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Prediction of Offshore Photovoltaic Installed Capacity Driven by Both System Dynamics and Policy Factors

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ABSTRACT

To address the impact of photovoltaic (PV) policies on the expansion of offshore PV installed capacity, this study proposes a prediction model based on system dynamics (SD) theory. This model quantifies policy types and practical situations, and the scoring results reflect the policy's influence effectiveness. The Grey Wolf Optimizer (GWO) is employed to optimize the influence coefficients of supportive, guiding, and developmental policy effectiveness within the model, thereby improving the model's precision and accuracy. First, a system dynamics model was constructed to analyze the relationships among PV power generation costs, revenues, installation willingness, and installed capacity. Then, the policy implementation effect was integrated into the SD model in the form of policy effectiveness, and a policy effectiveness evaluation system was established. Finally, simulation prediction and analysis were conducted. Predicted values of offshore PV installed capacity in Jiangsu Province from 2021 to 2024 were compared with actual data to verify the effectiveness of the model. Subsequently, offshore PV installed capacity and investment costs from 2025 to 2030 were simulated and analyzed. Case study results indicate that the predictions of the proposed model are consistent with industry development trends and provide valuable references.

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1. Introduction

With the ongoing transformation of the energy structure, offshore PV has emerged as a key research area due to its dual advantages of utilizing marine space resources and smoothing energy fluctuations [1-3]. In this context, evaluating the actual impact of PV policies on the offshore PV industry and accurately predicting changes in installed capacity can provide valuable insights for power grid operations and economic planning.

In recent years, numerous domestic and international scholars have researched and analyzed PV installed capacity forecasting. Reference [4] proposed an incentive policy forecasting model based on PV industry profits and costs, along with a user decision-making model for grid-connected PV methods. This served as the foundation for a system dynamics model of distributed PV installed capacity that incorporates the evolution of incentive policies. Reference [5] developed an evaluation model based on three dimensions: renewable energy policy intensity, policy objectives, and policy measures. The results indicate that the number of renewable energy policy documents issued in China generally follows the trend of overall policy effectiveness, , while average policy effectiveness remains relatively stable. In terms of trends, policy measures received higher average scores, suggesting that efforts should focus on enhancing the average effectiveness of policy intensity and objectives. Reference [6] collected PV industrial policy documents from 2010 to 2020, established a quantitative evaluation model, calculated annual policy effectiveness, and evaluated the implementation effects of different policy instruments. The results show that the number of PV industrial policies is generally consistent with the overall trend of policy effectiveness, albeit with significant fluctuations, while the average annual effectiveness varies less. Thus, it was found that, compared to environmental policies, the implementation effects of supply-side and demand-side policies are less effective.

The above studies evolve and predict the impact of China's PV policies from perspectives such as investment costs, policy intensity, and subsidies incentives, but they do not deeply investigate the influence of PV policies. Currently, the mainstream approach among domestic and foreign scholars for analyzing policy impacts on industry development is to quantify policy effects as policy effectiveness for analysis and evaluation. This paper integrates a system dynamics model, introduces policy effectiveness into the system dynamics model, and incorporates policy implementation effects into the causal feedback loop, thereby reducing prediction error [7-9].

Due to the difficulty in determining the influence coefficients of different types of policy effectiveness, random assignment can reduce accuracy. Therefore, swarm intelligence algorithms commonly used for optimization are particularly important. The GWO is an intelligent optimization algorithm inspired by the hunting behavior of grey wolf packs, proposed by Mirjalili *et al*. in 2014. This algorithm mimics the hierarchy and hunting mechanism of grey wolf society and achieves adaptive adjustment of core parameters through simply control of the number of wolves and the maximum number of iterations [10-14]. Using the root mean square error between the predicted and actual values as the objective function, the parameter set with the lowest fitness value is obtained, yielding the influence coefficients for supporting, guiding, and development-oriented policies.

Based on the aforementioned research, this paper proposes a system dynamics-based forecasting model for offshore PV installed capacity that considers the impact of different policies. Policy texts related to PV in China from 2019 to 2024 are transformed into policy effectiveness and introduced into the system dynamics forecasting model to analyze the impact of different policy types on offshore PV installed capacity. The grey wolf algorithm is then applied to optimize and calculate the influence coefficients of different policies, enabling the prediction of China's offshore PV installed capacity from 2021 to 2030. This provides a reference for subsequent power grid operations and economic planning.

The innovation of this research lies in transforming "policy effectiveness" from a static "switch variable" into a quantifiable, feedback-enabled endogenous dynamic variable, systematically embedding it into the SD framework, thereby constructing an integrated simulation model that aligns with real policy operation logic. The photovoltaic policy system was disaggregated into three major dimensions: supply-side, demand-side, and environmental. Static policy assumptions were dynamized, significantly enhancing the model's explanatory and predictive power for policy evolution. Building upon this, the study further introduces the GWO algorithm, using historical newly added installed capacity curves as the training target, to optimize the effectiveness parameters for supply, demand, and environmental policies, thereby improving the accuracy and speed of the capacity prediction process. This coupled framework demonstrates the impact of different policy types on installed capacity, providing verifiable dimensions and a basis for renewable energy policies.

2. System Dynamics Modeling

System dynamics is suitable for complex networks influenced by multiple parameters, possesses strong multi-information processing capabilities, and is applicable to dynamic behavior analysis of nonlinear relationships in networks [15-19]. This paper takes offshore PV installed capacity as the research object, comprehensively considers policy factors that directly affect the total revenue from offshore PV power sales such as per-kWh subsidies, sales electricity price, and benchmark on-grid electricity price and constructs a system dynamics prediction model for offshore PV installed capacity. Causal feedback relationships between different variables are represented by arrows, indicating that an increase or decrease in one variable causes changes in associated variables. The established system dynamics simulation model is shown in Fig. (**1**).

