Scholar Publishing Group
Academic Journal of Energy
https://doi.org/10.38007/RE.2022.030205
ISSN 2790-2714 Vol. 3, Issue 2: 40-47

Short-term Forecasting Method of Solar Photovoltaic Power Generation Based on Organic Rankine Cycle

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Keywords: Organic Rankine Cycle, Solar Energy, Photovoltaic Power Generation, Short-term Forecasting

Abstract: With the development of science and technology and the progress of human society, the demand for renewable energy continues to increase, and the production of photovoltaic energy develops rapidly, but the production of photovoltaic energy is affected by many factors, such as temperature, light intensity, wind speed, geographical location Wait. The purpose of this paper is to study the short-term prediction method based on the organic Rankine cycle, propose a differential autoregressive moving average (ARIMA) model and a combined sequence-to-sequence (Seq2Seq) model, and on this basis, enter the short-term Interval forecasting method of photovoltaic power generation. Compared with a single model, the improvement of the proposed method is reflected in the use of the Seq2Seq model in the recurrent neural network to be good at capturing data normality to make up for the shortcomings of the ARIMA model itself, so as to achieve complementary advantages between the two. Both models and full interval forecasts. Under sunny weather conditions, when the confidence level is 95%, the method in this paper is used to construct the photovoltaic power generation power prediction interval. The average width percentage of the PIMWP interval value reaches the minimum value of 15.3, and the coverage percentage interval PICP also reaches 92.1%. This method can be used to carry out interval forecast.

1. Introduction

Solar energy is recognized as the perfect renewable energy source. Solar photovoltaic power generation base is an important way to use solar energy, which can reduce many environmental problems caused by traditional energy and solve the existing energy crisis at the same time. However, affected by the intensity of solar radiation and meteorological conditions, the power generation is extremely random, fluctuating and intermittent, which brings severe challenges to large-scale grid-connected photovoltaic power generation. Therefore, it is of great practical significance to accurately predict photovoltaic power generation [1-2].

With the accelerating consumption of traditional fossil energy, the storage of non-renewable energy has been far behind the pace of human development. Chintala V uses the Organic Rankine Cycle (ORC) to recover waste heat from compression ignition (CI) engines and generate additional power output. The waste heat recovery capabilities of the CI engine exhaust, water jacket, and transport charge air are reviewed. Research challenges related to ORC engine technology are discussed, such as choice of organic working fluid, evaporator/condenser type, back pressure due to additional ORC elements in the exhaust line [3]. Chaudhari K proposed a hybrid optimization algorithm for energy storage management that alternates between deterministic and decision-based strategies based on electricity cost ratios. The cost decomposition model of the energy storage system (ESS) of the photovoltaic electric vehicle charging station and the production cost level The algorithm is divided into three parts: the real-time electricity cost is divided into different cost segments, and the photovoltaic power generation is calculated in real time. Optimization of operating costs based on solar radiation data, photovoltaic efficiency, and electric vehicle charging stations and energy storage systems. Taking Singapore as an example, extensive simulation studies have been conducted using asymmetric computational EV charging models to check the effectiveness of the algorithms. In addition, a detailed analysis of subsidies and incentives provided by government agencies to increase renewable energy penetration [4]. Ahmad SK research optimizes hydropower generation by optimizing reservoir operations based on short-term flow forecasts derived from publicly available Numerical Weather Prediction (NWP) models. The forecast field of the Global Forecast System (GFS) NWP model is used to force the Variable Infiltration Capacity (VIC) hydrological model to predict reservoir flow for 1-16 days. Optimizing reservoir operations depends on upcoming forecasts. The concept has been demonstrated in two dams in the United States. The results show that more hydropower benefits can be achieved consistently compared to traditional operations without optimization and weather forecasting. Flood protection and dam shelters not compromised as opportunities to improve water efficiency are explored [5]. Therefore, the theoretical and practical significance of the short-term prediction method of solar photovoltaic power generation based on organic Rankine cycle is obvious.

