Evaluation of PV Industry Policy Efficiency based on Three-stage SBM Model

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***Abstract*—From the perspective of policy performance, this paper uses three-stage SBM model to quantitatively study the policy performance of photovoltaic industry in 31 provinces. In the first stage, the SBM-DEA model is used to evaluate the efficiency of photovoltaic policy to illustrate the impact of government input, and the unexpected output is also considered. In the second stage, we adjust the raw data. Then, in the third stage, the SBM model is used to evaluate the efficiency again, and the pure management efficiency of each decision-making unit is obtained. The results showed that: (1) external environmental factors have certain effects on the PV industry policy efficiency of various provinces; (2) there is obvious spatial imbalance in the efficiency level of photovoltaic policies in the four major regions of China. The new policy of differential subsidies should be implemented according to the specific development environment of each region. Finally, based on the results of empirical analysis, some suggestions are put forward.**

***Index Terms*—photovoltaic industry, policy efficiency, three-stage SBM model**

I. INTRODUCTAION

With the depletion of fossil fuel resources and the deteriorating environment, the development of renewable energy has become a global choice[1]. Solar energy is recognized as one of the most promising alternatives to fossil fuels because of it's relative cleanliness and safety[2]. Through more than ten years of development, the PV industry has become one of the few strategic emerging industries in China which can participate in international competition simultaneously. And it's expected to reach the international leading level. The development of China's PV industry is inseparable from the support of policy. International experience shows that the industrial policy is source of industrial formation and development[3]. The focus of this paper is to analyze the main factors affecting about PV efficiency policies in each province, which solve the main problems facing the PV industry by giving policy recommendation

II. LITERATURE REVIEW

A. *PV industry policy performance*

Domestic scholars' research on PV industry policy mostly focuses on the evolution process, current situation and existing deficiencies. However there is a lack of research about the performance of PV industry policy, and the quantitative analysis is less. Such as Li Yanbin analyzed the relationship between the market structure and performance of China's PV industry which used the relevant data of 9 PV listed companies from 2008 to 2014. However, It's applied research methods mainly carry out correlation and regression analysis and do not evaluate the efficiency of the PV industry[4]. Chang used the DEA model to analyzed the financial data of the top 10 solar companies in the world. He believes that solar companies should scale down and turn investment perspective into R&D investment[5]. Zhang used the DEA model to evaluate the financial data of 58 PV listed companies in China and study the operating performance, industrial agglomeration and spatial characteristics of China's PV industry[6]. You Huaimo used the DEA model and the dynamic Malmquist index model to study the relevant input and output data of China's 24 listed PV companies from 2008 to 2014[7]. The above three scholars have selected the most basic BCC model and CCR model when using the DEA method for analysis. Although the effect of evaluation efficiency can be achieved, the research results may be biased by environmental and random factors, so it is necessary to apply An improved DEA model to evaluate PV policy performance.

B. *Three-stage DEA model*

The three-stage DEA model which based on the DEA model first appeared in Fried(2002) paper[8]. The model is based on the application of Stochastic Frontier Analysis (SFA) theory. which can filter out the environmental influence and random factors on the evaluation object. The application of the three-stage DEA model in domestic papers first appeared in 2008[9]. In the following years, the number of papers using this model has gradually increased. Now the number of domestic papers involved has reached more than 100. The summary is divided into two categories: considering expected output and undesired output.

Cui Q has redefined the transportation energy efficiency, and he proposed a three-stage virtual frontier DEA model. In the evaluation process, keep the DMU set unchanged, making the results more reasonable than the super-efficient DEA model[10]. Zhang Wang and Zhao used a three-stage DEA modeling method to eliminate the external environment influence and statistical noise. They making the results better than the traditional DEA model[11-13]. Gao Wei used the panel data of 12 wind power listed companies in China from 2010 to 2015. He adopted the three-stage DEA model to measure the innovation efficiency of China's wind power industry and conducted a convergence test[14]. Feng Chujian applied a three-stage DEA model and cluster analysis method to quantitatively study the performance of PV industry policies in 18 countries from the perspective of policy performance, and put forward some suggestions based on the results of empirical analysis[15].

