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Working Paper 104
http://ceep.bit.edu.cn/english/publications/wp/index.htm

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April 2017

This paper can be cited as: *Wang Z, Li Y, Wang K, Huang Z. 2017. Environment-adjusted operational performance evaluation of solar photovoltaic power plants: A three stage efficiency analysis. CEEP-BIT Working Paper.*

The authors gratefully acknowledge the financial support from the National Natural Science Foundation of China under the grant nos. 71471018, 71573016 and 71521002; the Social Science Foundation of Beijing under the grant no. 16JDGLB013; the National Key R&D Program under the grant no. 2016YFA0602603. The views expressed in this paper are solely authors' own and do not necessarily reflect the views of the supporting agencies and Beijing Institute of Technology. The authors alone are responsible for any remaining deficiencies.

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Environment-adjusted operational performance evaluation of solar photovoltaic power plants: A three stage efficiency analysis

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Abstract: There is widespread concern that environmental factor may not be playing a pivotal role in influencing the generation performance of solar photovoltaic (PV) plants. The aim of this paper is to provide a fair and impartial operational performance evaluation of solar PV power plants taking into account of the impacts of environmental factors from real field data. Stochastic frontier analysis (SFA) is used to attribute the impacts of environmental factors (temperature, cloud amount, elevation, wind speed and precipitation) on inputs (like insolation and daylight hours) of solar PV power plants; while data envelopment analysis (DEA) is used to compute the environment-adjusted operational efficiency of these plants. SFA is utilized in the adjustment process for its merit of separating statistical noise from the error term, and DEA is used for its advantage of capturing the interaction among multiple inputs and outputs in a scalar value. The empirical analysis shows that the average operational efficiency of 70 grid-connected solar PV power plants in the United States slightly declines after accounting the impacts of environmental factors and statistical noise. Finally, the results partially support the initial concern from the statistical perspective and temperature is found to be the most significant influencing environmental factor, while precipitation and wind speed show no significant influence on operational efficiency. Therefore, the necessity of accounting for the impacts of environmental factors in the performance evaluation of solar PV power plants should not be omitted.

Keywords: Solar PV power plants; Environmental factors; Data envelopment analysis; Slacks; Stochastic frontier analysis

Introduction

Facing with energy poverty, energy security and increasing concern over climate change, there is a growing consensus that low-carbon economy is our inevitable choice. Solar energy has been favored by a lot of countries because of its characteristics like inexhaustible, environmental friendly, no noise, and low maintenance cost. Since 2010, the world has added more solar photovoltaic (PV) capacity than in the previous four decades. As for the United States, the leading promoter of new energy, solar PV power has been growing at high rates over the past few years, owing to cost reductions in the production of PV modules and PV technology development which solved intermittency problem. In 2014, the U.S. solar industry reached the 20 gigawatt milestone, generating enough electrical capacity to power more than 4 million American homes.

The large-scale deployment of solar PV installations has inspired more research interest in efficiency improvement of solar PV systems. Many researchers have reviewed technology progress in solar PV system to enhance the quality and operational performance of solar PV system [1-5]. Also, there are

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several researches and reviews on discussing the possible approaches to improve solar PV system efficiency. For example, McColl et al. (2015) compared how thermal management like sun-tracking or water cooling affect the performance of solar PV modules [6]. Effects of various cooling techniques like natural and forced air cooling, hydraulic cooling, heat pipe cooling, cooling with phase change materials and thermoelectric cooling of PV panels were compared and discussed [7]. Irwan et al. (2015) showed the effect of water cooling on the efficiency of PV panel through experiment [8]. The effects of nanofluids on the performance of solar collector and the efficiency of solar system have been examined in [9]. Different solar PV maximum power point tracking techniques have been comprehensively reviewed in [10].

Apart from continuous technology improvement, generation performance is usually improved through selecting benchmarks for better managerial cases. However, there are various uncontrollable environmental factors that affect the electricity generation of a PV power plant. Critical environmental factors that affect the generation and operation of the entire PV system have also been studied, including factors like temperature, solar irradiance, elevation, precipitation and soiling [11]. It is necessary to take the environmental factors into account so that people could have a realistic expectation of overall operational efficiency of solar PV power plant. Operational efficiency hereby means the relative generation performance of solar PV power plants, with the impacts of environmental factors controlled. The aim of this paper is to use a quantitative approach to facilitate benchmark selection and efficiency comparisons of solar PV power plants before and after controlling the impacts of environmental factors and statistical noise.

This paper is organized as follows: Section 2.1 provides a review on the environmental factors and ambient conditions affecting the generation performance of solar PV power plants. Section 2.2 reviews the traditional Data Envelopment Analysis (DEA) based performance evaluation on solar plants without considering the impacts of environmental factors. Section 2.3 reviews the evolution of performance evaluation methods accounting for the impacts of environmental factors. The research gap of environment-adjusted operational performance evaluation of solar PV power plants is identified. Section 3 presents the multi-stage efficiency analysis approach used in this paper for environmental-adjusted performance evaluation. An empirical analysis of operational performance evaluation of the U.S. solar PV power plants is provided in Section 4. Section 5 concludes the paper.

Literature review

Effects of environmental factors on the performance of solar PV system

This section reviews the eight major environmental factors that affect the performance of solar PV system in existing literatures.

Temperature

Apart from the impacts of total solar irradiance, incidence angle of the incident solar radiation and air mass, which affect the reception of solar insolation, PV temperature is the most important factor that affects PV efficiency [12]. Dinçer (2010) examined that solar cells tend to produce higher voltage as the temperature drops, resulting in higher solar cell efficiency. With the temperature increases, the band gap of intrinsic semiconductor shrinks and the open circuit voltage decreases, resulting in more absorbed incident energy [13]. Skoplaki et al. (2009) briefly discussed the correlation between the operating temperature of PV modules and other variables including, e.g., solar radiation flux, back-side cell temperature, ambient temperature and wind speed [14]. McColl et al. (2015) compared how thermal management like sun-tracking or water cooling affected the performance of solar PV modules [6]. García-Domingo et al. (2014) found that increment of ambient temperature exerted a negative effect on the performance of concentrated PV module [15]. As insolation and conversion efficiency is expressed as a function of module temperature, Nishioka et al. (2003) found that the conversion efficiency decreases with a rise of the module temperature. They also concluded that PV system conversion efficiency decreases faster when the module temperature exceeds 25°C [16]. Experiment found that water cooling can decrease the operating temperature by 5°C to 23°C and increase the generation by 9-22 % [8].