This paper studies the short-term prediction method of solar photovoltaic power generation based on organic Rankine cycle, which can expand the power grid, reduce fuel consumption, reduce system reserve capacity, and improve the economy of power grid operation. The grid connection of photovoltaics will have a great impact on the stability of the grid. Develop response plans in advance to reduce operating costs. As an emerging industry that has developed and attracted worldwide attention, photovoltaic energy bases are more competitive than traditional energy production methods. Unlike traditional power generation, photovoltaic power generation is highly random, unstable and arbitrary, but if this behavior can be properly simulated or predicted, photovoltaic power generation can play a better role.

2. Research on Short-term Forecasting Method of Organic Rankine Cycle and Solar Photovoltaic Power Generation

2.1 Principle of Solar Organic Rankine Cycle

The solar organic Rankine cycle is similar to the traditional water vapor Rankine cycle, but there are two obvious differences: 1. The boiler is replaced by a solar collector that collects solar heat; 2. It is replaced by an organic working medium with a lower evaporation temperature steam. The solar organic Rankine cycle system uses the solar heat collection system to collect solar heat as the heat source of the ORC system. The solar energy system uses heat transfer oil as the working medium to enter the evaporator of the ORC system. The liquid organic working medium of the ORC system is heated, and the organic working medium is heated. The gas is gasified into a high-temperature gas working medium, which enters the expander to do expansion work, and the expansion work is converted into electric energy through electrical energy. The generator is connected to the extension [6-7]. The low-temperature, low-pressure gaseous medium enters the condenser and liquefies into a low-temperature, low-pressure working medium. After being compressed by the working water pump, it enters the evaporator again to complete the complete Rankine cycle [8-9].

2.2 ARIMA Model

As can be seen from the name, the ARIMA model has one more difference process than the ARMA model [10-11]. The ARIMA(p,d,q) model satisfies the following equations:

$$(1-B)^d Y_t = \frac{\Theta(B)}{\phi(B)} e_t \qquad (1)$$

In the formula, Ø(B), Θ(B) are the autoregressive operator and the moving average operator after the delay operator is introduced into the AR model and the MA model, respectively, et is a random error, usually a white noise sequence [12-13].

2.3 Seq2seq Model

In deep learning, the Sequence to Sequence (Seq2seq) model is often mentioned. It refers to the transformation of one sequence into another sequence. Tasks such as machine translation, session recognition, and time series prediction all belong to the Seq2seq task, and the encoder-decoder [38] framework is used to solve this sequence problem. A complete Seq2seq model, based on the Encoder-Decoder architecture, consists of three parts: encoder, intermediate vector and decoder [14-15]. The composition of the encoder and the decoder is basically the same, and they are both composed of stacked recurrent units. Generally, RNN is used as the recurrent unit. In this paper, LSTM is used as its recurrent unit. The intermediate vector c is the final hidden state generated by the encoder. For any time series Source=(x1,x2,...,xm), the desired sequence Target=(y1,y2,...,ym) can be obtained through the Encoder-Decoder framework. The role of the encoder is to turn it into a fixed intermediate vector. The given time series can be of fixed length or indefinite length, and the output intermediate vector is of fixed length, and the encoder will encode the time series information input by the model while outputting the intermediate vector [16].

3. Modeling and Research on Short-Term Forecasting Method of Solar Photovoltaic Power Generation

3.1 Short-term Prediction Methods Based on Solar Radiation and Photovoltaic Power Generation System Models

The short-term forecasting method based on solar radiation and photovoltaic power generation system model, as the first solar power generation forecasting method, has been widely studied around the world and achieved good results. As a purely physical prediction method, combined with the working principle of photovoltaic module power generation, the short-term solar power generation prediction results obtained are generally more accurate. Generally divided into the following steps:

The first step is to establish the I/V characteristic curve of photovoltaic modules under standard test conditions (AM1.5, 1000W/m2, 25 ℃).

