the solutions is short-term prediction of cloud cover at the observed location (10 to 15 minutes in advance within a radius of 2000 meters). Narrowed spatial and temporal frames allow more accurate cloud cover prediction.

The application of a reliable forecasting system for power generation reduces the need for balancing power, i.e., power reserves needed to cover the deviation of production from renewable sources from the contracted schedule. Thus, more accurate forecasting reduces the cost of integrating renewable energy sources into the power system [3]. In addition, reducing constraints on electricity generation due to high variability leads to higher utilisation of existing systems, which, in addition to lowering the cost of integration into the system, allows for lower electricity prices for consumers within the power system [4].

In order to successfully predict electricity production from a series of images of the sky hemispheres above the photovoltaic power plant, a correlation must be found between the information contained in these images and the amount of incoming solar radiation. The amount of solar radiation at the location of the photovoltaic power plant is directly related to the current production output of this power plant.

In addition to the information contained in the image, it is possible to use other parameters that could have an impact on the solar radiation and, consequently, on the production of the photovoltaic power plant. These parameters are temperature, relative humidity and air pressure, as well as wind speed and direction. The mentioned parameters can be measured with a small meteorological station [5].

An analysis of the impact of various parameters (such as temperature, dew point temperature, relative humidity, visibility, air pressure, wind speed, cloud cover, wind direction, and precipitation) on the output power of a power plant at a given site shows a low correlation between each individual parameter and the output power. However, the use of combinations of multiple parameters may result in a higher correlation [6]. In this study, we explore the possibility of using only a single input, a photograph of the sky, to estimate power output. It is possible to conduct the study using multiple input parameters along with the image to achieve higher correlation, but this approach would complicate data collection and processing.

There are also different methods of processing photos of the hemisphere of the sky. Cloud motion vectors calculated from a series of photos can increase the accuracy of prediction systems for PV production[7]. By determining the position of the cloud on a series of photos and comparing it to two consecutive photos, the cloud motion vector can be determined. Information about the size of the cloud and its direction and speed of movement is used to determine the possibility of future shading of the observed plant and thus the future production of the photovoltaic power plant at the observed location [8].

Power production model for a photovoltaic power plant based on sky images can be used for short-term forecasting of the same power plant[9]. The next frame prediction algorithm [10] can be used to generate and thus predict the future levels of cloud cover over the observed power plant based on the clouds' movement trend and changes of light in the photo. By combining these two algorithms, it is possible to perform short-term solar forecasting. The method whose development is described in this paper is the first step in this direction.

2. Forecasting method

A. Convolutional Neural Network

Convolutional neural networks are an upgrade to regular neural networks. Like regular networks, they consist of an input, an output, and multiple hidden layers. Their distinctive feature is the convolutional layers, which help to process photos efficiently and find correlations between individual features of the images and the desired output values. The architecture of a convolutional neural network shown in Figure 1 enables the finding of features in photos and compressing them into a manageable amount of data. The individual elements of a convolutional neural network are described in the following text.

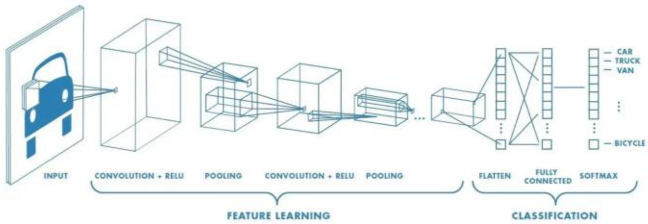

Fig. 1.Convolutional Neural Network Architecture [11]

B. Input data

For research purposes, a database is used that contains hemispherical images of the sky with various degrees of cloud cover and corresponding measurements of the output power of the photovoltaic power plant [12]. The system for collecting photos consists of a Raspberry Pi mini-computer (Raspberry Pi 3 Model B) and a high-resolution programmable camera with a wide-angle lens. The system is controlled wirelessly and is programmed to automatically collect photos with a 10 second time interval from 8:00 AM to 4:45 PM. The photos are stored in JPG format with a resolution of 1024x768 pixels.
In order for the output power of the photovoltaic power plant to be relevant, a photo collection system was placed right next to the photovoltaic power plant. The location of the photovoltaic power plant is on the roof of the Sustainable Buildings Research Centre (SBRC) at the University of Wollongong, Innovation Campus in Australia (34.40°N, 150.90°E.