Solar irradiance

The research of García-Domingo et al. (2014) showed that direct normal irradiance has a major role in affecting the performance of concentrated PV module [15]. Through an indoor lab experiment, Jiang et al. (2011) found that the relationship between solar density and generation efficiency is inverse U-shaped when keeping dust density fixed, with generation efficiency reached its highest value at medium level of solar intensity [17]. Similarly, an inverse U-shaped curve is identified between generation efficiency and total solar irradiance in outdoor conditions [12].

Elevation

Raja (1995) asserted that insolation becomes tenser with elevation increases, because of lower air pressure, shorter path through the atmosphere, and the decreasing concentration of unmixed gases and aerosols [18]. Gökmen et al. (2016) noted that places, like hills and mountains, with high elevation should pay special attention to the cooling effect of wind [19]. However, the experiment data of Elkhatib et al. (2015) on rooftops between 200 and 800 feet showed no significant improvement of generation efficiency with increased elevation [20].

Wind speed

Wind has a cooling effect and can help the ventilation of PV system [15, 19, 21, 22]. Results from Gökmen et al. (2016) mathematical model and experimental case study showed that wind speed can greatly affect the operating performance of a PV system, especially in windy locations [15, 19]. Conversion efficiency in windy location increased up to 18% compared with windless location in the study of Obara et al. (2014) [22]. However, Gaglia et al. (2017) claimed that the positive cooling effect of wind speed is relatively small comparing to the negative effect of temperature and solar insolation on PV efficiency [12].

Soiling

Dust accumulation, which is always depicted by soiling ratio, is a vital factor influencing the performance of PV system as it blocks the insolation transmitted through the PV module and thus the solar energy converted by the modules [17, 23]. Indoor experiment of Jiang et al. (2011) showed that dust accumulation has a negative linear relationship with generation efficiency [17]. Outdoor experiment of Paudyal et al. (2016) found that the high dust concentration at bottom could result in hot spot and ultimately permanent module damage [24]. Adinoyi et al. (2013) studied the performances of PV modules exposed to outdoor conditions and concluded that the decrease in electricity generation is the result of dust frequency and intensity. Trackers and more frequent cleaning schedules can help to improve generation efficiency in dusty conditions [25]. Cleaning is recommended immediately after dust period, with running water and use of a sponge [26]. Micheli et al. (2016) analyzed the data from six soiling station and found good correlation between the soiling ratio and particular matter [27]. Linear correlation was also found between reduction of PV module efficiency and dust density [28]. Researches have also investigated how different physical properties of soiling affect the performance of PV modules [29-32].

Precipitation

Adinoyi et al. (2013) testified that precipitation improves the generation of solar PV modules in dusty areas, but cannot be relied upon for cleaning [25]. On the contrary, Kalogirou concluded that the occasion rain during winter is enough to keep panels clean [26]. Micheli et al. (2013) observed that precipitation raise the soiling ratio after a long dry season or a dusty period. In particular, soiling ratio is more correlated with frequency of rain than the amount of precipitation [27].

Latitude

Latitude controls the duration of daylight and the path oblique rays travelled from the sun. High-latitude regions usually have lower levels of sunshine and low-latitude regions have higher levels [18].

Clouds

Kankiewicz et al. (2013) observed the impact of passage of clouds on the performance of a utility-scale solar PV power plant (25 MW DeSoto Next Generation Solar Energy), and found that the fluctuations in generation were dampened as PV modules were grouped together [33]. Cloud edge effects, which induce electricity generation to slightly increases as clouds begin impacting the plants, were found and discussed in [33] and [34].

Performance evaluation of solar PV power plants using DEA

Efforts have been made on evaluating the generation performance of solar PV power plants using the widely applied DEA model. Li et al. (2016) made a performance evaluation of 38 listed Chinese PV companies through input-oriented dynamic SBM model and found no connection between listing market and efficiency values [35]. Azadeh et al. (2008) proposed an integrated hierarchical DEA approach to identify the best choice of the location of solar power plant. There are 2 levels in their DEA model. In level 1, they used technical and social parameters including population, distance of power distribution networks and land cost to find the best region in each city. In level 2, they used geographical parameters, including solar global radiation, availability to water, intensity of natural disasters occurrence and quantity of proper topographical and geological areas, to determine which cities should be prioritized in building solar power plants. At last, they combined the ratings in these 2 levels to identify the optimal location for solar plants [36]. Sueyoshi et al. (2014) compared generation performance of PV power plants in Germany and the U.S. based on input-oriented and output-oriented DEA with insolation, number of PV modules, land area and average annual sunshine as inputs and installed capacity and annual generation as outputs. Their conclusion was that land use and solar irradiation are not essential influence factors on PV power plants' efficiency [37].

Incorporating environmental factors into DEA

The traditional performance evaluation is biased as they cannot account for uncontrollable factors and measurement errors. Researchers have been working on multi-stage approaches to control the influences of environmental factors and statistical noise.

Fried et al. (1999) proposed a three stage procedure to measure the managerial efficiency that controls the impacts of environmental factors [38]. The first stage applied DEA model to compute the initial efficiency and input slacks. The second stage was the estimate of a set of equations with input slacks as dependent variables and environmental factors as independent variables. These equations were used to quantify the influence of environmental factors on the excessive use of inputs. Appropriate econometric technique could be ordinary least squares (OLS), seemingly unrelated regression (SUR) or tobit regression depending on characteristics of the data. Tobit regression was chosen as slacks are truncated at zero. Then, the parameters generated from tobit regression were used to predict the total input slacks. The difference between the predicted total input slacks and the maximum one, which represent the most disadvantaged environment, are used to adjust the initial inputs. The adjustment added an additional amount of 'input' to units which are in relatively favorable environment. The final stage was a repeat of the model in the first stage with the adjusted inputs and initial outputs. They applied this method to a sample of hospital-affiliated nursing homes and found that most nursing homes have a higher efficiency scores after considering the impact of environmental factors, and the efficiency ranks also changed. Fang et al. (2013) used this method to measure the energy-saving target for Taiwan's service sectors, which was the summation of radial adjustment and non-radial slacks, as a better replacement of energy inefficiency indicator [39]. Avkiran (2009) modified the four-stage method with applying SBM model in the first and last stages and tobit regression in the second and third stages to measure the impact of interest rates on Australia's and New Zealand's bank efficiency [40].