Xie and Huang construct a three-stage DEA model to measure energy efficiency. They respectively used carbon dioxide emissions and sulfur dioxide emissions as undesired outputs[16-17]. Yang Chuanming comprehensively considers the relationship between economic growth and environmental load. He selected input-output indicators and environmental variables and used three-stage DEA and Malmquist models to measure the efficiency of Jiangsu logistics industry[18]. Based on the panel data of the inter-provincial regions from 2006 to 2015, Guo Sidai used a three-stage DEA model to evaluate the environmental efficiency levels, trends and differences of the regions in the same environment, and explored the factors affecting China's environmental efficiency[19]. Based on the three-stage DEA model, Liu Wei measured the R&D innovation efficiency of China's high-tech industry based on the control of environmental factors[20]. Liu X used a three-stage DEA model to estimate the low carbon economic efficiency of the 20 largest carbon emitters from 2000 to 2012. The results suggest that developed countries should help developing countries reduce carbon emissions by opening or expanding trade[21]. Ren Yi mainly studies the spatial differentiation characteristics and development trends of industrial energy efficiency in the Yangtze River Economic Belt from the aspects of external environment, efficiency structure and inter-provincial differences during the “10th Five-Year plan” from the “12th Five-Year plan”[22]. Dong F combines Ruggiero's three-stage model with the super-efficient DEA model (SE-DEA) to consider environmental factors and compare Chinese interprovincial CEE on new production frontiers[23].

III. RESEARCH METHOD

The three-stage SBM model method steps are as follows;

The first stage: Unlike traditional DEA models, the SBM model can handle undesired outputs and consider the effects of slack variables. Therefore, in order to reflect the preferences and feasibility of the policy, this paper chooses the input-oriented undesired SBM model based on the Tone method[24]. Omit the amount of slack in the output in the basic form of the objective function, including additional constraints $e^T\lambda=1$ (e is the unit vector) when the variable returns are variable (VRS). The input-oriented SBM model under VRS is:

$$\rho = \min 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}$$

Subject to: $x_0 = X\lambda + S^-$

$$y_0^g = Y^g\lambda - S^g$$

$$y_0^b = Y^b\lambda + S^b$$

$$e^T\lambda = 1$$

$$\lambda \ge 0, S^- \ge 0, S^g \ge 0, S^b \ge 0 \tag{1}$$

The second stage: The input slack variables are affected by external environmental, random errors and internal management factors in the first stage. The traditional DEA model can not accurately reflect the impact of internal management or external environment. Even all decision units face the same luck the efficiency value, but all the influencing factors are attributed to internal management. Fried found out the environmental variables by constructing a similar SFA model and adjusted the input according to the results. The expression is as follows:

$$S_{mi} = f^m(Z_i;\beta^m) + V_{mi} + U_{mi} \tag{2}$$

$m=1,2,\ldots,M$ means “m” inputs, $i=1,2,\ldots,I$ means “i” decision units. S_{mi} is the slack variable of the “i” decision unit on the m input. It represents the difference between the ideal input and the actual input. $f^m(Z_i;\beta^m)$ is used to indicate the influence of environmental factors on S_{mi} , short-cut $f^m(Z_i;\beta^m)=Z_i\beta^m$ process: Z_i is the observed k-dimensional environment variable. β^m is the parameter vector corresponding to the environment variable. $V_{mi}+U_{mi}$ is the joint error term ε_i . V_{mi} indicates random error, normal distribution. $V_{mi}\in N(0,\sigma_{vm}^2)$. U_{mi} indicates management inefficiency, truncated normal distribution. $U_{mi}\in N(\mu_u,\sigma_{um}^2)$, $\mu_u=0, U_{mi}>0$. V_{mi} is independent of U_{mi} independence.

