Applied Production Analysis (ECO615)

Efficiency of India's Solar Power Sector:

A Two-Stage Bootstrap DEA Approach

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Abstract

This study analyses the technical efficiency of the solar power industry in India using Data Envelopment Analysis (DEA) and further explores the effects of environmental variables on solar electricity generation through Simar & Wilson's (2007) bootstrap method. For the analysis, we consider installed capacity as input, and electricity generated and Capacity Utilisation Factor (CUF) as outputs for first stage DEA. Additionally, it considers solar insolation, air temperature, and relative humidity as environmental variables in the second stage. We obtain a mean efficiency score of 0.610 for the solar power generation sector in India, prior to bias correction, which adjusts to 0.336 post-correction. Notably, we find that solar irradiance and temperature exert a positive and statistically significant effect on efficiency scores, while humidity is found not to have a significant impact.

Keywords: Solar power, Technical efficiency, Data Envelopment Analysis (DEA).

1. INTRODUCTION

Our nation faces a daunting challenge due to the rapid surge in population growth, leading to an escalating demand for energy resources. The modern world heavily relies on energy consumption, primarily met through conventional means like fossil fuels. However, in recent decades, the spectre of global warming has emerged as a pressing concern. The extensive use of fossil fuels in electricity generation has significantly escalated atmospheric pollutant levels, contributing to global warming. The resultant emissions, including carbon dioxide and other harmful compounds, have precipitated severe environmental repercussions such as climate change. Compounding these issues is the gradual depletion of crude oil and fossil fuel reserves. These intertwined challenges underscore the imperative for transitioning to sustainable alternative energy sources.

Many countries have explored a range of alternative energy sources, including solar, wind, hydroelectric, and geothermal power. Among these options, solar energy has emerged as a particularly popular choice worldwide. Its widespread appeal stems from the abundance of sunlight, which requires only an initial investment, making it economically attractive. Moreover, its negligible pollution footprint and low maintenance requirements have captured the attention of investors and researchers alike. The inexhaustible nature of solar energy, and the amount of sunlight reaching the Earth's surface annually, surpassing global energy consumption by a factor of 10,000 [3], further enhances its appeal.

Solar energy's potential in India is staggering, recognizing which, the India Meteorological Department (IMD) has underscored India's capacity for solar energy harnessing. A significant portion of the country experiences sunny weather for 250 to 300 days each year. Annual global radiation ranges from 1600 to 2200 kWh/sq.m., comparable to levels observed in tropical and subtropical regions. Recent estimates suggest that India's solar energy potential exceeds 7,000 million GWh annually. Regions like Rajasthan and northern Gujarat receive the highest annual global radiation levels in India, making them prime candidates for large-scale solar power projects. The arid landscapes of Rajasthan, devoid of extensive vegetation, offer ideal conditions for the establishment of expansive solar-powered central power plants [7].

Given this background, the critical task is to efficiently utilise this energy resource and use it to its fullest potential. Nations have been trying to develop solar power plants that are technically and productively efficient and sustainable in the long run. Research studies have also revolved around analysing the efficiency of installed solar power plants. Along with the technical efficiency, another factor that needs to be considered is the impact on the environmental variables. Installation and operation of substantial solar plants consume a significant amount of land and water, which can also lead to habitat loss. In this sense, optimising solar energy through loss minimisation is crucial for developing solar energy-based systems. The purpose of the present study is to investigate the technical efficiency of the solar sector in India and to study the impact of such plants on environmental variables.

The proposed methodology combines Data Envelopment Analysis (DEA) and Simar-Wilson's two-stage analysis. The results of this study highlight the regional disparities in the efficiency of solar electricity generation in India and offer insights into critical geographical locations where efficiency improvements are needed.

2. LITERATURE REVIEW

In 1957, M. J. Farrell authored "The Measurement of Productive Efficiency," a seminal work published in the Royal Statistical Society journal [12]. This publication laid the groundwork for the development of Data Envelopment Analysis (DEA), a methodological framework devised during a research endeavour led by E. Rhodes. The research aimed to evaluate the efficacy of an educational initiative targeting underprivileged students in the United States, under the guidance of A. Charnes and W. W. Cooper. DEA represents a nonparametric analytical technique employed to assess the production efficiency of decision-making units (DMUs). One of the pivotal features that contributed to DEA's prominence is its capacity to consider multiple variables concurrently. In 1978, Charnes, Cooper, and Rhodes (CCR) elucidated the methodology for efficiency estimation in DEA, drawing upon the envelope theorem of Farrell and the nonparametric approaches.

A notable advantage of the deterministic nonparametric method is its independence from a priori knowledge of production functions. The methodology hinges upon delineating Efficiency Frontier Curves (EFCs), which serve to connect the inputs and outputs of DMUs. Outputs situated on the curve are deemed efficient, whereas those positioned off the curve are deemed inefficient. The advent of such an analytical methodology has engendered a paradigm shift in evaluating DMU efficiency, fostering notable advancements in the field [6].