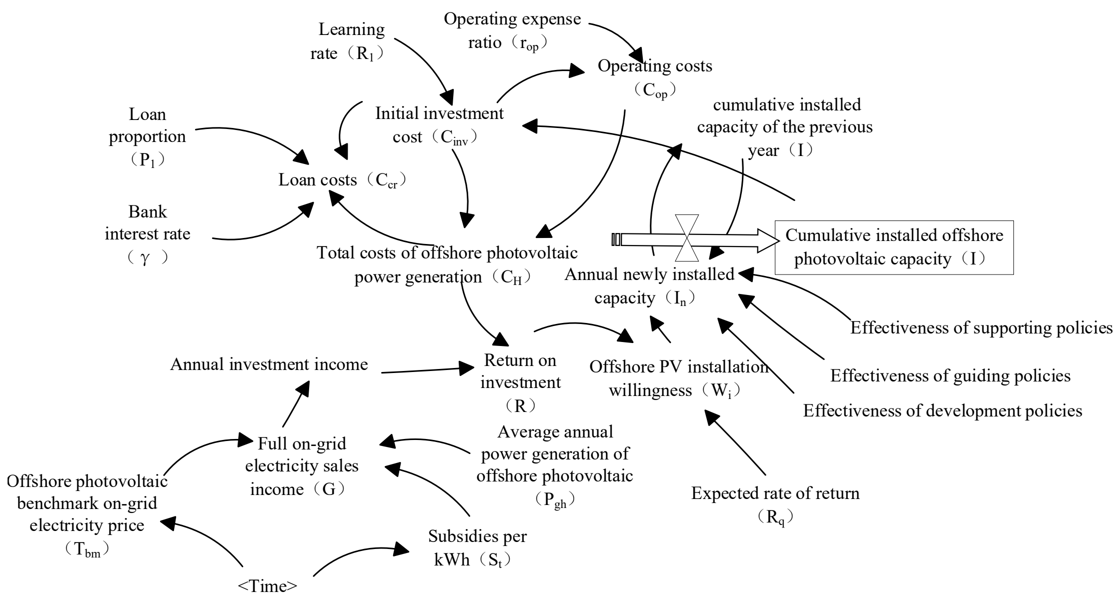

Figure 1: Policy and offshore PV development system dynamics model.

2.1. Model Building Analysis

The model constructed in this section sets the cumulative installed capacity of offshore PV as the primary state variable, with the corresponding flow variable being the annual newly installed capacity [20-25]. The remaining components, such as return on investment, willingness to install offshore PV, and total costs of PV power generation, are auxiliary variables. The influence mechanism between variables is as follows.

(1) The cumulative installed capacity of offshore PV, statistically measured at the end of each year, is taken as the cumulative amount, with the flow being the newly installed offshore PV capacity in the target year. The newly installed capacity in the target year is mainly affected by two factors: the newly installed capacity in the previous year and the willingness to install offshore PV in the target year. Therefore, determining the newly installed capacity in a given year requires calculating the actual installation willingness for offshore PV in that year.

(2) The willingness to install offshore PV power generation systems depends on the actual economic benefits of offshore PV projects. When the return on investment meets or exceeds expectations i.e., the higher the actual return on investment and the shorter the investment recovery period, the stronger the investment enthusiasm, and the greater the newly installed capacity of offshore PVs in that year.

(3) Offshore PV can participate in electricity market transactions through models such as "full on-grid" to sell electricity and can also obtain profits from national per-kWh subsidies in addition to electricity price revenue. These two sources collectively constitute the annual return on offshore PV investment. Power generation revenue is directly related to factors such as per-kWh subsidies, sales electricity prices, and on-grid electricity price, which are often adjusted based on government or grid documents, causing revenue fluctuations that affect project investment willingness.

(4) Typically, investment costs include initial investment cost (i.e., installation cost), operating costs, and loan costs. According to the learning effect of the offshore PV industry, installation cost usually decreases gradually as the cumulative installed capacity of offshore PV expands. Thus, an increase in offshore PV installed capacity leads to changes in investment costs, forming a feedback loop between installed capacity and return on investment.

2.2. Specific Modeling of Each Module

The system dynamics model built in this study is divided into four modules: revenue module, costs module, installation willingness module, and installed capacity module [26-32]. The specific modeling processes for each module are as follows.

2.2.1. Revenue Module

The revenue module in the system dynamics model primarily consists of power generation revenue. The revenue obtained by offshore PV through "full grid connection" is expressed as:

$$G(t) = P_{\text{gh}} \cdot T_{\text{bm}} + P_{\text{gh}} \cdot S_t \tag{1}$$

where $G(t)$ is the power generation revenue from full on-grid access in year t; T_{bm} is the benchmark on-grid electricity price for PV power; P_{gh} is the annual average power generation of offshore PV, and S_t is the per-kWh subsidy from the renewable energy development fund.

2.2.2. Cost Module

The total cost of investing in offshore PV power generation systems typically includes initial investment cost, loan cost, and operating cost, as follows:

$$C_H(t) = C_{\text{inv}}(t) + C_{\text{op}}(t) + C_{\text{cr}}(t) \tag{2}$$

where $C_H(t)$ is the total offshore PV power generation cost in year t; $C_{\text{inv}}(t)$, $C_{\text{op}}(t)$, and $C_{\text{cr}}(t)$ are the initial investment cost, operating cost, and loan cost in year t, respectively.

The initial investment cost covers equipment purchase costs (e.g., PV modules and grid-connected inverters), system design costs, installation costs, and other related expenses. The initial investment cost of offshore PV systems decreases as the PV industry expands. The learning curve is often used to describe this phenomenon. The equation is as follows:

$$C_{\text{inv}}(t) = C_{\text{inv0}} \left[\frac{I(t)}{I_0}\right]^{\lambda} \tag{3}$$

$$R_l = 1 - 2^{\lambda} \tag{4}$$

where $C_{\text{inv}}(t)$ is the initial investment cost of the selected base year; $I(t)$ is the cumulative installed capacity of offshore PV in year t; I_0 is the cumulative installed capacity in the base year; λ is the elasticity coefficient, and R_1 is the learning rate, indicating that when the installed capacity doubles, the initial investment cost reduces to $1 - R_l$of the previous value.