Through the estimated values of parameters such as β^m , σ^2 and γ by maximum likelihood estimation. Then calculate V_{mi} and U_{mi} according to the above parameters. Finally, the new input value in the homogeneous environment is obtained by the following formula.

$$X_{mi}^* = X_{mi} + \left[\max(Z_i\beta^m) - Z_i\beta^m\right] + \left[\max(V_{mi}) - V_{mi}\right]$$
$$m=1,2,\cdots,M; i=n=1,2,\cdots,I \tag{3}$$

X_{mi}^* is the new input value after the original input X_{mi} is homogenized and adjusted. The first bracket is the influence of environmental factors; It means in the worst environmental conditions. Other decision-making units are adjusted based on it. If the conditions are good, we should add more investment, vice versa. The second bracket is the random error factor. The principle is the same as above, even all decision units face the same luck

The third stage: Calculate the relative efficiency of each decision unit by substituting the homogenous input values of the environmental and stochastic factors X_{mi}^* into the SBM model. The efficiency value obtained at this time is the efficiency value that eliminates the influence of the environment and random errors.

IV. RESULTS AND ANALYSIS

A. *Indicator selection*

Input indicators, it mainly indicators of personnel and funding. This paper comprehensively considers the characteristics of previous research and PV industry, and selects input variables with certain industrial characteristics, namely, government R&D expenditure, enterprise R&D expenditure and industrial technology. The data comes from the China Science and Technology Statistical Yearbook.

Output indicators, it mainly the value created by the investment in the PV industry. This paper selects two indicators which responsive to the direct output of PV cumulative installed capacity and new PV installed capacity as the expected output of the PV industry. Li has found that the emission of pollutant gases will cause an increase in aerosol concentration and affect the efficiency of PV power generation[25]. Therefore, the use of sulfur dioxide emissions as the undesired output of the PV industry. The cumulative installed capacity of PV and the new installed capacity of PV can reflect the economic value of the application of innovation results. Sulfur dioxide emissions can reflect the green development value of innovations. The data comes from the China Science and Technology Statistical Yearbook.

Environmental variables, it mainly refer to factors affecting the operational efficiency of the PV industry but not within the subjective control of the sample. They include the overall environment such as the macroeconomic environment and government support incentive policies, as well as industry characteristics such as market structure and scale. According to the characteristics of the PV industry and the availability of data, this paper selects three environmental variables: total electricity consumption, per capita GDP and population. The data comes from the China Science and Technology Statistical Yearbook.

In order to eliminate the lag in the input and output in time, in the selection of data, the input and output indicators select the data of the t-year and t+1 years respectively. In order to reduce the volatility of the data due to a single year. The input indicators of this paper are the average values from 2013 to 2015, the output indicators are the averages from 2014 to 2016, and the environmental indicators are the averages from 2013 to 2015.

From Table 1, we can know the descriptive statistical analysis of energy efficiency input-output indicators.

TABLE 1 STATISTICAL DESCRIPTION OF INPUT AND OUTPUT

	Government R&D (Billion)	Enterprise R&D (Billion)	Technician	PV Cumulative Capacity	PV New Capacity	Sulfur Dioxide Emissions
Max	723.75	1447.55	7928	603.44	167.33	141.68
Min	21507.00	4048.00	204.33	0.17	0.01	0.5
Average	87.63	314.44	3032	157.27	63.82	53.08
Standard Deviation	133.70	383.92	1737	178.16	55.66	33.06
Standard Deviation Coefficient	1.53	1.22	0.57	1.13	0.87	0.62

From Table 1, it can be seen that the average value of government R&D investment is 8,763 billion RMB, the standard deviation is 13.37 billion RMB, and the standard deviation coefficient is 1.53, which indicating that the input index is more discrete.