Data for September 10, 2019 were selected to perform the analysis. The selected database consists of 2978 photos. The selected day was chosen due to the large number of different characteristic moments during which there are significant variations in the output power of the photovoltaic power plant, as can be seen in Figure 2. In the period from 6 to 9:30 AM, there was almost continuous shade with occasional incidence of sunlight. From 9:30 to 11 AM, it was cloudless, and then there were occasional clouds. In the time period from 11:30 AM to 12:30 PM, there was a cloud edge effect, during which production is higher than it would be if the sky were clear, not only because of direct sunlight, but also because of scattered radiation caused by nearby clouds. The cloud edge effect further complicates the integration of renewable energy sources into the grid by increasing the total output at the moment of shading [13].

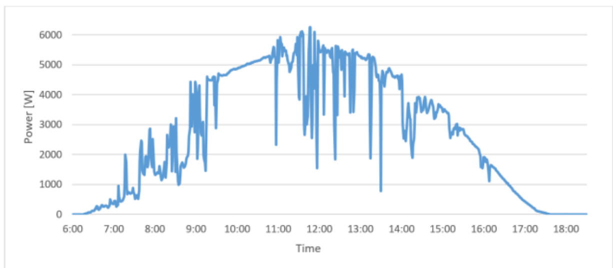

Fig. 2. Input data: Power on 09/10/2019

The given database was used due to the high temporal resolution of the contained data, which allows the construction of a more accurate model to predict the production of a photovoltaic power plant. Short-term prediction of production requires data collection with high temporal resolution (Δt < 1 min) due to the high dynamics in the change of solar irradiance.

The photos of the hemisphere taken at the location of the observed power plant are associated with the current output power such that the photos contained in the database have been renamed according to the corresponding current power. The database can be expanded by adding more information to the title of the photo, such as the current time, temperature, relative humidity, etc. The database used consists only of photos of the hemisphere of the sky and information about the output power of the power plant, in order to simplify the system for predicting the current output power of the power plant from photos. The newly obtained database with unified photos and current output data is shown in Figure 3. The photos in Figure 3 are randomly selected from the database. Figure 3 also shows a correlation between visible clouds and current production, confirming the accuracy of the input database. The method of using the name of the photo to store the data eliminates the need for an additional database linking the name of the photo to the production parameters at the time the photo was taken.

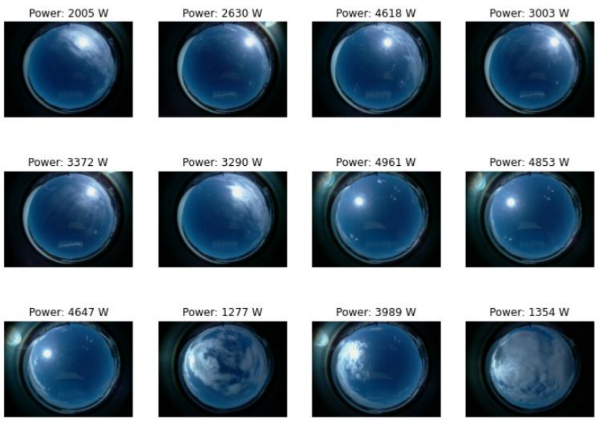

Fig. 3. Part of the input photo database

Figure 4 shows the distribution of input data, which confirms the diversity of the database used. The diversity of input data is critical to building a robust model. The diversity of weather conditions included in the database used allows the model to adapt to weather conditions expected in the vicinity of the power plant.