Operating costs are estimated as a proportion of the initial investment cost, with the operating cost rate set as r_{op}:

$$C_{\mathrm{op}}(t) = C_{\mathrm{inv}}(t) \cdot r_{\mathrm{op}} \tag{5}$$

Assuming the loan proportion (%) of the initial investment cost is P_1, and the bank interest rate is γ, the loan cost is:

$$C_{\mathrm{cr}}(t) = C_{\mathrm{inv}}(t) \cdot P_l \cdot \gamma \tag{6}$$

2.2.3. Installation Intention Module

Research indicates that the ratio of actual to expected return on investment directly affects investment decisions for offshore PV projects. The installation intention is expressed as:

$$W_i(t) = \frac{R(t)}{R_q} \tag{7}$$

where $W_i(t)$ is the installation intention in year t; $R(t)$ is the actual return on investment in year t; and R_q is the expected return on investment.

The return on investment is defined as the ratio of annual income to the total investment costs:

$$R_t = \frac{G(t)}{C_H(t)} \times 100\% \tag{8}$$

2.2.4. Installed Capacity Module

The annual cumulative installed capacity $I(t)$ of offshore PV is the sum of the previous year's cumulative installed capacity $I(t-1)$ and the newly installed capacity$I_n(t)$ of that year. The newly installed capacity in a given year is proportional to the product of the installation intention and the newly installed capacity of the previous year:

$$I(t) = W_i(t) \cdot I_n(t-1) + I(t-1) \tag{9}$$

3. policy Effectiveness Evaluation System

To comprehensively consider the multi-level impacts of policies on offshore PV development and improve prediction accuracy, this paper introduces the policy implementation effects as policy effectiveness into the system dynamics model and applies the Grey Wolf Optimizer algorithm for optimization.

3.1. Policy Effectiveness Evaluation Module

This paper evaluates the implementation effect of China's PV policies from three perspectives: policy intensity, policy objectives, and policy measures, based on established domestic and international policy effectiveness evaluation systems. The evaluation criteria are shown in Table **1** [33-39].

The three types are classified as follows:

1. Supporting policies: The government promotes the high-quality development of the PV industry through technical support, PV poverty alleviation, and financial subsidies.
2. Guiding policies: The government uses policy planning, project pilots and other measures to drive PV industry development through planning coordination, guidance, and other methods.
3. Development policies: The government focuses on creating a vigorous development environment and market order through legal supervision, tax exemption, specification formulation, and other methods.

After formulating the quantization assessment method for PV policies, the annual policy effectiveness of each type is calculated as follows:

Table 1: Policy document quantification table.

Policy Text	Quantitative Score	Quantitative Standard
Policy Impact	5	Statutes promulgated by the National People's Congress and its Standing Committee
	4	Regulations promulgated by the State Council and various ministries and commissions
	3	Interim regulations promulgated by the State Council, and regulations, provisions, and decisions promulgated by various ministries and commissions
	2	Plans, outlines, and interim provisions of various ministries and commissions
	1	Notices and announcements promulgated by various ministries and commissions
Policy Objective	5	Policy objectives are clear and quantifiable, and clear standards are proposed
	3	Policy objectives are relatively specific, but lack quantifiable standards
	1	The policy's expectations and visions were only expressed from a macro perspective
Policy Measures	5	The measure system is complete, and entities bearing liability and enforcement mechanisms are clarified
	4	Detailed implementation measures are proposed for specific PV projects, specifying content, arrangements, etc., for a certain period
	3	Basic implementation measures and relevant policy observations are proposed regarding PVs, but overall, macro-level requirements are proposed
	2	The policy involves PVs, and some basic enforcement content is proposed
	1	Merely PVs are mentioned, and specific implementation means are not proposed

$$P_{\mathrm{ES}}(t) = \sum_{i=1}^{n_s} (g_i + m_i)\, p_i \tag{10}$$

$$P_{\mathrm{ED}}(t) = \sum_{i=1}^{n_d} (g_i + m_i)\, p_i \tag{11}$$

$$P_{\mathrm{EE}}(t) = \sum_{i=1}^{n_e} (g_i + m_i)\, p_i \tag{12}$$

where t is the year of policy implementation; $P_{\mathrm{ES}}(t)$, $P_{\mathrm{ED}}(t)$, and $P_{\mathrm{EE}}(t)$ are the overall policy effectiveness of support, guidance, and development policies in year t; n_s, n_d, and n_e are the total quantity of support, guidance, and development policies in year t; g_i,m_i, and $p_i$are the policy destination score, policy measure score, and policy strength score of the *i*-th PV policy, respectively.

After introducing the policy effectiveness module, the cumulative installed offshore PV capacity per year can be expressed based on equation (9) as:

$$I(t) = I_n(t)[1 + \eta_s P_{\mathrm{ES}}(t - l_s) + \eta_d P_{\mathrm{ED}}(t - l_d) + \eta_e P_{\mathrm{EE}}(t - l_e)] + I(t - 1) \tag{13}$$

where η_s, $\eta_d$and $\eta_e$are the influence coefficients of supporting, guiding, and development policy effects on the annual newly installed capacity, respectively; and l_s, l_d, and l_e are the lag periods of the supporting, guiding, and development policy effects, respectively.

For policy effectiveness assessment values, considering policy lag effects, monetary policy has a long implementation lag, and fiscal policy has a long decision-making lag. While developed regions, despite smooth transmission, have long cycles, emerging markets may experience faster but more unstable effects due to immature institutions, or may fail entirely. Therefore, policies related to the photovoltaic industry, promulgated by the State Council and various ministries and commissions from 2019 to 2024, were retrieved from websites for effectiveness assessment. Policy effects from 2025 to 2030 were estimated based on 2019 to 2024 data. Given the chaotic nature of annual policy effects, the ARMA time series model integrating trending and mean-regression theories was used for forecasting. The statistical results of policy effects from 2019 to 2030 are shown in Fig. (**2**).