Fried et al. (2002) further improve the four stage method to control the influences of both environmental factors and statistical noise with Stochastic Frontier Analysis (SFA) regression [41]. Most studies have chosen tobit regression, but the advantage of using SFA to regress total input slacks against environmental factors is that its error term can include the influence of the asymmetric managerial inefficiency term. They applied the so-called three stage method to the same sample of hospital-affiliated nursing homes and found that most of these nursing homes were worse off after purging the influences of both environmental factors and statistical noise. Xu et al. (2016) applied this method to evaluate the influence of social media on the popularity of scenic spots in China [42]. Cui et al. (2015) also used this method to evaluate the resource utilization efficiency of coal and added bootstrap DEA model to correct the bias[43]. Avkiran et al. (2008) proposed to use Slack Based Measure (SBM) model that can measure both input and output slacks at the first and last stages and use SFA regression to adjust both inputs and outputs [44].

Another branch of method has removed the impacts of environmental factors prior to performance evaluation. Hof et al. (2004) proposed a method to homogenize the environmental factors before processing the DEA models. As their input is also influencing the environmental factors, they regressed input against environmental factors in the first place using OLS regression, and use the parameters from the OLS regression to predict the adjusted input with the mean value of environmental factors [45]. Then they used the adjusted input and observed output to run the DEA model. They measured the efficiency of forest and rangeland, and concluded that without limiting the interruptions of human activities, there were still chances to improve forest and rangeland conditions. Macpherson et al. (2013) used this method to access how climate, hydrology, and topography are influencing deposition, runoff, invasive species, and forest fragmentation in the United States Mid-Atlantic region. Because of spatial auto-correlation existence in some of the regressions, they used spatial autoregressive (SAR) models to purge some of the input data of exogenous environmental factors. The rank of watersheds changed substantially after purging the influences of exogenous environmental factors, especially if we divide them into different eco-region [46].

Among the various methods which control the influences of environmental factors in DEA model, we have opted for the three-stage model proposed by Avkiran et al. (2008) [44] as we believe it to be most appropriate for our research question[†]. This paper tries to find out the operational efficiency and adjusted operational efficiency of solar PV power plants. Of which, the operational efficiency measures the relative performance of each solar PV power's electricity production process and environment-adjusted operational efficiency measures the performance of production process in which effects of uncontrollable environmental factors and statistical noise are netted out. To achieve this purpose, we adopt a three stage efficiency analysis approach. Stage 1 measures the operational efficiency with SBM model, stage 2 adjusts the inputs with environmental factors and stage 3 calculates the environment-adjusted operational efficiency with the adjusted inputs.

The rapid development and deployment of photovoltaic installations stimulated more research interests in efficiency improvement in recent years, even one percent more generation is of capital

[†] For more information about the procedures, advantages and disadvantages of different methods in the inclusion of environmental factors in DEA models, see the comparison made by Pastor (2002) [47] and Yang and Pollitt (2009) [48].

importance for sustainable and green energy development. Environmental factors can significantly affect the efficiency of solar PV system and have not been considered broadly in PV systems yet. Few researches have evaluated the performance of solar plants from a statistical perspective, and the impacts of environmental factors have not been accounted. In this paper, the research gap of operational performance evaluation of solar PV power plants with consideration of environmental factors has been bridged. Potential impacts of some environmental factors, such as wind speed, elevation and precipitation, are estimated. This paper is intended to help plant managers to more accurately estimate the operational efficiency rankings between existing solar PV plants from real field data.

Methodology: Three stage approach using SBM model and SFA regression

This section describes the three stage analysis based on earlier work of Fried et al. (2002) [41] and Avkiran et al. (2008) [44] to measure the operational efficiency and environment adjusted operational efficiency of solar PV power plants.

Stage 1: Initial SBM model

DEA is a non-parametric approach to measuring the relative efficiency of decision making units (DMUs), which have multiple inputs and multiple outputs. DEA has distinct advantage over traditional ratio analysis in capturing the interaction among multiple inputs and outputs in a scalar value, without making an assumption about the distribution of the data or assuming a particular production technology. DEA treats the entities as a black box where knowing the details of the actual production process is not necessary [49].

In this paper, we use SBM model rather than the standard DEA models, such as CCR (Charnes, Cooper, & Rhodes) model [50] or BCC (Banker, Charnes, & Cooper) model [51], because SBM model is a non-radial efficiency method that deals directly with the neglected input and output slacks in CCR model. Tone (2001) introduced the slacks based measure of efficiency in DEA and made comparisons with CCR model and the Russel measure of efficiency [52]. Tone testified that the optimal SBM efficiency is not greater than the optimal CCR efficiency and that a DMU is CCR-efficient if and only if it is SBM-efficient. Cooper et al. (2007) also pointed out that SBM model has units invariant and monotone properties [53]. Choi et al. (2012) pointed out that the radial efficiency method does not provide information regarding the efficiency of a specific input or output involved and all of the input efficiencies are measured at the same proportion [54]. While SBM model is a non-radial efficiency measure that deals directly with the input excess and output shortfall of the observation. SBM model projects the observations to the furthest point on the efficient frontier, in the sense that the objective function is to minimize the efficiency value ρ by finding the maximum amounts of slacks. The non-oriented constant returns to scale SBM model used in this paper is as follows:

$$\min \rho = \frac{1-\frac{1}{M}\sum_{i=1}^{M}\frac{s_i^-}{x_i^0}}{1+\frac{1}{N}\sum_{r=1}^{N}\frac{s_i^+}{x_i^0}}$$

$$\begin{aligned} s.t.\quad & x^0 = X\boldsymbol{\lambda} + \boldsymbol{s}^- \\ & y^0 = Y\boldsymbol{\lambda} - \boldsymbol{s}^+ \\ & \boldsymbol{\lambda} \geq 0, \boldsymbol{s}^+ \geq 0, \boldsymbol{s}^- \geq 0 \end{aligned} \tag{1}$$

We assume there are I DMUs and each DMU has M inputs and N outputs. The slack-based measure of efficiency, which account for the input excess and output shortfall in the calculation of a DMU's efficiency score, was reported as the scalar ρ in the objective function, with $0 \leq \rho \leq 1$. $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \dots, \lambda_I]$ is an intensity vector. $X = [\boldsymbol{X}_1, \boldsymbol{X}_2, \dots, \boldsymbol{X}_I]$ is a *M*H*N* matrix of input vectors. $Y = [\boldsymbol{Y}_1, \boldsymbol{Y}_2, \dots, \boldsymbol{Y}_I]$ is a *N*H*I* matrix of output vectors. x^0 and y^0 are input and output vectors of the DMU being evaluated. $\boldsymbol{s}^+$ and $\boldsymbol{s}^-$ are input and output slacks, which represent the decrease in input and increase in output for a DMU to become efficient (ρ=1).

