

# A Markov chain based photovoltaic power simulation method

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**Abstract.** Photovoltaic power generation has volatility and randomness, which affects the safety and reliability of the power system. In order to achieve accurate simulation of photovoltaic output, this paper proposes a photovoltaic power timing simulation method based on rolling sampled Markov chain model. Firstly, establish a photovoltaic output model and analyze the actual output characteristics; Then, based on the first-order Markov chain model, the relationship between adjacent days is considered, and a multistate transition probability matrix is established to construct an annual time series output model; Finally, based on the annual output data of a photovoltaic power station and historical meteorological monitoring data, an example is simulated to verify the effectiveness of the proposed method.

**Keywords:** Photovoltaic power generation, Markov chain, Time series power simulation, Power system

## 1. Introduction

In 2021, China's newly installed renewable energy capacity reached 134 million kilowatts, accounting for 76.1% of the country's newly added power generation capacity; The renewable energy generation has reached 2.48 trillion kilowatt hours, accounting for 29.8% of the total electricity consumption in society. It is predicted that the annual wind and photovoltaic power generation in China will reach 63.6% of the total annual power generation by 2050 [1-2]. The volatility and randomness of photovoltaics make their large-scale integration complex the structure and operational characteristics of power systems [3-5]. At the same time, the contradiction between the installed capacity of renewable energy and the limited system absorption capacity leads to a large number of "wind and solar curtailment" phenomena [6-7]. Therefore, reliable simulation of renewable energy output is particularly important for improving resource utilization and meeting the requirements of renewable energy station planning [8-10].

There are currently many studies on the timing production of renewable energy output. The reference [10] considers scenarios with different penetration rates of new energy, and combines the marginal probability distribution of new energy output, volatility of stochastic processes, and spatiotemporal correlation to establish a time-series production model for wind and photovoltaic power generation. The reference [11] comprehensively considered factors such as wind and solar power output characteristics and load characteristics, and constructed an annual time series production simulation model for the power grid containing new energy generation; The reference [12] proposes a time-series production simulation calculation method for power grid consumption of wind power output based on a large-scale wind power network, combining maximum load and minimum coincidence prediction methods.

Due to the gap between the models and constraints established by the current time series power simulation method and the actual situation, the seasonal and weather characteristics of new energy output, as well as the correlation between adjacent daytime output, cannot fully reflect the objective situation of new energy output [13]. Therefore, based on the construction of seasonal and weather state probability transition matrices, this article proposes a photovoltaic time series power simulation model based on rolling sampled Markov chains. Taking a photovoltaic power station in Jiangsu Province as an example, the model construction and simulation of photovoltaic output were completed, and the traditional sampling simulation, rolling sampling simulation generated sequence, and historical sequence were comprehensively compared. Through numerical examples, it has been verified that the rolling sampling simulation method proposed in this article not only considers the influence of seasons and weather on photovoltaic output, but also eliminates the fragmentation between adjacent months. The simulation results are superior to traditional algorithms.

## 2. Photovoltaic output model

The semiconductor photoelectric effect principle used in photovoltaic power generation converts light energy into electrical energy. Research has found that the output of photovoltaic power generation is as shown in equation (1) [14].

$$I_Q = N_a I_e - N_a I_h \left[ e^{\frac{q(U + I_h R_b)}{mKT N_b}} - 1 \right] \quad (1)$$

In the formula:  $I_Q$  is the load current,  $I_e$  is the photo generated current,  $I_h$  is the reverse saturation current value of the P-N junction,  $K$  is the Boltzmann constant,  $m$  is the ideal current factor,  $T$  is the battery temperature,  $U$  is the applied voltage value,  $R_b$  is the equivalent resistance value of the series resistor,  $N_b$  is the number of series resistors, and  $N_a$  is the number of parallel resistors.

Photovoltaic power generation is mainly affected by factors such as battery temperature and photocurrent, and the magnitude of photocurrent is mainly determined by the intensity of light radiation. Generally speaking, as the intensity of light radiation increases within a certain range, the more charge carriers are excited in the semiconductor material, resulting in a larger photogenerated current. The relationship between photogenerated current and light radiation intensity can be shown by equation (2).

$$I_e = \eta \cdot P_0 \cdot e^{-\alpha d} \quad (2)$$

In the formula,  $\eta$  is the photoelectric conversion efficiency,  $P_0$  is the incident light power density,  $\alpha$  is the absorption coefficient of semiconductor materials, and  $d$  is the optical path length.

In a photovoltaic power plant, assuming the presence of multiple photovoltaic panels of a certain area, the expression for photovoltaic power generation is shown in (3).