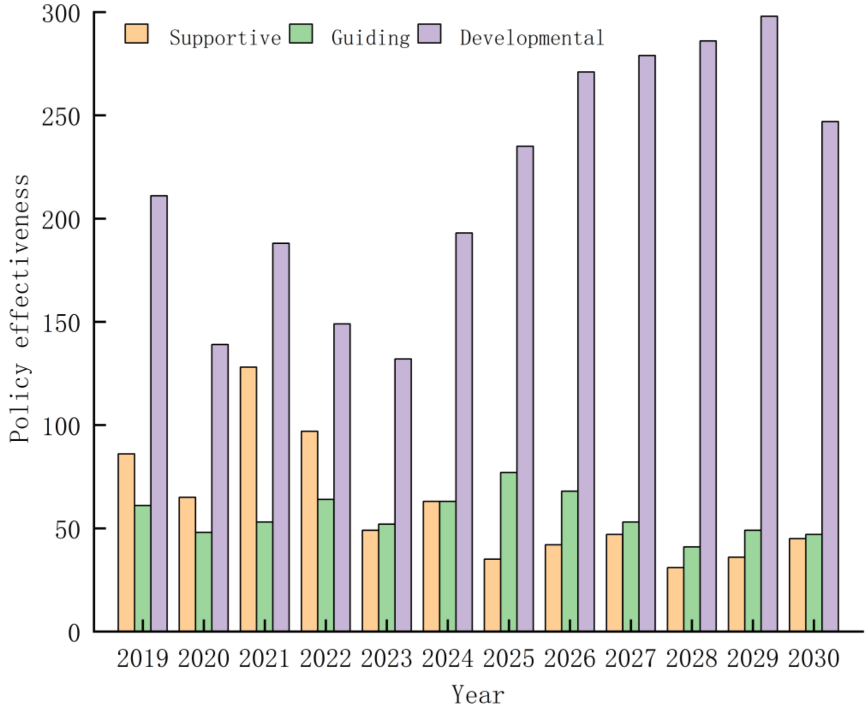

Figure 2: Policy effectiveness statistics, 2019-2030.

3.2. Grey Wolf Optimizer

Since the influence coefficients of supportive, guiding, and developmental policies on the annual newly installed capacity of offshore PV power are difficult to determine, the Grey Wolf Optimizer algorithm is used to optimize these parameters to improve forecasting accuracy and effectiveness [40-46].

GWO was proposed by Mirijalili *et al*. in 2014 as a swarm intelligence optimization algorithm based on grey wolves hunting behavior. The GWO algorithm has attracted attention due to its simple structure and global convergence advantages [47-50]. During hunting, grey wolves update their positions by tracking the top three wolves. In a D-dimensional space, a population of N grey wolves is represented as $\boldsymbol{X} = (\boldsymbol{X_1}, \boldsymbol{X_2}, ..., \boldsymbol{X_N})$, and the vector position of the *i*-th grey wolf is $\boldsymbol{X_i} = [\boldsymbol{X_{i1}}, \boldsymbol{X_{i2}}, ..., \boldsymbol{X_{iD}}]^T$. After solving the fitness value for each wolf and determining their fitness and positions, candidate wolves adjust their mobility vector according to:

$$\begin{cases} X_1 = X_\alpha - A_1 \cdot (D_\alpha) \\ X_2 = X_\beta - A_2 \cdot (D_\beta) \\ X_3 = X_\delta - A_3 \cdot (D_\delta) \end{cases} \tag{14}$$

$$A_k = 2a \cdot r_1 - a, \quad k = 1,2,3 \tag{15}$$

where $\boldsymbol{D_\alpha}$, $\boldsymbol{D_\beta}$, and $\boldsymbol{D_\delta}$ represent the distances of gray wolf $\boldsymbol{X_i}$ from the top three wolves , $\boldsymbol{X_1}$, $\boldsymbol{X_2}$, ..., $\boldsymbol{X_3}$ respectively, represent the mobility vectors toward $\boldsymbol{X_i}$, $\boldsymbol{\alpha}$ is the convergence factor, and $\boldsymbol{r_1}$ is a random number in [0, 1].

The GWO algorithm is improved by adjusting the self-adapting value of the parameter $\boldsymbol{\alpha}$ and updating the candidate wolf's position using a weighted sum of the top three wolves' positions. The candidate wolf updates its fitness and positioning via Equation (19) to enhance local and global convergence:

$$w_1 = 2A_1 \cdot r_2, \quad w_2 = 2A_2 \cdot r_2, \quad w_3 = 2A_3 \cdot r_2 \tag{16}$$

$$a(t) = \frac{1-(iter/iter_{max}}{1-\mu\cdot(iter/iter_{max}} \tag{17}$$

$$X(t+1) = \frac{w_1 \cdot X_1 + w_2 \cdot X_2 + w_3 \cdot X_3}{w_1 + w_2 + w_3} \tag{18}$$

where $r_2$is a random number in [0, 1]; $iter$is the current iteration number; $iter_{max}$is the maximum iteration number; μ is a nonlinear coefficient in (0, 3).

The GWO algorithm flow is shown in Fig. (**3**), where the objective function is the root mean squared error (RMSE) between predicted and actual values. RMSEbest, RMSEmin, and RMSEi are the global minimum RMSE, current minimum RMSE, and RMSE of the *i*-th iteration, respectively. By adjusting model parameters (or algorithm parameters), RMSE is minimized to bring predicted values closer to actual values.