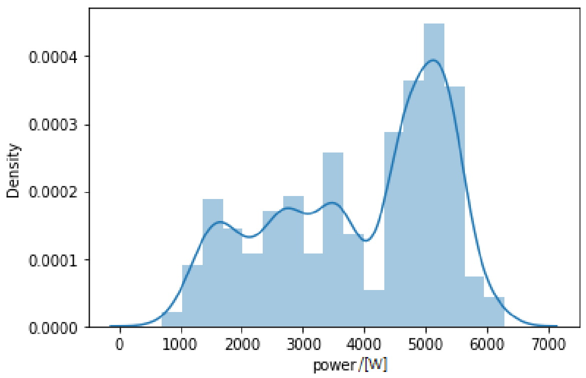

Fig. 4. Distribution of input data

C. Neural network construction

The input layer consists of pre-processed, standardized photos. The photos used in the training phase and in the normal use of the model may have different characteristics in terms of format, resolution, color spectrum, proportions, etc. The input photos are normalized in order to standardize their characteristics, making it easier to train the network. Pre-processing of the photos is carried out on all photos used for training and validation of the neural network, as well as for the photos used in the final model. Figure 5 shows an example of how the photo resizing algorithm works. The left side shows the original photo with a resolution of 1024x768 pixels, while the right side shows the processed photo with a resolution of 128x128 pixels. This resolution was chosen to facilitate further processing and analysis of the photos.

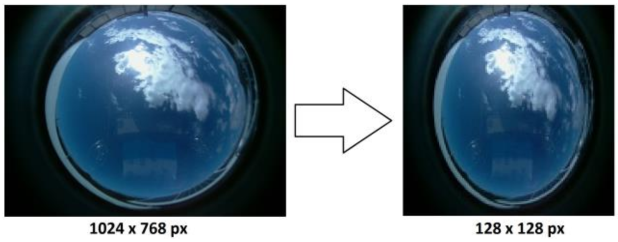

Fig. 5. Photo pre-processing

Convolutional layers of a neural network are used to generate a new set of photos containing different features of the topography from an input photo. Each new photo is generated using a feature detector and contains features of the image that, during network training, have proven to be most useful in predicting the correct outcome. While the new set of photos includes a larger number of photos than the input, it has a significantly lower resolution, which speeds up the algorithm considerably. Reducing the resolution of the input photo and finding features within the photo not only reduces the need for large computational power, but also allows the algorithm to generalise, which significantly increases its accuracy in predicting the result using new, unseen photos. The feature map obtained from the convolutional layer is used as the input photo for the next layer, whether it is a max-pooling layer or a new convolutional layer. An example of a convolution performed on a photo is shown in Figure 6. During the training of the convolutional neural network, the algorithm uses several different feature detectors, and the values of each individual detector are optimised.

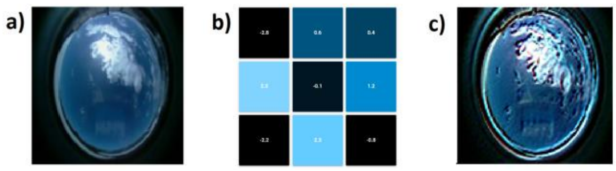

Fig. 6. Convolution. a) input photo, b) feature detector, c) feature map [14]

The pooling layer is used to reduce the resolution and thus the computational power required for processing. Convolutional networks provide a new photograph for each feature detector used. The pooling layer reduces the dimensions of these photos without compromising the information they contain. The most commonly used pooling algorithm is maximum pooling (or max-pooling), which takes the largest element from the observed submatrix and returns it as the result. The reduction in complexity achieved by the pooling algorithm contributes to faster training and execution of the model. The pooling layer, like the convolutional layer, contributes to generalization by compressing the data, which reduces the possibility of overfitting the neural network.