A vast amount of study material has been produced in tandem with the growth of the solar energy sector in India, discussing its tremendous scope in the country. The primary reason for this is India's geographical location. Our country receives solar radiation of around 3000 hours of sunshine on a yearly basis. Most parts of the country receive around 4-7 KW hours of solar radiation per sq meters [9]. The country has also launched various missions to achieve targets of solar electricity production. One such critical mission is the National Solar Mission introduced by the Ministry of New And Renewable Energy in 2014. The mission aimed to achieve a cumulative installed solar capacity of 20,000 MW by 2020, attaining the proposed target installation capacity before the stipulated time period. The increased generation of electricity from the solar sector can be understood by analysing the overall electricity generation statistics from 2000 to 2003[8]. This success pertains to many factors, including materials, other components, and the workings of the power plants. One major factor is the photovoltaic panels, which are cost-efficient, requires less maintenance and reliable, which make them more popular. Also, recently there has been a surge in the usage of PV panels to generate solar electricity in Indian power plants.

Various studies from diverse regions worldwide have examined the efficiency and operational dynamics of solar power plants. For instance, Besarati et al. (2013) investigated the performance of solar photovoltaic (SPV) power plants across 50 Iranian cities using RETScreen software [10]. Their findings revealed substantial variations in capacity factors, with Bushier recording the highest at 26.1% and Anzali registering the lowest at 16.5%, yielding a mean capacity factor of 22.27%. Similarly, in Egypt, Elhodeiby et al. (2011) [13] conducted a performance analysis of a 3.6 kW rooftop grid-connected solar photovoltaic system, while Pavlovic et al. (2013) explored the feasibility of employing different solar PV module types for generating electricity through 1 MW PV power plants in Serbia [11].

Research Gaps

Despite this wealth of literature, there remains a conspicuous dearth of studies specifically scrutinising the **(i) technical efficiency of individual states as discrete Decision-Making Units** (DMUs). Addressing this gap necessitates a comprehensive analysis of each state's efficiency to discern potential areas for enhancement. Additionally, it is imperative to delve into the **(ii) environmental influences on power plants.** Furthermore, a study has underscored the potential influence of factors such as insolation, air temperature, speed of the wind, and humidity on the performance of solar PV panels [5], warranting meticulous investigation. By conducting in-depth analyses in these domains, we aim to obtain valuable insights to inform strategies for optimising the efficiency and environmental sustainability of solar power plants.

3. DATA AND METHODOLOGY

Data sources & variables

The data pertaining to the solar power sector utilised in this study is sourced from the India Climate And Energy Dashboard (ICED). Developed by NITI Aayog, ICED is a prominent initiative offering comprehensive data encompassing India's energy landscape, environmental factors, and relevant economic indicators. For our analysis, we rely on cross-sectional data pertaining to the year 2022, representing the most recent available dataset. In our methodology, we treat Indian states as distinct Decision Making Units (DMUs). We utilise installed capacity (MW) as the input variable, while electricity generation (BU) and Capacity Utilization Factor (%) serve as the output variables.

For **environmental variables**, the data used is extracted from NASA's Prediction Of Worldwide Energy Resources (POWER) database. We include solar insolation, air temperature and relative humidity as potential influencing factors on solar electricity generation, as suggested by Hachicha et al. (2019) [5]. Please refer to Table 1 for descriptive statistics of the variables used.

Table 1. Descriptive statistics of study variables.

Indicator	Variable	Mean	Standard Deviation	Min	Max
Installed Capacity (MW)	IC	2894.894	4587.249	11.79	19510.60
Electricity Generation (BU)	EG	3962.071	7380.755	1.76	34305.94
Capacity Utilisation Factor	CUF	12.144	6.826	1.48	25.17
Solar Insolation (kW-hr/m^2/day)	SI	4.845	.415	3.429	5.449
Air Temperature (°C)	AT	24.044	5.384	-.759	28.521
Relative Humidity (%)	RH	64.196	9.133	49.945	82.079

In the analysis, 30 Indian states/UTs are considered as individual DMUs, excluding those where solar electricity generation is zero.

Methodology

(i) Output-oriented DEA

This study utilises a sophisticated efficiency analysis technique called Data Envelopment Analysis (DEA) with an output-oriented approach, assuming a Variable Returns to Scale (VRS) frontier due to the considerable diversity in the capacity and size of the Decision Making Units (DMUs), which are Indian states in our analysis. The main goal is to assess the technical efficiency of each DMU (state) in the country. In the Charnes-Cooper-Rhodes (CCR) model, the efficiency scores are based on the unit data of DMUs, assuming a constant return to scale. DMUs with an efficiency score of 1 are considered benchmarks for comparison with other DMUs, although these results are relative rather than absolute. The BCC model, introduced in 1984, further refines efficiency assessment by allowing for variable returns to scale and ensuring comparable scale sizes for measured units, ultimately highlighting the most efficient DMUs based on input or output levels.