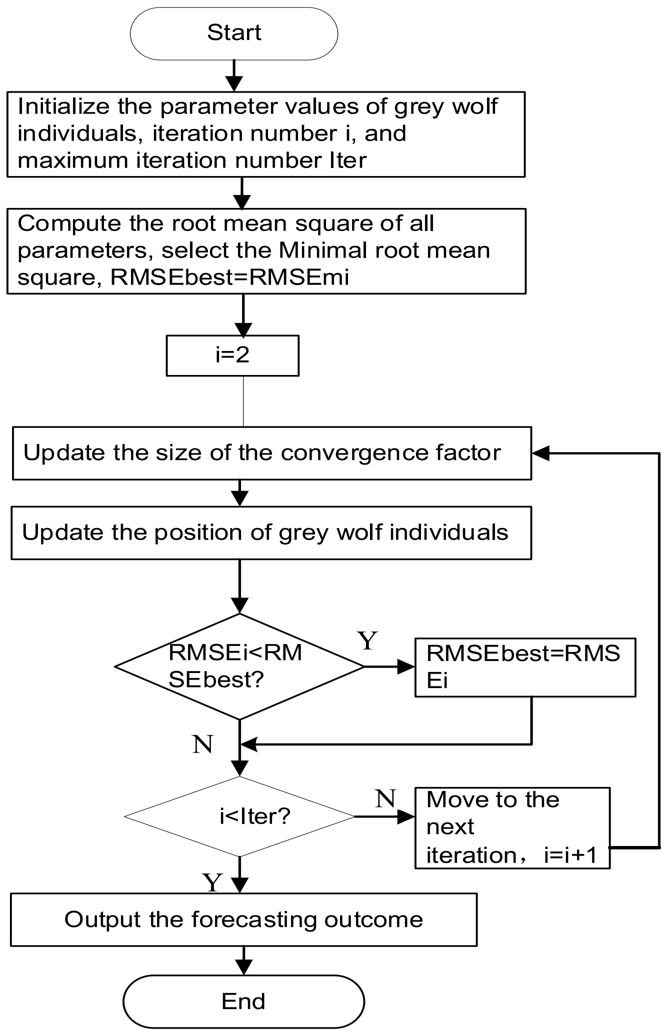

Figure 3: Flowchart of system dynamics model solution based on Grey Wolf Optimization Algorithm.

The influence coefficients of supportive, guiding, and developmental Policy effectiveness are optimized using GWO. The resulting coefficients are 0.00192, 0.00325, and -0.00164, respectively. The convergence curve is shown in Fig. (**4**).

From the figure, it can be observed that after 50 iterations, the fitness value gradually stabilizes, and further increasing the number of iterations offers only limited improvements in solution precision. Considering the trade-off between computational efficiency and solution accuracy, the maximum number of iterations is ultimately set to 50 in this study. Additionally, the population size is set to 30, a size that ensures the algorithm's convergence performance while effectively maintaining diversity.

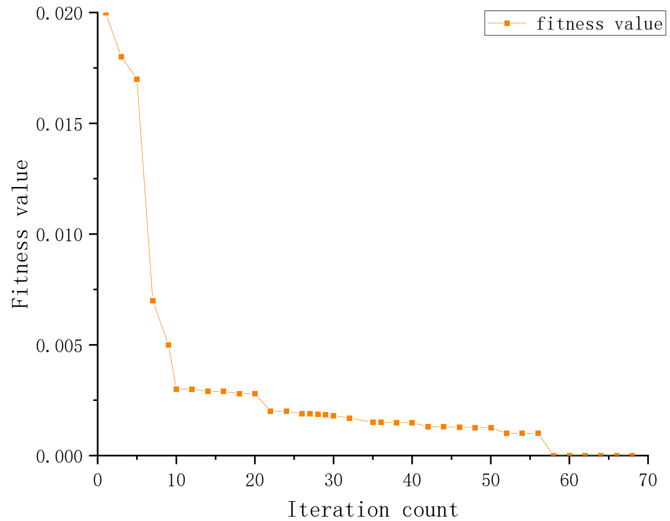

Figure 4: GWO Algorithm Convergence Process.

4. Simulation Analysis

4.1. Parameter Setting

This study uses Vensim PLE software to develop an SD-based prediction model for offshore PV installed capacity and investment costs. Data from the National Energy Administration (NEA) and the GWO method are used to calibrate and optimize simulation parameters. The model predicts development trends of offshore PV installed capacity and initial investment cost in Jiangsu Province, China from 2021 to 2030.

According to the National Development and Reform Commission (NDRC) policy issued in June 2021, for Jiangsu Province in 2021(the initial simulation year), new centralized PV power stations and industrial/commercial distributed PV projects filed since 2021 adopt grid parity, with on-grid electricity prices set according to the local coal-fired power benchmark price. Projects completed before 2021 follow the original electricity price policy.

For offshore PV benchmark projects from 2021 onward, on-grid electricity price changes are simulated using the "coal-fired power benchmark price + floating adjustment" method. As of 2021, no offshore PV feed-in tariff subsidies had been introduced. For reference, the NDRC has clarified a subsidy of CNY 0.42/kWh for distributed PV; data for 2022–2024 were obtained from relevant documents.

This study collected data on annual effective utilization hours of PV power in nearshore cities of Jiangsu Province, calculated the average annual power generation per unit installed capacity, and set the 2021 installation cost as the base year initial investment cost (2021). Based on market research, the procurement cost of offshore PV equipment in Jiangsu in 2021 was approximately CNY 3/W. Considering installation and design costs, the initial investment cost was determined to be CNY 6.2/W.

Based on current market operations and relevant research, the loan-to-investment ratio (%) for PV power generation projects is 35%-70%; bank loan interest rates are 3.5%-6.5%; and the expected return on investment (ROI) is generally 5%-15%. For these variables, the GWO algorithm is used for optimization.

The initial parameter settings are shown in Table **2**.

4.2. Simulation Result Analysis

With 2021 as the initial year, the proposed model is used to forecast and analyze the development trends of cumulative installed capacity and initial investment cost of offshore PV in Jiangsu Province from 2021 to 2030.

Table 2: Initial parameter settings.

Model Parameters	Initial Value	Model Parameters	Initial Value
T_s/*Yuan*·(kW·h)$^{-1}$	0.5283	C_{inv0}/*Yuan*·kW^{-1}	6200
S_t/*Yuan*·(kW·h)$^{-1}$	0.42	R_1/ %	15
T_{des}/*Yuan*·(kW·h)$^{-1}$	0.391	T_{bm}/*Yuan*·(kW·h)$^{-1}$	0.391

4.2.1. Model Validity Verification

The proposed model is used for backtesting of offshore PV installed capacity in Jiangsu Province from 2021 to 2024. The backtesting results are shown in Fig. (**5**). By comparing the predicted values with the actual values, it can be observed that the average percentage error between the predicted cumulative installed capacity (considering policy effectiveness) and the actual cumulative installed capacity is 5%, confirming the model's prediction accuracy.