Stage 2: SFA regression

In the second stage, we focus on input slacks $s^- = x^0 - \boldsymbol{X\lambda}$ which include the effects of environmental factors, managerial inefficiencies and statistical noise. We use SFA to regress *M* input slacks from stage 1 against environmental factors. Here, we assume these *M* separate SFA regressions taking the following form:

$$s_{ij}^- = f^i(z_j; \beta^i) + e_{ij}, \; i=1,2,\dots,M, \; j=1,2,\dots,I \qquad (2)$$

where dependent variables are M input slacks, independent variables are *K* environmental factors $\boldsymbol{z_j}$ =[z_j, z_j,…, z_{Kj}], j=1,2,…,I. $f^i(z_j; \beta^i)$ are input slacks attributable to environmental factors, with β^i to be estimated through SFA regression by maximum likelihood method. We assume the relationship between $\boldsymbol{z_j}$ and β^i forms a Cobb-Douglas production function as [38, 40, 41, 44], thus $s_{ij}^- = z_j\beta^i + e_{ij}$. Error term $e_{ij}= u_{ij} + v_{ij}$ are composed of managerial inefficiencies u_{ij} and statistical noise v_{ij}. Examples of statistical noise include strike, equipment failure, and measurement error; examples of managerial inefficiency include incompetency, inadequate staffing, and inadequate equipment [44]. In consistency with stochastic frontier cost function mode, we assume the one-sided component $u_{ij} \sim N^+(u, \sigma_{ui}^2)$ and the symmetric error component $v_{ij} \sim N(0, \sigma_{vi}^2)$ are distributed independently of each other and of $\boldsymbol{z_j}$.

We use the method proposed by Jondrow et al. (1982) [55] to separate the managerial inefficiency u_{ij} from the error term e_{ij} and compute estimators for statistical noise v_{ij} by:

$$\hat{E}[v_{ij} | u_{ij} + v_{ij}] = s_{ij}^- - z_j\beta^i - \hat{E}[u_{ij} | u_{ij} + v_{ij}], \; i=1,2,\dots,M, \; j=1,2,\dots,I \qquad (3)$$

in which β^i provide the estimates of input slack usage attributable to environmental factors. Particularly, if $\gamma^i = \sigma_{ui}^2/(\sigma_{vi}^2 + \sigma_{ui}^2)$ is closer to 1, the effect of managerial inefficiency dominates that of statistical noise in the determination of slack in usage of input i. If $\gamma^i = \sigma_{ui}^2/(\sigma_{vi}^2 + \sigma_{ui}^2)$ is closer to 0, then the effect of statistical noise dominates that of managerial inefficiency in the determination of slack in usage of input i.

After computing the coefficients for statistical noise v_{ij} and the effects of environmental factors, we can adjust the original input upward by:

$$x_{ij}^A = x_{ij} + \left[\max_j\{\boldsymbol{z_j\beta^i}\} - \boldsymbol{z_j\beta^i}\right] + \left[\max_j\{\widehat{v_{ij}}\} - \widehat{v_{ij}}\right] \qquad (4)$$

where x_{ij}^A and x_{ij} are the adjusted and original input for DMU$_i$, respectively. Here the reason why we choose to adjust input upward but not downward is to avoid that some DMUs may be on such adverse conditions that their input may become negative if we adjust the original input downward. $\boldsymbol{z_j\beta^i}$ is the estimated effects of environmental factors on input slacks and $\max_j\{\boldsymbol{z_j\beta^i}\}$ represent the worst ambient condition in the sample. Through the adjustment $\max_j\{\boldsymbol{z_j\beta^i}\} - \boldsymbol{z_j\beta^i}$, we put all the DMUs in the worst ambient condition encountered in the sample. v_{ij} is the estimated statistical noise and $\max_j\{\widehat{v_{ij}}\}$ represents the unluckiest condition encountered in the sample, examples of statistical noise include strike by employees, equipment failure and measuring errors etc.

Stage 3: Repetition of stage 1 SBM model

In the final stage, we conduct the SBM model again with adjusted input and original output. The efficiency scores from stage 3 have environmental factors and statistical noise netted out, and thus is a pure evaluation of operational efficiency.

Environment-adjusted operational efficiency of the U.S. solar PV power plants

In terms of solar power generation, there are basically two kinds of technology, either convert sunlight directly into electricity using photovoltaic technology, or indirectly through heat engine using concentrated solar power (CSP) technology. We apply the three stage model to a sample of 70 solar PV power plants in the United States in 2010. A solar PV power plant is a power station that generates electrical power by using photovoltaic cells. All of the 70 power plants are solar PV power plants using either PV technology or concentrated photovoltaic (CPV) technology and feeds generated electricity into the public grid.

Input and output descriptions

In this paper, the output is net electricity generation, and four inputs are nameplate capacity, PV panel area, insolation and daylight hours. The solar PV power plants with missing values and potential outliers are identified and removed from the sample, total sample size is 70. The description and sources of the data used in this study are described as follows:

Net generation: Total reported net electricity generation from the solar PV power plant.

Nameplate capacity: Installed electricity generation capacity of the solar PV power plant.

PV panel area: PV panel area is the measure of PV panel covered area of the solar PV power plant and is gathered through power plant introductions, feasibility studies and reports.

Insolation: Annual average amount of solar radiation incident on a horizontal surface at the surface of the earth.

Daylight hours: The number of hours between sunrise and sunset.

Net generation and nameplate capacity are collected from the Emissions & Generation Resource Integrated Database (eGRID) 9th edition released in February 24th 2014[‡]. Annual average insolation incident on a horizontal surface and annual average daylight hours are obtained from NASA database by searching the plant's longitude and latitude. The descriptive statistics of the sample data is presented in Table 1.

[Insert Table 1 here]

The input and output variables are chosen after considering the input–output characteristics of solar PV power generation and experiences from previous studies. According to Mondol (2006), PV surface orientation and inclination have little impact on the performance of a high efficiency inverter [56]. Optimal sizing of inverter is accounted as managerial inefficiency in the three stage analysis, therefore we do not include these factors in our study. We assume that the effects of different PV

‡ http://www.epa.gov/cleanenergy/energy-resources/egrid/

system equipment like batteries, charge controllers and inverters are the same across all the solar PV power plants. Also, Sueyoshi et al. (2014) evaluated the performance of solar PV power plants with insolation, number of PV modules, land area and average annual sunshine as inputs and installed capacity and annual generation as outputs [37].

Stage 1: Initial SBM evaluation

In the first stage, we use SBM model with the constant return to scale assumption to estimate solar power plant's original operational efficiency and calculate its input slacks. The slack of daylight hours and insolation in SBM model of stage 1 is presented in Table 6. We found that the target value of daylight hours and insolation is less than 30% of the observed value of daylight hours and insolation, which indicate the absorbed incident energy and the utilization level of daylight hours are relatively low.