Flattening layer is used to convert a set of photos or two-dimensional matrices into a one-dimensional array or vector. The principle of the flattening algorithm is shown in Figure 7. The one-dimensional array is used as the input layer for the next part of the neural network. This may be an artificial neural network, Deep Learning, or a fully connected layer.

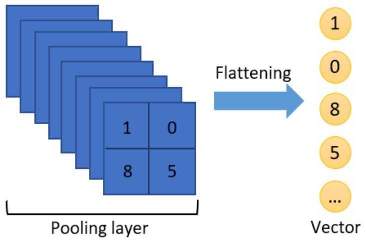

Fig. 7. Flattening

An artificial neural network finds the correlation between the features of the photos and the desired parameter. Each element of the network adds the output values of the connected "neurons" by weight and, using the activation function, generates an output parameter that is in some way related to the features of the input photos and the desired output parameter. A neural network may consist of one or more connected layers. An artificial neural network with multiple connected layers is called a deep neural network.

The dropout regularization method is used to avoid overfitting of a neural network. In order for the model to work well not only with the dataset used for training, but also with new data, the possibility of overfitting the model must be reduced. One of the methods by which this can be achieved is dropout. In each iteration of network training, dropout deactivates a certain percentage of neurons. The deactivation of randomly selected neurons results in a new model topology. Models that use dropout function reach the target accuracy over test data more slowly, but their accuracy over unseen data is higher. Figure 8 shows a dropout model of a neural network.

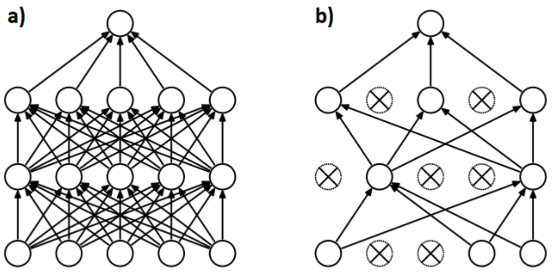

Fig. 8. Dropout model of a neural network. a) standard neural network with 2 hidden layers. b) example of sparse network [15]

The output layer is the last layer in a neural network where the desired predictions are made. It has its own set of functions that are applied before the final result is obtained.

The model was created using the Google Colab virtual software environment. Google Colab provides a free Cloud service with the ability to use a free remote graphics card. The model was created using the Python programming language and TensorFlow, a software library for numerical computation and the Keras programming interface. Access to the software code is available here: https://colab.research.google.com/drive/1_JUhm8XMT3rpE6Sv7R4KDxWTV8OC-A0n?usp=sharing.
The summary of the model is shown in Figure 9.

```
Model: "model"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 input_1 (InputLayer)         [(None, 128, 128, 3)]     0

 conv2d (Conv2D)              (None, 126, 126, 32)      896

 max_pooling2d (MaxPooling2D)  (None, 63, 63, 32)       0

 conv2d_1 (Conv2D)            (None, 61, 61, 64)        18496

 max_pooling2d_1 (MaxPooling2D)  (None, 30, 30, 64)     0

 conv2d_2 (Conv2D)            (None, 28, 28, 128)       73856

 max_pooling2d_2 (MaxPooling2D)  (None, 14, 14, 128)    0

 conv2d_3 (Conv2D)            (None, 12, 12, 256)       295168

 max_pooling2d_3 (MaxPooling2D)  (None, 6, 6, 256)      0


 flatten (Flatten)            (None, 9216)              0

 dense (Dense)                (None, 256)               2359552

 dropout (Dropout)            (None, 256)               0

 power_out (Dense)            (None, 1)                 257

=================================================================
Total params: 2,748,225
Trainable params: 2,748,225
Non-trainable params: 0
_________________________________________________________________
```

Fig. 9. Model summary

3. Results

The results of the convolutional neural network model conducted within the Google Colab virtual programming environment are shown in Figure 10. The mean absolute error (MAE) represents the average absolute difference between the values obtained from the model and the historical observed data. The mean squared error (MSE) is the average squared difference between the estimated values and the actual values. The root mean squared error (RMSE) is the square root of the MSE. Its value is on the same scale as the values obtained by the model. The Variance Score is a specific indicator of the representativeness of the model. The model is more representative the closer the Variance Score is to one. Within this model, the following values were achieved: MAE: 125.38, MSE: 57566.87, RMSE: 239.93 and Vaciance score: 0.970.