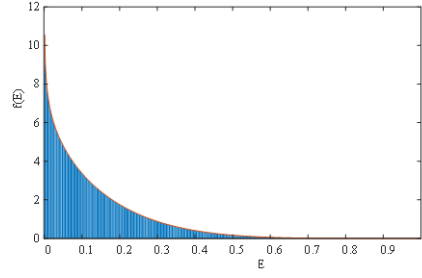
$$\begin{cases} P_{pv} = k S H_e \\ S = \sum_{j=1}^n S_j \end{cases} \quad (3)$$

In the formula,  $S$  is the total area of the photovoltaic panel,  $H_e$  is the solar irradiation intensity per unit area, and  $k$  is the conversion efficiency.

After research, it was found that the probability distribution of light intensity is similar to that of wind speed and can be represented by the Beta distribution function. That is, the probability density function of light intensity is shown in equation (4), as shown in Figure 1:

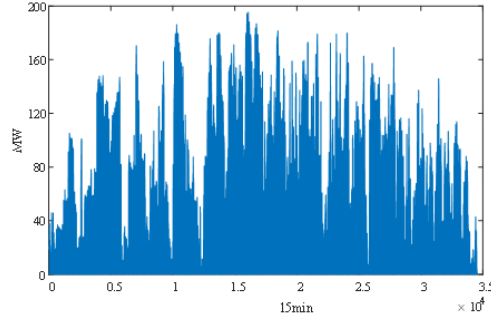
$$f\left(\frac{H}{H_{\max}}\right) = \frac{\Gamma(\theta + \beta)}{\Gamma(\theta)\Gamma(\beta)} \left(\frac{H}{H_{\max}}\right)^{\beta-1} \left(1 - \frac{H}{H_{\max}}\right)^{\theta-1} \quad (4)$$

In the formula,  $H$  is the actual intensity value of light, and  $H_{\max}$  is the maximum actual intensity value of light during the corresponding time period,  $\beta$  and  $\theta$  are function shape parameters.



**Figure 1.** Probability density curve of light intensity

Through the model analysis in the previous text, it can be found that the radiation intensity  $H_e$  of light can be determined by two discrete variables: the actual intensity  $H$  of light and the maximum value  $H_{max}$  of light, while the output power  $P_{pv}$  of photovoltaic power generation can be expressed linearly by the radiation intensity  $H_e$ . Therefore, this article believes that the output power of photovoltaic power generation and the intensity of light follow the same type of stochastic process. The actual intensity of light  $H$  is influenced by various factors. Figure 2 shows the 8760-hour photovoltaic output timing chart.



**Figure 2.** 8760h PV output curve

### 3. Markov Chain Photovoltaic Output Simulation Model

The rolling sampling Markov chain simulation method used in this article is based on the traditional Markov chain simulation method, which only has one state transition matrix. According to different months, seasons, and weather types, the transition probability matrix is divided into multiple interconnected output state transition probability matrices and weather transition probability matrices by rolling sampling the photovoltaic output historical data with a sampling period of 10 days and a sampling step of 1 day. Reduced the time span of the sampling interval, eliminated the discontinuity in the traditional method of the first and last days of adjacent months, and thus improved the accuracy of the model.

#### 3.1. A weather probability transition matrix considering seasonal characteristics

The probability transition matrix of weather, as the core of Markov time series simulation method, needs to classify weather types. Considering the factors of seasonal changes, the photovoltaic output is characterized by different output characteristics in four seasons within 12 months of a year. Therefore, the weather type for the whole year is first set, and based on this, the weather with higher frequency each month is statistically analyzed using a rolling sampling Markov chain, and a corresponding weather probability transition matrix is established. For example, in January, a weather probability transition matrix is established for 6 types of weather. The matrix form is as follows, where S, L, M, C, Y, and H represent the 6 types of weather that occur in a month, and  $P(L|S)$  represents the probability of the previous day's weather type S being L for that day.

$$P_{wt} = \begin{bmatrix} P(S|S) & P(L|S) & P(M|S) & P(C|S) & P(Y|S) & P(H|S) \\ P(S|L) & P(L|L) & P(M|L) & P(C|L) & P(Y|L) & P(H|L) \\ P(S|M) & P(L|M) & P(M|M) & P(C|M) & P(Y|M) & P(H|M) \\ P(S|C) & P(L|C) & P(M|C) & P(C|C) & P(Y|C) & P(H|C) \\ P(S|Y) & P(L|Y) & P(M|Y) & P(C|Y) & P(Y|Y) & P(H|Y) \\ P(S|H) & P(L|H) & P(M|H) & P(C|H) & P(Y|H) & P(H|H) \end{bmatrix} \quad (5)$$