Stage 2: Decomposing stage 1 slacks through SFA adjustment

The impacts of environmental factors on input slacks are calculated in the stage 2 using SFA regression. We use the parameters estimated from the SFA regression to adjust the original input data in the first stage. Only two of the four inputs, insolation and daylight hours, are influenced by environmental factors, we hereby only adjust insolation and daylight hours. We are informed that the environmental factors in solar power can include a number of atmospheric, topographic and geographical external factors, like module temperature, ambient temperature, wind speed, dust accumulation, humidity, etc. [13, 15, 18, 19, 25, 57]. Whereas we only account for the impact of six environmental factors in this empirical case study for simplicity and data availability.

4.3.1. Selection and description of environmental factors

As stated by Meral et al. (2011), there are many factors affecting the operation and efficiency of PV based electricity generation system, such as PV cell technology, ambient conditions and selection of equipment [57]. In this case study, we have not accounted for PV cell technology or the selection of equipment due to data restrictions.

According to Dinçer (2010), Meral et al. (2011) and García-Domingo et al. (2014), module temperature and ambient temperature have a great influence on the behavior of a PV system, as it modifies solar system's efficiency and output energy [13, 15, 57]. Meral et al. (2011) and Adinoyi et al. (2013) stated that the atmospheric factors such as wind speed, cloud cover and dust accumulation have impact on solar system's output [25, 57]. Wind can help the ventilation of PV system and has cooling effect on PV panels especially in windy locations [19]. Adinoyi et al. (2013) testified that precipitation improved the generation of solar PV modules in Dhahran [25]. Raja (1995) asserted that insolation is tenser with elevation increases, because of lower air pressure, shorter path through the atmosphere and the decreasing concentration of unmixed gases and aerosols [18].

Overall, the environmental factors used in the study include cloud information, meteorological factors (temperature, wind, precipitation) and topographic factors (elevation). The description and sources of the environmental factors used in this paper are as follows:

Temperature: Temperature values are for 10 meters above the surface of the earth.

Wind speed: Wind speed values are for 50 meters above the surface of the earth.

Cloud amount: Daylight cloud amount is the percent of cloud amount during daylight within a region.

Precipitation: Precipitation is the average daily rain rate.

Elevation: Elevation for the solar PV power plants is taken from the NASA GEOS-4 model.

Latitude: Latitude contains the information of the solar PV power plant's latitude. When not available, the plant's county centroid's y-coordinate is used.

Latitude is obtained from eGRID database. All the other environmental factors are gathered from the NASA Langley Research Center Atmospheric Science Data Center Surface meteorological and Solar Energy (SSE) web portal[§]. Considering the availability and integrity of data, the data of environmental factors used in this paper are the average value over 10 to 22-year period. The descriptive statistics of environmental factors is presented in Table 2.

[Insert Table 2 here]

4.3.2. Regression of daylight hours and insolation

In the SFA regression of insolation, we choose elevation, cloud amount, temperature, precipitation and wind speed, these five environmental factors, as dependent variables. In order to evaluate the relative importance of each environmental factor, we also compute the SFA regression with variables normalized. The results of the two SFA regressions against insolation are in Table 3.

[Insert Table 3 here]

Daylight hours vary with seasons on the planet's surface depending on the solar PV power plant's latitude. We conduct SFA regression of daylight hours with the latitude of each solar PV power plant. The result of the SFA regression reported in Table 4 verifies that daylight hours are significantly affected by latitude.

[Insert Table 4 here]

While the aim of input adjustment is to put every power plant in the worst ambient condition and the unluckiest situation encountered, to maintain consistency with the adjustment of insolation, we do not simply set the adjusted daylight hours to the minimum in the sample.

The likelihood ratio test shows that the slacks of daylight hours and insolation have a mixed chi-square distribution, which testifies that the error term in the SFA regression has a composed structure and it is effective to use SFA regression to separate the effect of managerial inefficiency from the error term.

The estimated values of $\gamma^i = \sigma_{ui}^2/(\sigma_{vi}^2 + \sigma_{ui}^2)$ are very close to 1, which suggest that the variation of the total slacks of daylight hours and insolation are both dominated by managerial inefficiency. Here, cases of statistical noise in solar PV power plants are dust, shadow or objects (e.g., ornithocopros, leafs etc.) on the PV panels, equipment failures, strikes and measuring error. Examples of managerial inefficiency include manpower shortages, incompetency of PV panel cleaning and inadequate equipment arrangement (e.g., inadequate inverter size, PV surface

§ https://eosweb.larc.nasa.gov/cgi-bin/sse/sse.cgi?skip@larc.nasa.gov+s04#s04 orientation, inclination etc.). Possible explanations also include: First, the value of daylight hours in this paper is the number of hours between sunrise and sunset while insolation changes substantially during this period. Second, due to the technology restriction in PV power generation, the highest PV system conversion efficiency is still less than 45% and thus affecting the utilization of solar resources. Third, part of the power generated may not have been fed into the grid but wasted or self-used by the plant.

From the standardized regression coefficients, we can see that temperature has the most significant influence on the utilization of solar insolation and thermal management of solar PV modules should be paid special attention in enhancing electricity generation. Temperature affects the slack of insolation positively while precipitation negatively, which means that temperature has a negative influence on the utilization of solar insolation and precipitation a positive one. Cloud amount also have a positive effect on insolation utilization, which may be a result of cloud's cooling effect on the solar PV system. Elevation and wind speed do not have significant influence on insolation. The sample's average elevation value is 615.186 meters and elevation does not make a magnitude difference in affecting insolation reception. Since wind speed in the sample varies from 5.1 m/s to 6.7 m/s with standard deviation of 0.6, the standardized coefficient of wind is also insignificant.

4.3.3. Input data adjustments

We use the coefficients from the SFA regression to predict the slacks of insolation and that of daylight hours attributed to environmental factors. Statistical noise is also separated from the error term. Through equation (4), we can calculate the adjusted insolation and daylight hours which have netted out the impact of environmental factors and statistical noise. Table 5 is the comparison of the original and adjusted input data.

[Insert Table 5 here]

Stage 3: estimating the environment-adjusted operational efficiency with adjusted inputs

In this stage, we import the adjusted insolation, adjusted daylight hours, original net generation, nameplate capacity and PV panel area in the SBM model to calculate the environment-adjusted operational efficiency, thus has the result netted out the influence of environmental factors and statistical noise.