The second step is to predict or measure the current solar radiation intensity and temperature.

In the third step, the I/V characteristic curve of the photovoltaic module under the current working condition is obtained according to the current solar radiation intensity, temperature and other conditions.

The fourth step is to obtain the final short-term output power prediction value based on the I/V characteristic curve under the current working conditions, and the MPPT conversion efficiency and the reliability efficiency of the power generation system are integrated.

3.2 Modeling Steps of Photovoltaic Power Interval Prediction Algorithm Based on ARIMA-Seq2Seq

(1) Divide the original data according to different weather conditions, and the historical data required to predict the power generation of each day, and divide them into training sets, verification sets and test sets.

(2) Use the ARIMA model to model and predict the power generation on the day to be verified, and obtain the preliminary predicted value. The predicted residual value is then calculated according to formula (5.13).

(3) Corresponding and merging the prediction residuals of each day and the corresponding main meteorological factors to form a new data set, which is used as the input of the Seq2Seq model for modeling, and the predicted value is set as ˆte; and the prediction of ARIMA The value and the residual term prediction value of Seq2Seq are linearly summed, and the final point prediction result is

(4) Construct the PV forecast interval on the verification day.

(5) Use the PV output prediction interval and evaluation index constructed on the verification day, and help the PSO algorithm to optimize the problem and obtain the best proportional coefficients bestα and bestβ.

(6) Use the above-trained combined model to predict the photovoltaic power generation data of the day to be measured, and obtain the point prediction result of the daily power to be measured.

(7) According to the best proportional coefficient determined by the validation set and the prediction result of the date to be tested, determine the upper and lower limits of the prediction interval of the date to be tested, and complete the interval prediction of photovoltaic power generation data.

(8) Use the interval prediction evaluation index to evaluate the results.

3.3 Model Evaluation

(1) Mean square error (MSE) is used to measure the deviation between the predicted value and the true value, and is the ratio of the squared sum of the deviation to the number of times. The smaller the MSE value, the better the effect.

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \qquad (2)$$

(2) Determination coefficient

$$R^2 = 1 - \frac{\sum_{i=1}^{m} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{m} (y_i - \bar{y})^2} \quad (3)$$

where yi is the actual value, m is the number of samples predicted by the model, and ŷi is the predicted value. R2 reflects the degree of fit to the observed value, the larger the R2, the better the prediction effect.

4. Analysis of Short-term Forecasting Method Model Results

4.1 Analysis of Prediction Results of ARIMA-Seq2Seq Combined Model

Using ARIMA to predict the linear components and Seq2Seq to further correct the residuals, the linear superposition is used to obtain the point prediction results, as shown in Figure 1.