B. *First stage results*

In order to prove the influence of undesired output on efficiency measurement, this paper also calculates the efficiency value of SBM model without considering undesired output. The efficiency value of the SBM model without considering the undesired output is solved by DEA-SOLVER Pro5.0 software, and the efficiency value of the SBM model considering the undesired output is solved by MATLAB software. The efficiency value is shown in Figure 1

From Figure 1, the provinces that are at the forefront of PV policy performance are Tibet, Gansu, Qinghai, Ningxia, and Xinjiang. Even considering the impact of environmental pollution in the above five provinces, they are still at the effective frontier. The policy efficiency values of the other 25 provinces are generally low, and there is still a large distance from the effective production frontier, indicating that they still have greater room for efficiency improvement. The results in Figure 1 also show that except for provinces with effective policy performance, most provinces have lower policy performance than efficiency values that do not consider environmental pollution. This shows that pollution emissions can significantly reduce the policy performance of each province.

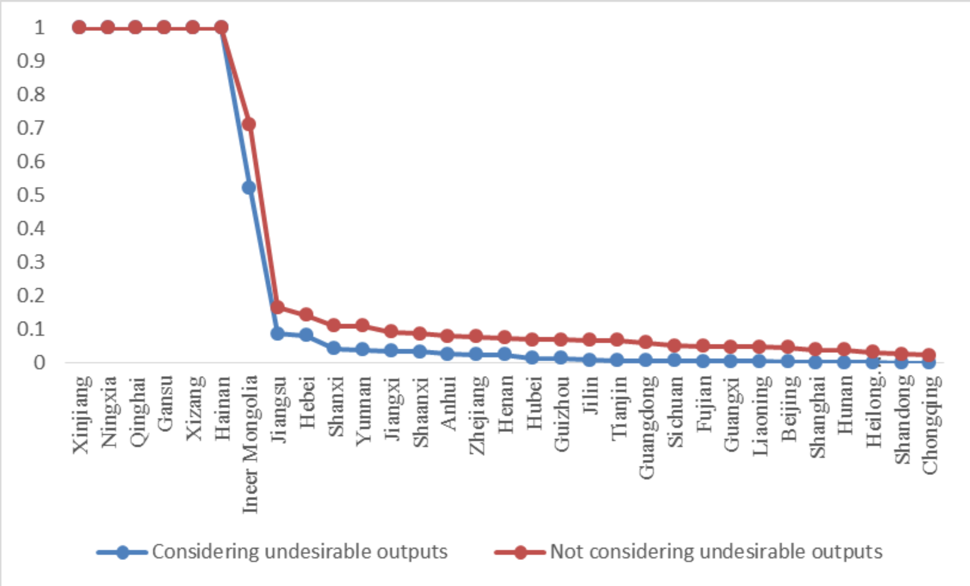

Figure 1 Whether the PV policy efficiency of provinces in the SBM model with undesired outputs is considered.

C. *Second stage result*

Through the calculation of the SBM model, it is found that there are some redundancy in the three input factors of each province and city, indicating that the government's R&D investment, enterprise R&D investment and industrial technology are the main reasons leading to the loss of efficiency of PV policy. Regression analysis of input redundancy using Frontier A, the results are shown in Table 2.

TABLE 2 REGRESSION ANALYSIS OF STOCHASTIC FRONTIER ANALYSIS

	Government R&D slack		**Enterprise R&D slack**		**Technician slack**	
	Coefficient	**T-Test;**	**Coefficient**	**T-Test;**	**Coefficient**	**T-Test;**
Constant	-409204.10	-409204.07***	-1243517.70	-1243517.70***	-294.11	-294.11***
Electricity Consumption	-1201.93	-921.70***	-1488.77	-1442.51***	-1.28	-4.52***
GDP	145.91	15.58***	117.03	40.45***	0.16	9.47***
Population	213.41	97.42***	60.73	51.12***	-0.05	-0.85-
δ^2	313650.11	313650.11***	360227.58	360227.58***	246467.23	246467.23**
γ	0.99	2101.61***	0.99	1450.31***	0.99	49339.56***
LR test of the one-sided error	81.44***		73.68***		63.66***	