Comparative analysis

The benchmarks in stage 1 and stage 3 are the same, both including five solar PV power plants: Prescott Airport, NRG Solar Blythe LLC, Victor Valley CC CPV Solar, Sacramento Soleil LLC and DeSoto Next Generation Solar Energy. The ranking of each solar power plant does not change much after controlling the impacts of environmental factors and statistical noise. If we compare the values of operational efficiencies of stage 1 with the environment-adjusted efficiencies of stage 3 directly, the efficiencies of stage 3 is slightly higher than that of stage 1. Particularly, only the efficiencies of solar PV power plants in California, Nevada, Arizona and Hawaii have decreased or unchanged, while the efficiency of solar PV power plants in other states have all increased. This suggest that California, Nevada, Arizona and Hawaii have relatively more favorable environment for solar PV power generation, so their plants' operational efficiency declined after controlling the favorable contribution of environmental factor and statistical noise. The Kendall rank correlation coefficient between original operational efficiency score and environment-adjusted operational efficiency score is 0.985, which is another evidence of the successful removal of the impacts of environmental factors.

Operational efficiency and environment-adjusted operational efficiency are calculated separately under different frontiers, and hence their values cannot be compared directly. A sample with 140 DMUs is set up, in which contains the original data of 70 original DMUs and 70 hypothetic DMUs with the adjusted data from stage 2, to facilitate the efficiency comparison before and after controlling the effects of environmental factors. We compute the SBM model again with data of these 140 DMUs. Since we have adjusted the inputs upward, the efficiencies of 70 hypothetic DMUs are less than or equal to the operational efficiency from stage 1and the environment-adjusted operational efficiency from stage 3. In another word, the frontier of the 140 DMUs is the same as the frontier of stage 1. We named the efficiencies of 70 hypothetic DMUs as operational efficiency with adjusted inputs and reported them in Table 6. Efficiency difference is the difference between operational efficiency with adjusted inputs and its corresponding original DMU's operational efficiency. DeSoto Next Generation Solar Energy has the smallest efficiency difference, meaning it has the most favorable ambient condition in the sample. Its overall efficiency would decrease by 9.1% if it is placed in the worst ambient condition.

[Insert Table 6 here]

Aside from five benchmarks in the sample, plants including Wyandot Solar Farm, Nellis Air Force Base Solar Array, Copper Mountain Solar I and Exelon Solar Chicago have efficiency difference smaller than 0.03. Smaller efficiency difference, which is the result of favorable ambient conditions and statistical noise, indicates better ambient conditions for solar power generation. Hence, similarities between ambient conditions of plants with smaller efficiency difference can be valuable for site selection of possible future solar PV power plants.

In the case of Wyandot Solar Farm, it has an efficiency difference of -0.036, which means its overall efficiency would decrease by 3.6% if it is in the worst ambient condition encountered in the sample of 70 grid-connected solar PV power plants. This indicates that Wyandot Solar Farm has benefited a lot from its favorable ambient condition. Its relatively higher efficiency from the stage 1 traditional performance evaluation can be partially attributed to the advantage caused by environmental factors.

For plants with larger efficiency difference, possible measures to improve operational efficiency include more frequent cleaning schedules for PV facilities, adding solar trackers, temperature control and so on. Cooling techniques, including natural and forced air cooling, hydraulic cooling, heat pipe cooling, cooling with phase change materials and thermoelectric cooling of PV panels, are highly recommended for utility-scale solar power plants [7]. Furthermore, the selection of module surface material, such as self-cleaning glass, may be helpful to prevent dust deposition and accumulation, and enhance the module power performance.

Policy implications

The U.S. has established an organized incentive policy system to advance renewable energy development. Federal and state policies are very supportive of solar PV power, so do their tax incentives. In order to make renewable energy to be developed to its full potential, the U.S is developing sustained federal and state policies and offering appropriate opportunities to encourage development and use of renewable energy. All public electric utilities are required to facilitate net metering in the Energy Policy Act of 2005, which allows renewable energy utilities to be compensated for electricity generated in excess of what they consume.

Several states are also making great effort in promoting renewable energy. Renewable Portfolio Standards (RPS) requires electricity utilities to achieve a minimum amount of renewable electricity sales or installed capacity based on a specified schedule of dates and mandates. In the United States, 31 out of the 50 states have some form of RPS programs [58]. Individual states like California, Florida, Hawaii, Maine, New York, Oregon and Vermont have their own feed-in-tariffs (FITs) system to offer a long-term purchase contract to renewable energy producers with price usually higher than market price. Tax incentives, rebates, and grants are also offered by states to encourage the use of renewable electricity by making its installation more cost effective.

To test the positive externalities and efficacy of policies and incentives in each state, we compared the electricity generation-weighted average operational efficiency with the number of incentives in each state (including regulatory policies and financial incentives for non-residential PV industry, all created before 2011). Generation-weighted state average efficiency is the average, weighted by net generation, of environment-adjusted operational efficiency for each state. We find that both financial and regulatory incentives do not have positive effect on operational efficiency in these 14 states, see Fig. 1 and Table 7.

[Insert Table 7 here]

In 2010, the federal government has 8 financial incentives and 2 regulatory policies, and each state has its own financial incentives and regulatory policies designed. The collected policies and incentives are all created before January 1st 2011 and are collected from the DSIRE database[**]. The financial incentives include corporate tax, feed in tariff, grant programs, green building incentives, industry recruitment/support, loan programs, pace financing, performance-based incentives, property tax incentives, rebate programs, renewable energy credits and sales tax incentives.

From Fig. 1 we can see that, though the number of solar PV power plants is positively correlated with the number of financial incentives, the incentives are not effective on improving the performance of the solar PV power plants. While these financial incentives may help with promoting solar PV power plant deployment across the country, there are no sign of positive externalities of investment or spillover effect of knowledge in the year 2010.

[Insert Figure 1 here]

Conclusions

There is widespread concern that environmental factor may not be playing a pivotal role in influencing the generation performance of solar PV plants. In this paper, the research gap of operational performance of solar PV power plants with consideration of environmental factors has been bridged. Traditional efficiency analysis assumes that all the solar plants are in the same ambient condition and rarely account for the variability of inputs like insolation. We use the three stage efficiency analysis approach to measure the environment-adjusted operational efficiency of solar PV power plants by netting out the effect of statistical noise and leveling the impacts of six environmental factors.