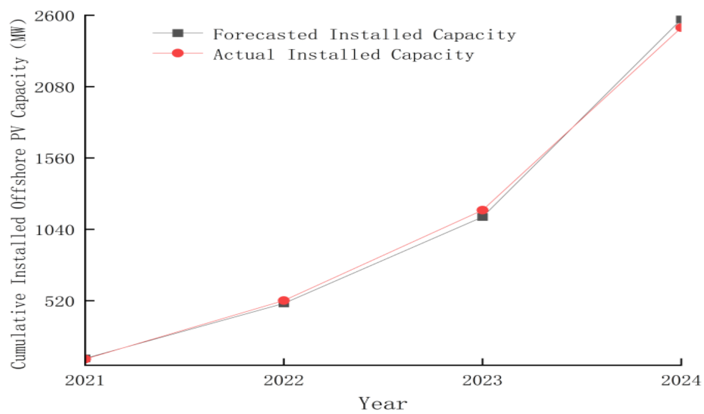

Figure 5: Backtesting of cumulative installed capacity of offshore PV.

4.2.2. Prediction of Future Data

After validating the model, it is used to predict and analyze the development trends of cumulative installed capacity and initial investment cost of offshore PV in Jiangsu Province from 2025 to 2030. The results are shown in Fig. (**6**).

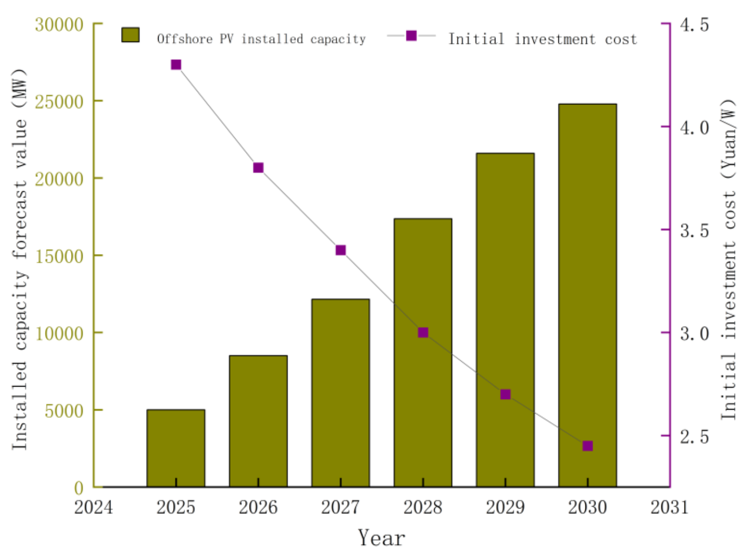

Figure 6: Development trend of cumulative installed capacity and cost of offshore PV.

As shown, Jiangsu Province has been steadily increased support for renewable energy, and offshore PV technology has advanced. Reduced costs of offshore PV modules offset the revenue gap from phased subsidy reductions, maintaining a high investment return rate and driving steady growth in installed capacity. The cumulative offshore PV installed capacity in Jiangsu Province is estimated to reach 24,557 MW by 2030, while the initial investment cost decreases to 2.44 Yuan/W.

5. Conclusion

This paper proposes a system dynamics prediction model that considers the impact of PV policy effectiveness on offshore PV installed capacity growth, with a focus on PV policies. The model predicts and analyzes China's cumulative offshore PV installed capacity from 2021 to 2030 and the initial investment cost from 2025 to 2030, and draws the following conclusions and future policy development recommendations:

1. Incorporating the effectiveness of different policy types into the system dynamics causal chain significantly improved prediction accuracy, reflected policy impacts, and brought predicted values closer to actual values. Using the policy-influenced System Dynamics Model, the development trends of cumulative installed capacity and initial investment cost from 2025 to 2030 were predicted.1. The results indicate that, with increasing policy support and technological advancements, installed capacity has gradually increased while investment costs have decreased. By 2030, cumulative installed capacity is projected to reach 24,557 MW, and the initial investment cost will decrease to 2.44 yuan/w.
2. Due to the difficulty in determining the influence coefficients of supportive, guiding, and developmental policies, the Grey Wolf Optimizer was employed for parameter optimization, which effectively improved prediction speed and accuracy. Therefore, policies need to clearly define the investment entities and construction standards for offshore PV, lower the grid connection threshold for projects, and ensure the effective implementation of policies.
3. Based on the results of policy impact effectiveness, policies that have a positive impact on the growth of offshore PV installed capacity should be prioritized for implementation and supplemented with corresponding subsidies. Simultaneously, the implementation effectiveness of policies is monitored in real time. In cases where the actual effects deviate from model predictions, the intensity and direction of policies are adjusted promptly, and policy support for these weak links is specifically strengthened to ensure comprehensive coverage of policy effects.
4. The proposed model can quantitatively assess the dynamic impact of key influencing factors on offshore photovoltaic installed capacity, reveal synergistic or substitutive relationships between different policy instruments, and facilitate the consideration of synergistic effects among different policy types. For example, model training has revealed that the combination of subsidy policies and tax break policies has a greater promotional effect on installed capacity growth than implementing subsidy policies alone. Therefore, implementers can better utilize model results for practical guidance.

Conflict of Interest

The authors declare no conflict of interest.

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References

[1] Li L, Zhang Z, Bi G, Kan X, Chen S. Research on carbon emission reduction policy for the power-generation industry based on system dynamics under the "Double Carbon" target. Power Syst Protect Control. 2024; 52(12): 69-81. https://doi.org/10.19783/j.cnki.pspc.231656

[2] Shu Z, Zhu K, Wang C. Virtual power plants participating in day-ahead electricity market bidding strategy considering carbon trading. Electr Power Eng Technol. 2024; 43(5): 58-68,149.

[3] Wu L, Liu F, Xin J. Installed capacity forecast of distributed PVs incorporating the influences of incentive policies. Proc CSU-EPSA. 2020;32(10):104-10.