Note: *** represents a 1% test by a significant level, - represents a failure to pass the significance test

From Table 2,the unilateral likelihood ratio test of the three SFA regression models passed the 1% significance level test. Which indicates that the existence of inefficient components in the mixed error term. So it is necessary to use SFA analysis. The table indicates the management inefficiency variance as the total variance, and its size reflects the proportion of management inefficiency and random factors. $\gamma \to 0$ explain that management inefficiency is in a secondary position, $\gamma \to 1$Explain that management inefficiency is at a primary position. γ is not equal to 0 at the 1% significance level, which proves that the management inefficiency and random factors under the mixed error cannot be ignored. Which indicates that the input redundancy is decomposed, and it is appropriate to use the SFA regression model. Since the slack variable of each input is taken as the explanatory variable, when the coefficient in the regression result is negative.It explain that increasing the corresponding environmental variables will weaken the slack variable of the input, which means that it can help reduce the input or increase the output. Similarly, when the regression coefficient is positive. It shows that increasing the environmental variable will lead to an increase in the corresponding input slack, resulting in increased input or reduced output[26]. The following analysis of each environment variable:

Electricity consumption: The variable has a negative regression coefficient for the three input relaxation variables, which indicates the total power consumption has a positive effect on the input slack variable. The large amount of electricity consumption has driven the government and enterprises to innovate in the PV industry, and it has given more funds and personnel support.

Regional Economic: The variable has a positive regression coefficient for the three input relaxation variables, which indicates that the improvement of the regional economic level has positive effect on the input. The reason may be because the government and enterprises pay more attention to the PV industry.

Population: The regression coefficient of the population has a positive value for the relaxation value of the R&D input variable. Which indicates that the population has a negative effect on the R&D investment slack variable. This shows that the increase in population will lead to a heavy burden on the government and enterprises, which will adversely affect the performance of PV policy. The regression coefficient of the population has a negative value for the number of industrial technology, but it has not passed the significant level test. Which indicating that the impact of population on the number of industrial technology is not significant.

In conclusion: The environmental variables have different effects on the input slack variables in different regions. Under the influence of external environmental factors, the deviation of PV policy performance in regions under different environments may be relatively large. Therefore, it is necessary to remove the action components of the environment and random factors to adjust the original input variables, so as to ensure that PV policy performance is closer to the actual level.

D. Third stage result

The regression coefficients of the environmental variables and the input variable relaxation values are mostly significant. Although the regression coefficient of the population's slack value for the number of industrial technology is not significant, the LR unilateral error test passes the test of 1% of the significant level. So all environmental variables are still taken into account when adjusting the input and output values. Using the formula to obtain adjusted input data and carbon dioxide emission data into the formula to obtain PV policy performance after removing environmental variables and random factors. From Figure 3, there is a significant difference between the efficiency values of PV policies in the first and third stage, it is necessary to adjust the original input values using environmental variables and random error terms.