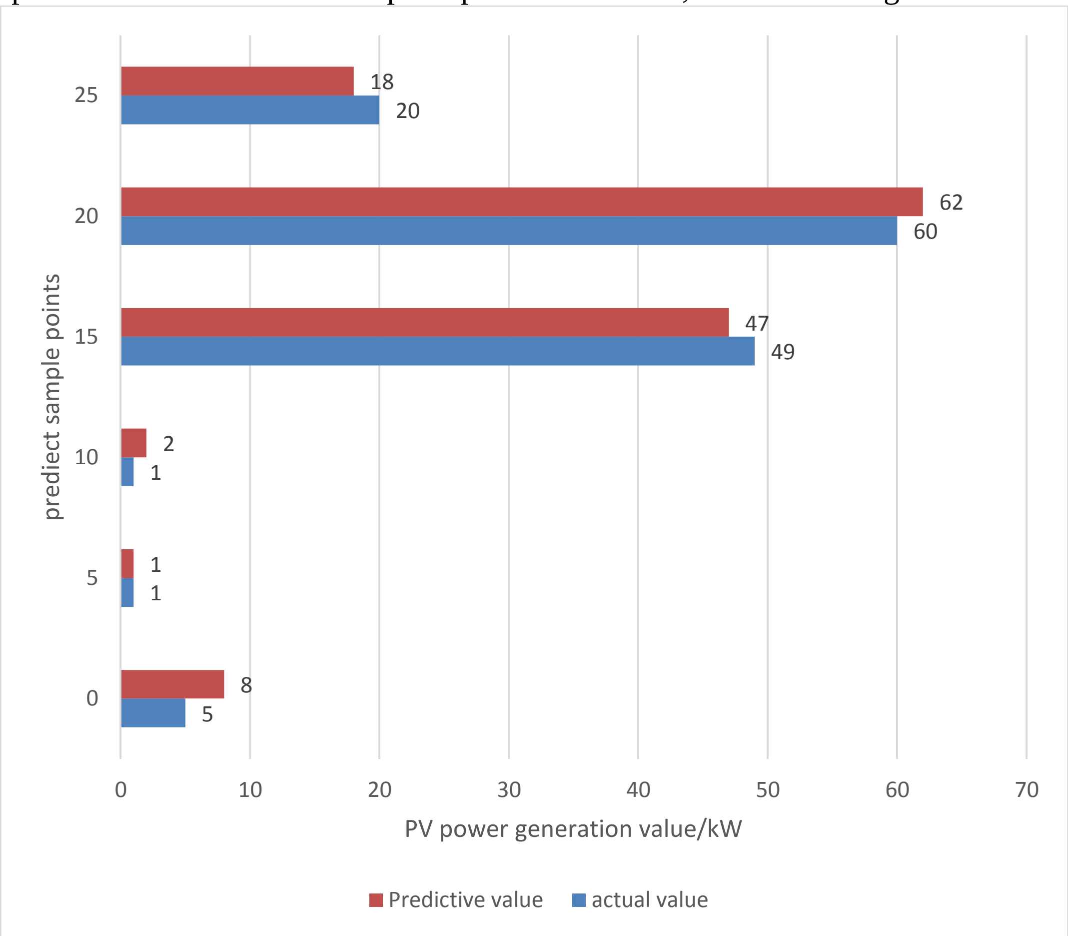

Figure 1. Point prediction results of ARIMA-Seq2Seq

It can be seen from the figure that the established combined forecasting model is more accurate for the point forecasting results on July 15. In order to highlight the advantages of the combined algorithm, the prediction results of the ARIMA and Seq2Scq models are compared, and the calculation results of the evaluation indicators are shown in Table 1.

Table 1. Performance Index Comparison Results

prediction algorithm	MAE	RMSE	MAPE	R2
ARIMA	18.21	15.43	6.12%	0.8912
Seq2Scq	15.63	17.65	5.14%	0.8421
ARIMA-Seq2Seq	8.31	10.54	2.54%	0.9546

By comparison, it is known that any evaluation index of the ARIMA-Seq2Seq combined model is improved compared with the single prediction model, which shows that the introduction of the idea of residual correction has well realized the combination of the advantages of the two models.

4.2 Analysis of Prediction Interval Evaluation Results

In order to further explain the advantages of the algorithm more scientifically and intuitively, the PICP, PINAW, AD and PISI indicators under the 95% confidence level under the three weather conditions were calculated respectively, as shown in Figure 2.