[4] Che X, Zhou P, Chai K. Regional policy effect on photovoltaic (PV) technology innovation: findings from 260 cities in China. Energy Policy. 2022; 162: 112807. https://doi.org/10.1016/j.enpol.2022.112807

[5] Lan Z. Evaluation of the efficacy, effect and coordination of renewable energy policies in China: quantitative analysis of policy documents from 1995 to 2018. J Dalian Univ Technol (Soc Sci). 2021; 42(5): 112-22. https://doi.org/10.19525/j.issn1008-407x.2021.05.014

[6] Wang B, Yu P. Evaluation on the policy efficacy and effect of photovoltaic industry: quantitative analysis of China's policy texts from 2010 to 2020. Soft Sci. 2022; 36(8): 9-16. https://doi.org/10.13956/j.ss.1001-8409.2022.08.02

[7] Wang G, Yang J, Fan J, Zhang G, Li Z. Load frequency optimization control of a photovoltaic microgrid based on the grey wolf algorithm. Electron Des Eng. 2025; 33(15): 148-52. https://doi.org/10.14022/j.issn1674-6236.2025.15.031

[8] Duan S, Jin X. Optimal allocation of distributed photovoltaics based on improved grey wolf algorithm. China New Technol Prod. 2025; (6): 23-5. https://doi.org/10.13612/j.cnki.cntp.2025.06.023

[9] Chen W, Xiang Y, Peng G, Liu Y, Liu J. System dynamic modeling and analysis of power system supply side morphological development with dual carbon targets. J Shanghai Jiao Tong Univ. 2021; 55(12): 1567-76. https://doi.org/10.16183/j.cnki.jsjtu.2021.294

[10] Duan W, Qi Y, Gong F, Xu D. A review on combination of system dynamics and economic management theories and methods. Stat Decis. 2022; 38(2): 41-6. https://doi.org/10.13546/j.cnki.tjyjc.2022.02.008

[11] Lu Z, Chen Y, Sun W. Feasibility analysis of photovoltaic power to grid parity based on optimized LCOE model. Acta Energiae Solaris Sinica. 2021; 42(8): 153-8. https://doi.org/10.19912/j.0254-0096.tynxb.2019-0571

[12] Cai Q, Ren H, Qiu L, Wu Q. Evolution of PV installed capacity and evaluation of policy effect based on system dynamics. Renew Energy. 2016; 34(4): 481-7. https://doi.org/10.13941/j.cnki.21-1469/tk.2016.04.002

[13] Wu L, Xin J, Wang C. Installed capacity forecasting for distributed photovoltaic considering herd mentality of users. Autom Electr Power Syst. 2022; 46(14): 83-92. https://doi.org/10.7500/AEPS20210902006

[14] Wang W, Zhao XG. Can the incentive policies promote the diffusion of distributed photovoltaic power in China? Environ Sci Pollut Res. 2022; 29(20): 30394-409. https://doi.org/10.1007/s11356-021-17753-3

[15] Kamboj VK, Nandi A, Bhadoria A, Sehgal S. An intensify Harris Hawks optimizer for numerical and engineering optimization problems. Appl Soft Comput. 2020; 89: 106018. https://doi.org/10.1016/j.asoc.2019.106018

[16] Song Y, Wang Y, Yuan S, Dai T. System dynamics analysis model of photovoltaic energy storage power station for grid parity. Proc CSU-EPSA. 2022; 34(7): 129-36. https://doi.org/10.19635/j.cnki.csu-epsa.000857

[17] Zeng F, Zhang J. Temporal and spatial characteristics of power system inertia and its analysis method. Proc CSEE. 2020; 40(1): 50-8. https://doi.org/10.13334/j.0258-8013.pcsee.190084

[18] Wen Y, Yang W, Lin X. Review and prospect of frequency stability analysis and control of low-inertia power systems. Electr Power Autom Equip. 2020; 40(9): 211-22. https://doi.org/10.16081/j.epae.202009043

[19] Li D, Dong N, Yao Y, Xu B. Equivalent inertia estimation of a power system containing wind power considering dispersion of frequency response and system partitioning. Power Syst Protect Control. 2023; 51(3): 36-45. https://doi.org/10.19783/j.cnki.pspc.220472

[20] Wang Q. Forecast of China's wind power installed capacity and corresponding CO_2 reduction from 2020 to 2060. Ecol Econ. 2021; 37(7): 13-21.

[21] Sun H, Wang B, Li W, Yang C, Wei W, Zhao B. Research on inertia system of frequency response for power system with high penetration electronics. Proc CSEE. 2020; 40(16): 5179-92. https://doi.org/10.13334/j.0258-8013.pcsee.200493

[22] Zhang X, Liu X, Zhong J. Integrated energy system planning considering a reward and punishment ladder-type carbon trading and electric-thermal transfer load uncertainty. Proc CSEE. 2020; 40(19): 6132-42. https://doi.org/10.13334/j.0258-8013.pcsee.191302

[23] Cao Y, Mu Y, Jia H, Yu X, Song Y, Wu K. Multi-stage planning of park-level integrated energy system considering construction time sequence. Proc CSEE. 2020; 40(21): 6815-28. https://doi.org/10.13334/j.0258-8013.pcsee.200622

[24] Fu W, Wang Y, Shen H, Tao P, Wang S, Li K, *et al*. Residential customer baseline load estimation based on Latin hypercube sampling and scenario subtraction. Power Syst Technol. 2022; 46(6): 2298-307. https://doi.org/10.13335/j.1000-3673.pst.2021.1207

[25] Chen C, Jia L, Zhao T, Shao C, Wang Y. Research review on topology and control strategy of PV and energy storage connected to railway traction power supply systems. Trans China Electrotech Soc. 2024; 39(24): 7874-901. https://doi.org/10.19595/j.cnki.1000-6753.tces.232167

[26] Alhousni FK, Nwokolo SC, Meyer EL, Alsenani TR, Alhinai HA, Ahia CC, *et al*. Multi-scale computational fluid dynamics and machine learning integration for hydrodynamic optimization of floating photovoltaic systems. Energy Inform. 2025; 8(1): 103. https://doi.org/10.1186/s42162-025-00567-9

[27] Zhao J, Tang O, Zhang Q, Zhou D. Can reshoring policies hinder China's photovoltaic module exports? A dynamic perspective. Energy. 2025; 327: 136382. https://doi.org/10.1016/j.energy.2025.136382

[28] Kaaviya R. Optimizing rooftop photovoltaic adoption in urban landscapes: a system dynamics approach for sustainable energy transitions in Chennai, India. Environ Prog Sustain Energy. 2025; 44(3): 14603. https://doi.org/10.1002/ep.14603