TABLE 3 COMPARISON OF EFFICIENCY EVALUATION RESULTS IN THE FIRST, THIRD STAGE

Area	Province	Before	After	Area	Province	Before	After
East Region	Beijing	0.0037	0.0411	Western Region	Inner Mongolia	0.5226	1.0000
	Tianjin	0.0075	1.0000		Guangxi	0.0046	0.0303
	Hebei	0.0823	1.0000		Chongqing	0.0001	0.0077
	Shanghai	0.0022	0.0369		Sichuan	0.0066	0.0886
	Jiangsu	0.0866	1.0000		Guizhou	0.0145	0.0450
	Zhejiang	0.0249	0.5614		Yunnan	0.0384	0.1800
	Fujian	0.0047	0.9995		Xizang	1.0000	1.0000
	Shandong	0.0007	0.0110		Shanxi	0.0337	0.9990
	Guangdong	0.0067	0.3280		Gansu	1.0000	1.0000
	Hainan	1.0000	1.0000		Qinghai	1.0000	1.0000
	Average	0.1219	0.5978		Ningxia	1.0000	0.7323
Central Region	Shanxi	0.0424	0.2013		Xinjiang	1.0000	1.0000
	Anhui	0.0274	0.3225		Average	0.4684	0.5902
	Jiangxi	0.0362	0.9996	Northeast Region	Liaoning	0.0046	0.1428
	Henan	0.0244	0.9999		Jilin	0.0080	0.9998
	Hubei	0.0147	0.9998		Heilongjiang	0.0018	0.0281
	Hunan	0.0019	0.9988		Average	0.0048	0.3902
	Average	0.0245	0.7536				

In terms of regions, the provinces with the frontiers of efficiency in the first and third phases are Hainan, Tibet, Gansu, Qinghai and Xinjiang. The province with reduced PV policy efficiency is Ningxia, indicating that the province’s previous high efficiency is closely related to its favorable external environment. The efficiency of PV policies 24 provinces has increased in the remaining, because of the relatively unfavorable external environment and not entirely because of their low internal management.

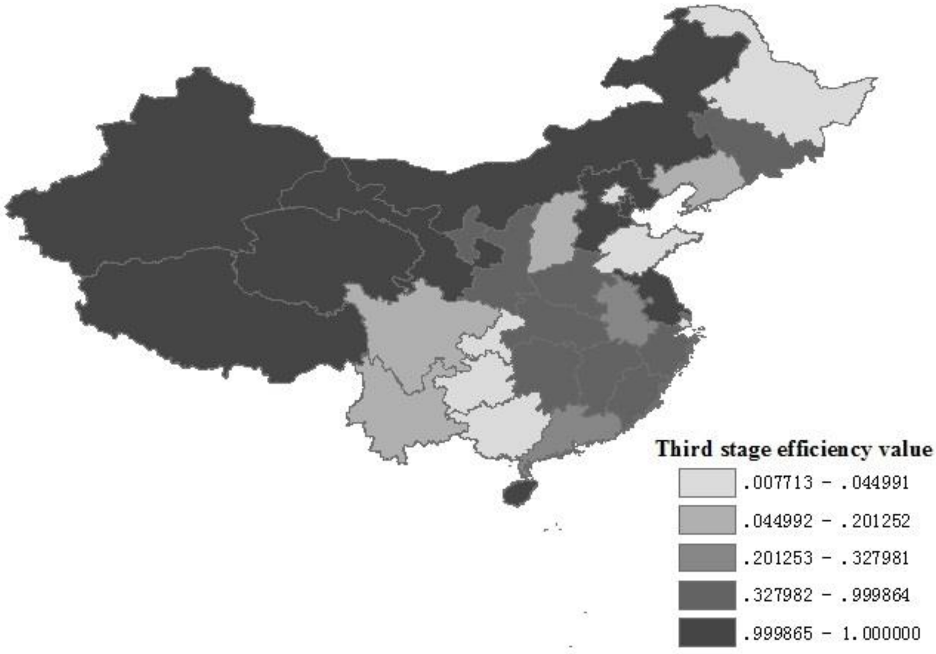

Fig. 2 Efficiency of PV policies in different provinces of China

East Region: Most of the eastern regions have low PV policy performance in first stage. After eliminating environmental and random factors, efficiency has increased significantly. The efficiency of Tianjin, Hebei and Jiangsu has even risen to the frontier of efficiency. The conclusion is that PV policy performance in the region is underestimated. Because of the shortage of land resources, there are no conditions for the construction of ground PV power stations in the eastern region. The state encourages the construction of distributed PV power generation systems in the eastern load center. Under the promotion of good economic strength and huge voltage power in the east, it will inevitably lead to an increase in the efficiency of PV policies.