### 3.2. State transition probability matrix considering seasonal and weather characteristics

Divide the output status sequence based on actual photovoltaic output or historical data of local weather factors. When selecting the output state, the output range is divided based on the actual power accuracy. When the output range is between  $P_{min}$  and  $P_{max}$ , selecting  $Pr$  as the accuracy value, the discrete state number  $N$  is  $(P_{max} - P_{min})/Pr$ , and the output sequence is  $\{X_1, X_2, \dots, X_t, \dots\}$ , where  $X_1$  corresponds to output  $(P_{min}, P_{min}+Pr)$ ,  $X_2$  corresponds to output state  $(P_{min}+Pr, P_{min}+2Pr)$ , and so on. Due to the differences in output characteristics under different weather conditions each month, compared to the original Markov model, which places all states into the same state transition matrix, this paper focuses on different months based on  $\alpha$  And weather type  $\beta$  Establish multiple state transition matrices  $P$  separately below  $\alpha, \beta$  Based on this, 365 state transition matrices were generated using a rolling sampling method. Compared to the original method, it eliminates the increase in error caused by the separation between adjacent months.

### 3.3. Simulated output sequence generation process

This article is based on the output situation and seasonal and weather characteristics of photovoltaic stations, and constructs a rolling sampling Markov chain model based photovoltaic output time series simulation method. The historical data is sampled by rolling with a sampling cycle of 10 days and a sampling step of 1 day. Specific step instructions:

Step 1: Sort the annual data by month  $\alpha$ , weather type  $\beta$  classify the daily photovoltaic output into upper and lower parts at 12:00 intervals, and obtain the power state transition probability matrix  $P_S$  of the photovoltaic output with a sampling period of 10 days;

Step 2: Assuming the initial moment is  $t_0$ , select the current output power value, determine its output state  $X_0$  through normalization operation, and select the initial month as  $\alpha_0$ , initial date is  $\eta_0$ ;

Step 3: Based on the initial  $\alpha_0$  and  $\eta_0$ . Determine the sampling starting point and generate the corresponding weather state transition matrix  $P_{\alpha_0, \beta}$  based on statistical probability for a total of 370 sets of data with a sampling period of 10 days. This matrix reflects the weather change patterns of adjacent two days and generates random numbers  $\varepsilon_0$ . Determine the initial weather type based on the probability matrix of weather state transition  $\beta_0$ .

Step 4: Obtain the next output state  $X_{t_1}$  from  $X_{t_0}$  and the power state transition matrix  $P_S$ , and generate a random number  $\varepsilon_1$ . Find the corresponding output change in the state transition probability matrix within the precision requirement value  $P_r$ , and superimpose it with the current output state to obtain the final  $X_{t_1}$ ;

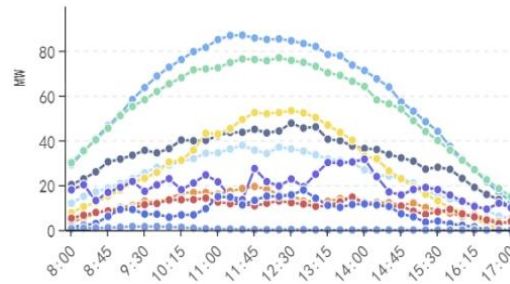
Step 5: Repeat step 4 in a loop until the simulation of the current day's output status is completed. Based on the weather conditions of the day, generate the predicted weather for the next day through the weather probability transition matrix, and generate the output status  $X_{m0}$  at the first moment of the next day. At the same time, generate the output status  $X_{m0}$  from the  $\beta_0$  and the probability matrix  $P$  of weather state transition  $P_{\alpha_0, \beta}$  tain the weather conditions for the next day  $\beta_1$ ;

Step 6: Execute steps 2 to 5, and also scroll back one day in sequence using the rolling sampling method to generate the output sequence for the next day, until all output sequences for 365 days of the year are generated.

#### 4. Simulation analysis

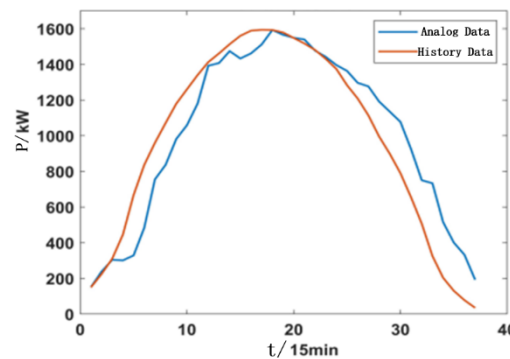
This example uses the daily radiation intensity data of a photovoltaic power station in Jiangsu Province from 8:00 to 17:00 throughout the year for simulation verification. The time interval for historical data is 15 minutes. The rated power of the photovoltaic power station is 3.5MW. Select 5kW as the required precision value for photovoltaic output.