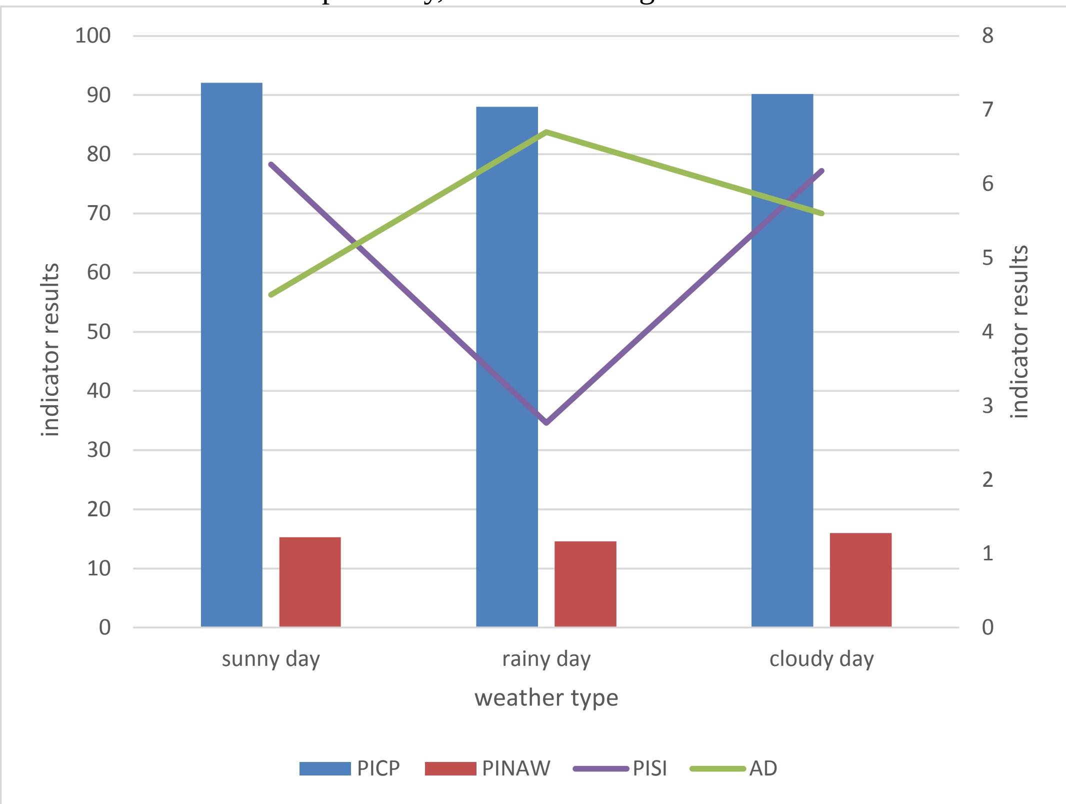

Figure 2. Prediction interval evaluation index results

It can be seen from the above calculation results that, on the whole, under the same confidence level, the prediction effect of sunny weather is the best, the prediction effect of cloudy weather is second, and the effect of rainy weather is the worst. Analysis of the reasons shows that the regularity of power generation is strong in sunny days, which is conducive to the combined model to capture the regularity between historical power generation data; while in cloudy and rainy days, photovoltaic power generation shows strong volatility, complicated changes, and relatively low accuracy. Under any weather condition, it can be seen that the higher the confidence level, the greater the corresponding interval coverage rate PICP, the greater the interval width percentage

PIMW, and the AD and PISI indices will decrease synchronously. In sunny weather, when the confidence level is 95%, the proposed method is used to construct the photovoltaic power generation power prediction interval, the average width percentage PIMWP value of the interval is the minimum value of 15.3, and the interval coverage rate PICP also reaches 92.1%, which further illustrates the proposed method. method can be used to make interval forecasts.

5.Conclusions

This paper proposes a differential autoregressive moving average model (ARIMA) and a sequence-to-sequence (Seq2Seq) combined model, and on this basis, introduces a short-term interval forecasting method for photovoltaic power generation power. The forecast of photovoltaic power generation plays an important role in the sustainable development and stability of my country's power grid. Compared with some developed countries, my country's photovoltaic power generation is still in a period of rapid development and has not been widely used in all aspects of life. At present, the accurate prediction is particularly important. This is not only the current national demand, but also provides a foundation for further research on photovoltaic power generation.

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