Central Region: After excluding environmental and random factors, the region’s efficiency gains are the largest. The conclusion is that PV policy performance in the region is underestimated. The central region is more able to guarantee the minimum utilization hours compared to the western region. It is more able to save land acquisition costs and is more competitive in the “leaders” base application. The performance of PV policies has improved significantly in the Chinese policies.

Western Region: The Northwest’s PV policy performance is the highest among the four regions in the first stage. After excluding the environment and random factors, the efficiency has increased but the magnitude is not large. The conclusion is that the effect of environmental factors on the efficiency of the western region is not significant. By 2016, Xinjiang is the largest province in the construction of PV power plants, Qinghai is the second largest PV installation province after Xinjiang, Inner Mongolia's ground PV power plant construction has grown steadily in the past three years. However, the problem of light abandonment in the western region is serious, and it belongs to economically underdeveloped regions. The demand for electricity is relatively small, and it is difficult to solve this problem in the short term.

Northeast Region: Either the first stage or the third stage is relatively inefficient, and the efficiency is slightly increased after removing the environment and random factors. As an old industrial base, the energy consumption structure in the Northeast has been relatively simple where PV market development is low. However, the Northeast has a strong advantage in land resources and solar radiation resources, and the Chinese indicators in the annual construction of PV power plants are beginning to tilt towards the region.

In conclusion, the environmental variables had impacted on the performance of PV policies in the four regions of China.

V. CONCLUSION

The findings of the study found:

After eliminating the influence of random error factors and external environmental factors, the efficiency of PV policy in the four regions of China has changed, and they are underestimated to varying degrees. Therefore, it is reasonable and necessary to use the three-stage DEA model instead of the classic DEA model to evaluate the efficiency of PV policies in various provinces of China.

There are obvious spatial imbalances in the efficiency level of PV policies in the four major regions of China. Although the four regions are on the rise, the upward trend in the western region is relatively slow, and the increase in the eastern and central regions is relatively large.

Environmental factors and random error factors have a significant impact on environmental efficiency. The total electricity consumption has a positive impact on the efficiency of PV policy. And the regional economic level and population have a negative impact on the efficiency of PV policy.

Based on the efficiency of PV policies in various provinces in China, combined with the new PV policy promulgated on May 31, 2018, this paper proposes the following suggestions:

Now, the PV industry continues to expand production and development under the stimulation of China's subsidy policy, and there is a phenomenon of overcapacity. So, the research and solve the problem of the consumption about PV power generation is extremely crucial for finding the right way to support the PV industry. According to international experience, the use of PV should be changed from subsidy to quota system, and the PV industry should be given additional income from renewable energy quotas and carbon allowances.

531 policy has released a signal to reduce subsidies, And electricity marketization is gradually being implemented. This requires more PV companies to use limited government subsidies to increase innovation, improve competitiveness in the power market, and put more energy into the field of technology research and development.

Due to the large environmental differences in the development of PV industry in the four major regions of China, it is necessary to implement a new subsidy for different regions, and regional enterprises can be treated differently to promote the development of the local PV industry. The develop power stations in western China that can achieve high quality design, construction, equipment and operation and maintenance. Vigorously develop distributed PV market in central and eastern China.

Now, the distributed PV + energy storage is also an important direction for the development of PV industry. Frequent policies on energy storage have driven the depth and breadth of participation in the power system. Energy storage and energy management systems can improve grid power quality, change energy usage habits, and improve energy management efficiency.

Chinese PV industry lacks authoritative analysis institutions and authoritative analysis data, which leads to the lack of strong support for the country in the future to introduce relevant policies. It can do some quantitative and systematic analysis to improve the research influence of the PV industry and the scientific nature of the policy.

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