From the statistical perspective, the evaluation results of 70 grid-connected solar PV power plants in

[**] http://www.dsireusa.org/

the U.S. support the concern that environmental factors may not be playing a pivotal role in influencing the generation performance of solar PV power plants. The favorable ambient conditions have increased the overall efficiencies of solar PV power plants by no more than 9%. Plants in unfavorable ambient conditions could emulate the management practices of benchmark PV power plants and upgrade relevant PV system equipment to keep up operational performance. The impacts of five environmental factors on the utilization of solar resources are estimated and temperature is found to be the most important variable in influencing the efficiency of solar PV power plants. Different kinds of cooling technologies should be applied based on the location of the PV power plant. Another finding is that although financial incentives in each state have accelerated the deployment of solar PV across the U.S., they do not have the positive externalities of enhancing the operational performance of the solar PV power plants.

Future researches can focus on including more input and output factors as well as environmental factors to account for more diverse environment and to enhance the comprehensiveness of environment-adjusted operational efficiency evaluation. Comparison with researches extended to longer period, and hence avoiding possible observation bias would also be valuable. The three stage method can be also applied to other units that are susceptible to the influence of environmental factors.

Acknowledgements

The authors gratefully acknowledge the financial support from the National Natural Science Foundation of China under the grant nos. 71471018, 71573016 and 71521002; the Social Science Foundation of Beijing under the grant no. 16JDGLB013; the National Key R&D Program under the grant no. 2016YFA0602603. Thanks to the reviewers for their valuable suggestions.

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Tables and figures

Table 1 Descriptive statistics of solar power plants in 2010 (sample size = 70)

	Output	Input			
Variables	Net generation	Nameplate capacity	PV panel area	Insolation	Daylight hours
Unit	MWh	MW	Acre	kWh/m^2/day	Hours
Mean	5654.6	4.7	37.8	4.7	4438.1
Maximum	53341.0	48.0	450.0	6.4	4451.2
Minimum	47.0	1.0	0.3	3.6	4419.5
Std. Dev.	9991.6	7.9	84.2	0.6	6.5

Table 2 Descriptive statistics of environmental factors

Variables	Latitude	Elevation	Cloud amount	Temperature	Precipitation	Wind speed
Unit	°	Meters	%	°C	mm/day	m/s
Mean	36.7	615.2	52.7	14.3	1.9	5.2
Maximum	42.1	2480.0	68.3	24.0	3.7	6.7
Minimum	20.8	6.0	34.8	3.8	0.5	4.1
Std. Dev.	3.8	659.7	9.9	4.2	1.2	0.6

Table 3 Regression result of insolation

Independent variable	**Dependent variable**			
	Original		Standardized	
	Parameter	T-statistics	Parameter	T-statistics
Constant	2.926***	7.739	0.858***	35.270
Elevation	0.001***	7.076	0.198*	1.762
Cloud amount	-0.024***	-7.059	-0.221**	-2.528
Temperature	0.115***	7.297	0.25*	1.880
Precipitation	-0.043***	-3.214	-0.050	-1.261
Wind speed	0.204***	3.553	0.071	1.427
$(\boldsymbol{\sigma_{vi}^2 + \sigma_{ui}^2})$	13.006***	8.411	2.350***	5.167
$\boldsymbol{\gamma^i = \sigma_{ui}^2/(\sigma_{vi}^2 + \sigma_{ui}^2)}$	1.000***	14849.556	1.000***	186798.190
$\boldsymbol{\mu}$	-6.594***	-6.637	-0.733	-1.422
Log likelihood ratio	-94.786	n.a.	-67.786	n.a.

Notes: *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 4 Regression result of daylight hours

Independent variable	Dependent variable	
	Parameter	T-statistics
Constant	4425.718***	122.010
Latitude	-2.882***	-3.083
$(\sigma_{vi}^2 + \sigma_{ui}^2)$	4454227.700***	4202049.000
$\gamma^i = \sigma_{ui}^2/(\sigma_{vi}^2 + \sigma_{ui}^2)$	1.000***	6556569.500
$\boldsymbol{\mu}$	-3151.384***	-26.826
Log likelihood ratio	-559.315	n.a.

Notes: *** indicates significant at 1% level

Table 5 Comparison of original and adjusted input data

Variables	Insolation	Adjusted insolation	Daylight hours	Adjusted daylight hours
Unit	kWh/m^2/day	kWh/m^2/day	Hours	Hours
Mean	4.7	6.4	4438.1	4484.3
Maximum	6.4	7. 4	4451.2	4512.7
Minimum	3.6	5.8	4419.5	4419.6
Std. Dev.	0.6	0.3	6.5	17.0

Table 6 Slacks in stage 1 SBM model and environment-adjusted operational efficiency

PV power plant name	Plant state abr.	Insolation slacks	Daylight hours slacks	Environment-adjusted operational efficiency	Operational efficiency with adjusted inputs
Lanai Solar-Electric Plant	HI	6.067	4166.023	0.187	0.185
UASTP Solar Facility	AZ	4.967	4178.190	0.006	0.006
RV CSU Power II LLC	CO	3.663	3811.904	0.003	0.003
Dow Jones South Brunswick Solar	NJ	3.633	4307.364	0.010	0.010
Knouse Solar Project 1	PA	2.893	3809.470	0.005	0.005
Roger Road WWTP	AZ	5.072	4196.275	0.081	0.080
Trenton Solar Farm	NJ	3.548	4236.868	0.023	0.022
Silver Lake Solar Farm	NJ	3.371	4084.420	0.017	0.016
DE Solar 10240 Old Dowd Rd	NC	3.750	4031.216	0.021	0.020
FRV SI Transport Solar LP	CA	4.828	4228.351	0.070	0.070
Taylorsville Solar LLC	NC	4.011	4320.636	0.079	0.078
CSU Fresno Solar Project	CA	5.158	4224.397	0.142	0.140
Chuckawalla Valley State Prison	CA	5.048	4219.835	0.252	0.249
Mariani Packing Vacaville Solar	CA	4.828	4228.655	0.145	0.143
Solar Photovoltaic Project #02	CA	4.878	4221.355	0.216	0.214
Kohls San Bernardino Solar Facility	CA	5.098	4224.397	0.231	0.229
SunEdison Procter & Gamble Oxnard	CA	5.058	4223.789	0.220	0.218
Gap Pacific Distribution Center	CA	5.107	4182.144	0.232	0.230
NEDC Solar Site	MA	3.448	4239.910	0.076	0.075
SunEdison Walgreens Moreno Valley	CA	4.878	4222.268	0.255	0.252
Walgreens Woodland Distribution Center	CA	4.828	4224.397	0.261	0.259
Bolthouse S&P and Rowen Farms Solar	CA	5.047	4181.231	0.277	0.274
Solar	CA	4.575	4014.957	0.112	0.110
Solar Photovoltaic Project #01	CA	4.845	4010.090	0.194	0.190
ETS Ewing Solar Facility	NJ	3.472	4172.880	0.093	0.092
ELACC Photovoltaic Power Facility	CA	4.638	4217.401	0.244	0.242
Sunset Reservoir North Basin	CA	3.434	3483.751	0.047	0.046
Crayola Solar Project	PA	3.478	4229.568	0.106	0.105
SunEdison Anheuser Busch Fairfield	CA	4.688	4227.439	0.257	0.254
Robert O Schulz Solar Farm	CA	4.972	4164.972	0.296	0.292
Shelby Solar Energy Generation Facility	NC	3.898	4218.922	0.165	0.163
DE Solar 1725 Drywall Dr	NC	3.978	4221.355	0.202	0.200
Belmar Solar Array	CO	4.176	4102.809	0.201	0.198
SunEdison LV Sutton Plant Site	NC	3.977	4179.102	0.213	0.210
Aqua Ingrams Mill	PA	3.628	4232.305	0.180	0.178
QVC Inc	NC	4.008	4225.918	0.225	0.222
Pocono Solar Project	PA	2.853	3813.424	0.057	0.056
DE Solar 657 Brigham Rd	NC	3.802	4161.930	0.178	0.176
Carson Solar I	CO	4.215	4018.607	0.209	0.205
PPL Renewable Energy Merck Solar	NJ	3.371	4084.724	0.159	0.156
DIA	CO	4.100	4039.429	0.257	0.252