[29] Marcuzzo R, Silberg TR, Uriona-Maldonado M. Growth of residential solar energy in Brazil: a system dynamics approach. Renew Sustain Energy Rev. 2025; 215: 115582. https://doi.org/10.1016/j.rser.2025.115582

[30] Dimd BD, Garcia AS, Bellmann M. Empirical analysis of bifacial photovoltaic modules in high-latitude regions: performance insights from a field laboratory in Norway. Energy Convers Manage. 2024; 325: 119396. https://doi.org/10.1016/j.enconman.2024.119396

[31] Alinia AM, Sheikholeslami M. Simulation of thermal storage system involving solar panel equipped with thermoelectric modules in existence of mixture of paraffin and nanomaterial. J Energy Storage. 2025; 106: 114699. https://doi.org/10.1016/j.est.2024.114699

[32] Zapata SS, Gomez DA, Aristizabal AJ, Castaneda M, Romero-Gelves JI. Assessing the diffusion of photovoltaic technology and electric vehicles using system dynamics modeling. J Cleaner Prod. 2024; 42(6): 2351-69. https://doi.org/10.1177/01445987241277917

[33] Satpathy A, Dhar S, Dash PK, Bisoi R, Nayak N. A new representation learning-based maximum power operation towards improved energy management integration with DG controllers for photovoltaic generators using online deep exponentially expanded RVFLN algorithm. Appl Soft Comput. 2024; 166: 112185. https://doi.org/10.1016/j.asoc.2024.112185

[34] Guo XR, Ming B, Cheng L, Yu M, San M, Jakub J. Modelling long-term operational dynamics of grid-connected hydro-photovoltaic hybrid systems. J Energy Storage. 2024; 99(Pt B): 113403. https://doi.org/10.1016/j.est.2024.113403

[35] Qingyang J, JiChunY, Yangying Z, Huide F. Energy and exergy analyses of PV, solar thermal and photovoltaic/thermal systems: a comparison study. Int J Low-Carbon Technol. 2021; 16(2): 604-11. https://doi.org/10.1093/ijlct/ctaa092

[36] Abdollahi R. Impact of wind on strength and deformation of solar photovoltaic modules. Environ Sci Pollut Res. 2021; 28(17): 1-10. https://doi.org/10.1007/s11356-020-12111-1

[37] Assoa YB, Thony P, Messaoudi P, Schmitt E, Bizzini O, Gelibert S, *et al*. Study of a building integrated bifacial photovoltaic façade. Sol Energy. 2021; 227: 497-515. https://doi.org/10.1016/j.solener.2021.09.004

[38] Al-Refaie A, Lepkova N. Satisfaction with rooftop photovoltaic systems and feed-in-tariffs effects on energy and environmental goals in Jordan. Processes. 2024; 12(6): 1175. https://doi.org/10.3390/pr12061175

[39] Kwok KH, Savaget P, Fukushige S, Halog A. The necessity for end-of-life photovoltaic technology waste management policy: a systematic review. J Cleaner Prod. 2024; 461: 142497. https://doi.org/10.1016/j.jclepro.2024.142497

[40] Wang Y, Wang R, Tanaka K, Ciais P, Penuelas J, Balkanski Y, *et al*. Global spatiotemporal optimization of photovoltaic and wind power to achieve the Paris Agreement targets. Nat Commun. 2025; 16(1): 2127. https://doi.org/10.1038/s41467-025-57292-w

[41] Eguchi S, Nakamoto Y, Takayabu H. Dynamics and regional heterogeneity in the generation efficiency of Japan's photovoltaic power plants focusing on new market entrants. Util Policy. 2025; 95: 101945. https://doi.org/10.1016/j.jup.2025.101945

[42] Schetinger AM, Lucena AFP. Evaluating policy frameworks and their role in the sustainable growth of distributed photovoltaic generation. Resources. 2025; 14(2): 28. https://doi.org/10.3390/resources14020028

[43] Kishita Y, Umeda Y. Development of Japan's photovoltaic deployment scenarios in 2030. Int J Autom Technol. 2017; 11(4): 583-91. https://doi.org/10.20965/ijat.2017.p0583

[44] Chen JL, Qing J, Cai QR. Impact of bi-directional electric vehicle and demand response on residential distributed PV capacity planning based on TOU pricing. J Environ Manage. 2024; 365: 120689. https://doi.org/10.1016/j.jenvman.2024.120689

[45] Wang JJ, Chen HY, Cao Y, Wang C, Li J. An integrated optimization framework for regional energy planning with a sustainability assessment model. Sustain Prod Consum. 2023; 36: 526-39. https://doi.org/10.1016/j.spc.2022.08.032

[46] Diahoychenko I, Petri¬chenko L. Comparative analysis of power distribution systems with individual prosumers owning photovoltaic installations and solar energy communities in terms of profitability and hosting capacity. Energies. 2022; 15(23): 8837. https://doi.org/10.3390/en15238837

[47] Al-Ghussain L, Ahmad AD, Abubaker AM, Hassan Ma. Techno-economic feasibility of thermal storage systems for the transition to 100% renewable grids. Renew Energy. 2022; 189: 800-12. https://doi.org/10.1016/j.renene.2022.03.054

[48] Kiseleva SV, Listiskaya NV, Mordynskiy AV, Frid SE. Short-term forecasting error assessment of solar power plant generation and the error influence on plant economics in conditions in Russia. Appl Sol Energy. 2022; 57(4): 347-53. https://doi.org/10.3103/S0003701X2104006X

[49] Liao QQ, Zhang YL, Tao YB, Ye JL, Li C. Economic analysis of an industrial photovoltaic system coupling with battery storage. Int J Energy Res. 2019; 43(12): 6461-74. https://doi.org/10.1002/er.4482

[50] Mensah LD, Yamoah JO, Adaramola MS. Performance evaluation of a utility-scale grid-tied solar photovoltaic (PV) installation in Ghana. Energy Sustain Dev. 2019; 48: 82-7. https://doi.org/10.1016/j.esd.2018.11.003