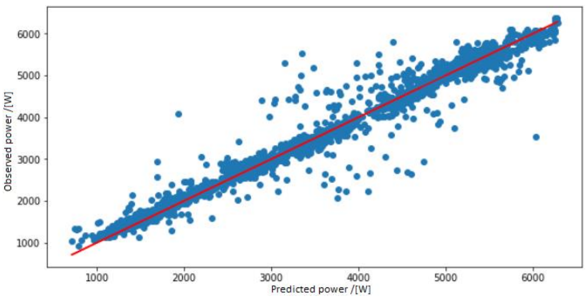

Fig. 10. Results of the convolutional neural network model

Figure 11 shows a comparison between actual and predicted power for a randomly selected photo.

Fig. 11. Power prediction for a randomly selected photo.

The graphical representation of the results in Figure 12 shows a comparison of actual power with predicted power for all input data. The analysis was performed using a database for September 10, 2019 consisting of 2978 photos of the hemisphere sky and the corresponding power production of a photovoltaic power plant.

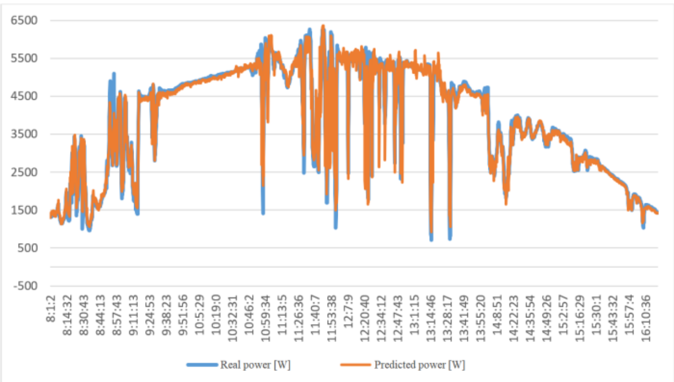

Fig. 12. Comparison of actual power output with predicted power output

The error distribution representing the difference between the actual measured power and the predicted power is shown in Figure 13.

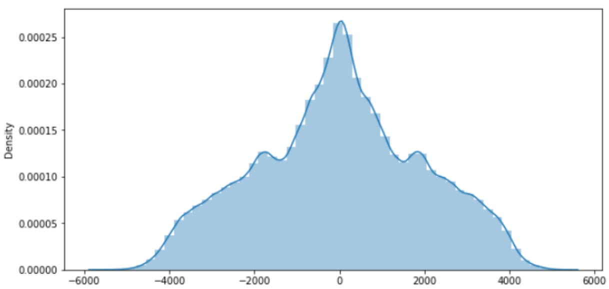

Fig. 13. Error distribution

A. Training of the network

The indicator of the success of the model through training iterations is the loss function. The loss function is useful for evaluating models that solve regression problems. Figure 14 shows the training loss function with data on losses over 200 training iterations and for data used for training (Training Loss) and for data used for model validation (Validation Loss) which make up 20% of the total data.