WWRF Solar Plant	CO	4.331	4083.811	0.248	0.244
Vaca Dixon Solar Station	CA	4.575	4017.694	0.284	0.279
SAS Solar Farm	NC	3.735	4015.261	0.185	0.182
RV CSU Power LLC	CO	3.940	4044.296	0.245	0.240
Hall's Warehouse Solar Project	NJ	3.371	4086.549	0.223	0.220
Pennsauken Solar	NJ	3.501	4126.367	0.226	0.222
CalRenew-1	CA	4.038	3383.593	0.235	0.226
Atlantic City Convention Center	NJ	3.405	4021.648	0.216	0.212
PSEG Hackettstown	NJ	3.245	3984.566	0.174	0.170
SunEdison Walmart Apple Valley DC	CA	3.956	3288.446	0.408	0.392
MF Mesa Lane LLC	PA	3.043	3811.904	0.209	0.204
Greater Sandhill I	CO	0.135	420.402	0.127	0.118
Blue Wing Solar Energy Generation	TX	1.142	1492.077	0.149	0.140
Cimmarron Solar Facility	NM	0.000	307.740	0.120	0.110
SunEdison Ironwood State Prison	CA	3.009	2550.358	0.484	0.456
El Dorado Energy Solar Expansion	NV	2.746	2325.137	0.445	0.418
Calpine Vineland Solar LLC	NJ	2.845	3576.774	0.309	0.299
Space Coast Next Generation Solar Energy	FL	2.226	2312.970	0.351	0.331
Jacksonville Solar	FL	0.744	1259.685	0.212	0.197
SunE Alamosa	CO	2.860	2704.502	0.410	0.388
Wyandot Solar Farm	OH	0.721	1914.164	0.213	0.200
Nellis Air Force Base Solar Array	NV	1.677	1481.596	0.566	0.528
Copper Mountain Solar I	NV	0.000	26.329	0.366	0.331
Exelon Solar Chicago	IL	1.499	2546.744	0.334	0.316
NRG Solar Blythe LLC	CA	0.000	0.000	1.000	0.941
Prescott Airport	AZ	0.000	0.000	1.000	0.940
Victor Valley CC CPV Solar	CA	0.000	0.000	1.000	0.935
Sacramento Soleil LLC	CA	0.000	0.000	1.000	0.919
DeSoto Next Generation Solar Energy	FL	0.000	0.000	1.000	0.909

Table 7 State average efficiency and number of policies and incentives

State	Solar PV power plants number	Generation-weighted state average efficiency	Financial incentive by each state	Regulatory policy by each state	Policies & Incentives#
Massachusetts	1	0.076	7	7	24
New Mexico	1	0.120	16	3	29
Texas	1	0.149	15	11	36
Pennsylvania	5	0.166	11	4	25
Hawaii	1	0.187	5	3	18
North Carolina	8	0.189	12	4	26
Ohio	1	0.213	7	5	22
New Jersey	10	0.233	5	7	22
Colorado	8	0.288	15	13	38
Illinois	1	0.334	8	6	24
Nevada	3	0.462	7	5	22
California	24	0.653	35	17	62
Florida	3	0.761	6	6	22
Arizona	3	0.892	10	10	30

Note: # includes all policies and incentives of both state government and federal government

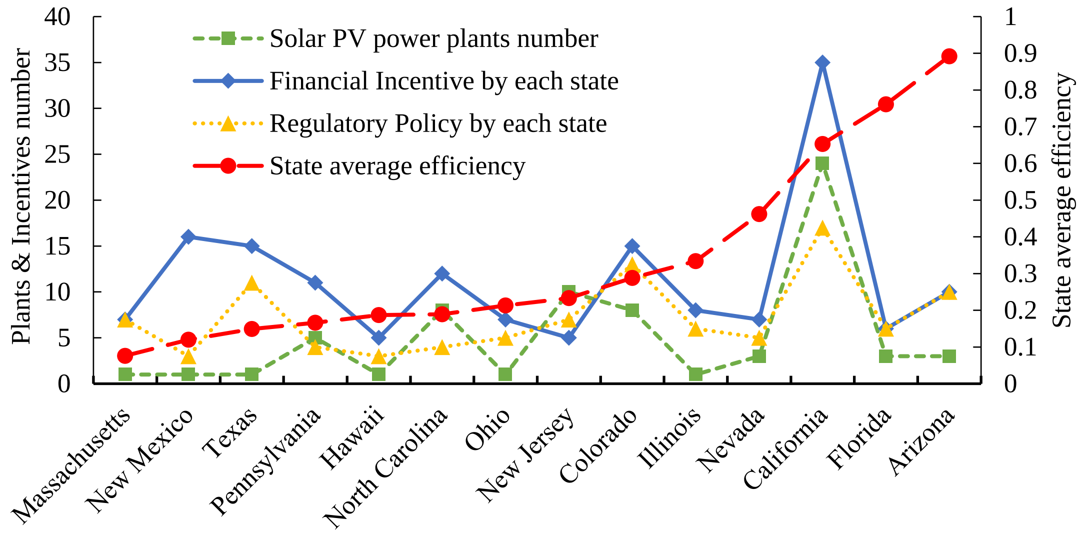

Figure 1 Comparison of state average efficiency, number of solar PV power plants and state policies and incentives