This article focuses on the 10 main weather types classified by the National Meteorological Administration of China. The schematic diagram of 10 typical daily output curves for different weather conditions is shown in Figure 4.



**Figure 3.** PV output diagram of ten weather types

Generate the annual photovoltaic output power sequence using the rolling sampling Markov chain simulation method. Obtain its simulated photovoltaic output sequence throughout the day and compare it with the historical output sequence, Jan data shown in Figure 4.



**Figure 4.** Jan time series model PV output sequence

Due to certain differences between the simulated weather conditions and historical reality, there is a certain error in the average photovoltaic output generated by the simulation compared to the historical sequence, but the overall trend of change is consistent. The entire probability matrix is consistent with the actual situation

#### 5. Conclusions

This article proposes a photovoltaic output time series simulation method based on Markov chain model. Eliminated the problem of decreased model accuracy caused by fragmentation in adjacent months. The calculation results show that the improved time series production simulation method is more in line with historical data in terms of maximum photovoltaic output, with small errors, proving that the improved method is effective and feasible, consistent with the actual output change trend.

## References

- [1] LIU Dunnan, LI Qi, QIN Lijuan, ZHAO Jiawei. Evaluation of Grid Accepting Renewable Energy in Multi-Time Scale [J]. Electric Power Construction, 2017, 38(07): 44-50.
- [2] DING Ming, LIN Yajuan, PAN Hao. Probabilistic Production Simulation Considering Time Sequence Characteristics of Load and New Energy [J]. Proceedings of the CSEE, 2022, 206(11): 33-35+39.
- [3] ZUO Liguang, LIU Zhouzhou, PENG Xu. Evaluation of Cross-regional New Energy Consumption in Power Grid Based on Timing Production Simulation [J]. ENERGY AND ENERGY CONSERVATION, 2022, 206(11): 33-35+39..
- [4] LI Yudun, XIE Kaigui. Reliability assessment of power systems containing multiple wind farms [J]. JOURNAL OF ELECTRIC POWER SCIENCE AND TECHNOLOGY, 2011, 26(01): 73-76+103.
- [5] X. Peng, G. Gao, G. Hu, Y. Guo, J. Cao and J. Zhao. Research on Inter-regional Renewable Energy Accommodation Assessment Method Based on Time Series Production Simulation[C]//2019 IEEE Sustainable Power and Energy Conference, 2019, pp. 2031-2036.
- [6] YU Haifeng, HUANG Jingjie, JIANG Shiyao, et al. The overall energy storage configuration of wind farms considering the service life of electric energy storage [J]. JOURNAL OF ELECTRIC POWER SCIENCE AND TECHNOLOGY, 2022, 37(04):152-160.
- [7] LIU Chun, QU Jixian, SHI Wenhui. Evaluation Method of Ability of Accommodation Renewable Energy Based on Probabilistic Production Simulation [J]. Proceedings of the CSEE, 2020, 40(10): 3134-3144.
- [8] CHEN Qichao, LI Hui, WANG Shuai, et al. Sequential Operation Simulation Technology for Renewable Energy Accommodation Considering Multi-Energy Complementarity [J]. Electric Power Construction, 2019, 40(07): 18-25.
- [9] MEI Shengwei, WANG Yingying, LIU Feng. Game Theory Planning Model and Analysis of Wind-light-storage Hybrid Power System [J]. Automation of Electric Power Systems, 2011, 35(20): 13-19.
- [10] LIU Zhen, ZHENG Wencong. Reliability Evaluation of Microgrid Based on Typical Daily Method [J]. Telecom Power Technology, 2018, 35(03): 11-13.
- [11] YAO Jianfeng, LING Jing, QU Linan, DING Leiming, ZHENG Xiang, GAO Bingtuan. The Construction Method of Typical Scenario Set for Renewable Energy Based on Improved FCM Clustering Algorithm [J]. Power System and Clean Energy, 2019, 35(04): 76-82.
- [12] ZHANG Jun, XU Xiaoyan, HUANG Yongning, CAO Yang, GU Yujia. Optimal proportion study of wind and PV capacity in Ningxia power grid based on time sequence simulation [J]. Power System Protection and Control, 2014, 42(19): 81-86.
- [13] WU Guannan, ZHANG Mingli, XU Jianyuan, et al. Time series production algorithm for evaluating wind power accommodation capacity [J]. Power System Protection and Control, 2017, 45(23): 151-157.
- [14] ZHANG Bingliang, ZHANG Boyi, WU Yaowu, et al. An Approach to Evaluate the Capacity Benefits and Energy Benefits of Wind Farms Based on Probabilistic Product Simulation [J]. Power System Protection and Control, 2013, 46(08): 74-79.