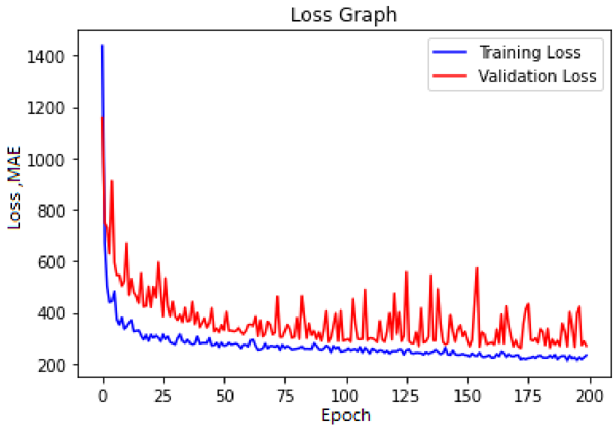

Fig. 14. Training and Validation Loss Functions

4. Discussion

The model developed in this paper was applied to photographs taken at only one location and on one specific day. The observed day is considered the worst case scenario because the weather on that day was extremely changeable. If photos collected on days with less meteorological variability were used, such as a sunny day or a consistently cloudy day, the correlation would be much higher. Photovoltaic power plant production prediction models show their robustness on days similar to the one used in this work.

The high dynamics of cloud cover on the observed day allows a clear view of the representativeness of a model that uses images from the actual power plant site. The information contained in the photos of a dynamic day provides an opportunity to compare correlations with other models, which are also tested on data recorded on days when short-term forecasts of photovoltaic power plant production would be most useful.

Figure 10. shows high agreement between actual and predicted outputs, indicating high correlation between the model and real physical processes. Figure 11 shows the predictions for a randomly selected photograph. The photo is distinctive in that it shows not only the relative position of the Sun, which indicates the time of day and thus the available solar radiation for that time of day, but also the reflected solar radiation from nearby clouds (cloud edge effect). It can be seen that the model provides high accuracy even though there are complex clouds on the image.

Figure 12. shows a high overlap between the actual production curve and the predicted production curve based on the cloud photos. For data in a period without

production fluctuations, e.g. at 10 AM, the results show how well the model predicts the output power. Also, after 2 PM, the output decreases due to the azimuth of the sun, which the model also correctly predicts. At sunset, the sky changes from blue to red, making the blue color darker. This fact and the visual location of the sun may allow the model to make accurate predictions. The error in approximate production is visible at 8:50 AM and 12:20 PM. In the aforementioned parts of the diagram, it can be seen that the actual output does not match the predicted output. The model is not suitable for extreme changes in cloud cover due to the relatively small amount of data used for training.

5. Conclusion

The research results presented in this article show a high correlation between the data contained within the the sky images taken at the photovoltaic power plant location and the output power of this power plant. Using the methods described in the apper, it is possible to accurately predict the output of a photovoltaic power plant based on sky imagery alone. The sky images can be acquired using a simple system consisting of a camera and a module for data transmission and processing.

High accuracy of the model can be achieved by using a larger number of input variables such as wind speed, temperature, current time and date, and satellite and radar images of clouds. However, the system tries to keep it as simple as possible by using as few input data as possible, which reduces its cost and the need for memory and computing power. To further generalize the model, it is necessary to use a larger database collected at sites of power plants with different ratings.

Next frame prediction algorithm can be used to generate future images. If the image analysis techniques described in this study are applied to these images, the algorithm has the potential to make short-term predictions of photovoltaic system production.

With the help of advanced algorithms, computer processing of a set of images can also read out other information, such as motion vectors of image features like clouds, relative position of clouds and sun on the images, subtraction of light from pixels at the location of the sun, etc. Using these parameters, a more accurate photovoltaic power output forecasting can be made.

The development of computer and processor optimization has led to the practical application of machine learning, artificial intelligence, and computer vision systems. Convolutional networks and recurrent neural networks enable image processing and prediction of future events based on trends contained in a set of photographs.

This work can serve as a reference point for validating more complex methods and provides insight into the topic of state estimation based on photo parameters of the observed process.

The next image prediction algorithm can predict future cloud formations at a power plant site. The algorithm described in this study can be used to estimate production from this predicted image and thus indirectly predict future production. The algorithm can also be used to simplify the photo collection system. By collecting photos, the current power can be predicted without using a current measurement module.

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