A basic representation of the model can be illustrated as follows:

Suppose we have n DMUs, where each DMU_j, (j = 1, 2… n) uses m inputs x_{ij} (i = 1… m) and produces outputs y_{rj} (r = 1… s). Let the input weights be v_i (i = 1… m) and the output weights be u_r (r = 1… s. The technical efficiency of each DMU_j, TE_j, is found by solving the linear programming problem specified as below,

$$\mathrm{TE} = max \Sigma_r u_r y_r$$
$$\text{subject to } \Sigma_i v_i x_i = 1,$$
$$u_r v_i \geq 0$$

(i) Regression analysis of determinants of efficiency - Simar & Wilson (2007) Bootstrap Regression

Traditional two-stage efficiency analyses, which perform DEA followed by Tobit or OLS regression, suffer from the following problems as per Simar & Wilson (2007):

- The underlying appropriate data-generating process for the second stage is not described, rendering the efficiency estimates inconsistent.

- Being estimated from the same data sample, estimates of efficiency suffer from serial correlation and sampling bias.

As a solution to the above, they proposed two bootstrap procedures, algorithms 1& 2. Algorithm 2 incorporates a parametric bootstrap approach to the first-stage problem, potentially improving the robustness and reliability of the estimates and confidence intervals.

Following the approach proposed by Simar and Wilson (2007), the paper assumes and tests the following regression specification:

$$TE_j = \alpha + Z_j\beta + \epsilon_j$$

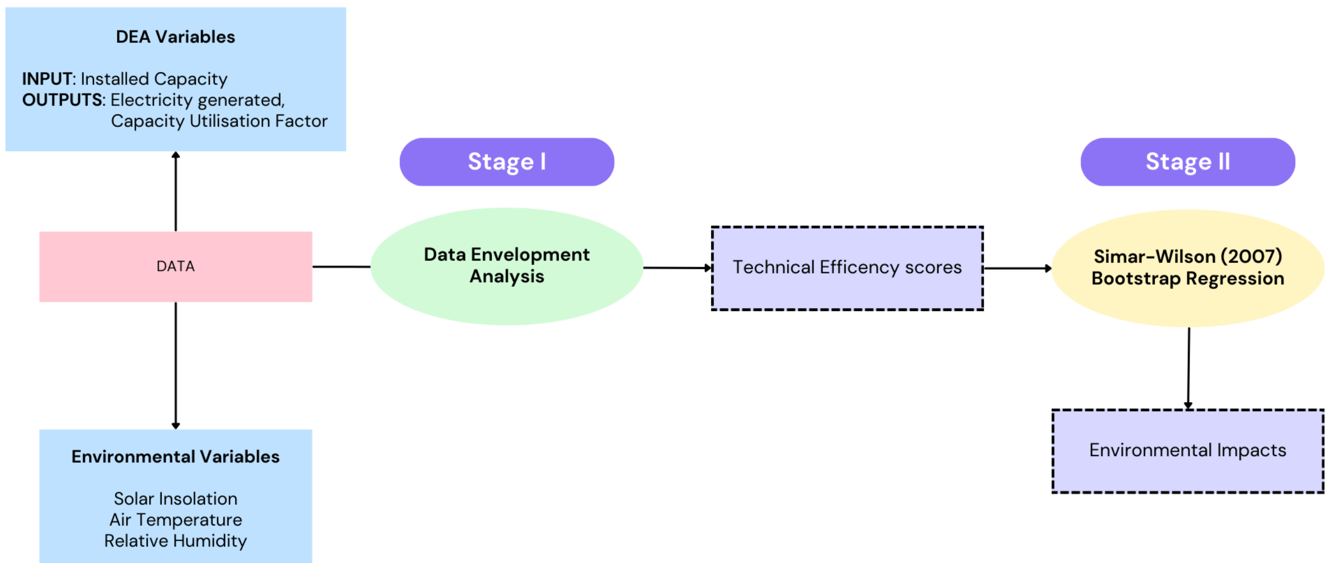
where α is the constant term, ε_j is statistical noise, and Z_j is a vector of observation-specific variables for DMU j that potentially influence DMU's efficiency score, TE_j.

Acknowledging that the range of ε_j is constrained by the requirement $\varepsilon_j \leq 1$ (as both sides of the above equation are limited to unity), we posit that this distribution follows a truncated normal distribution with a mean of zero prior to truncation, an unspecified variance, and a truncation point defined by this particular condition. Additionally, we substitute the unobserved true regressand TE_j with its DEA estimate $\widehat{TE_j}$. Thus, our econometric model can be expressed as follows:

$$\widehat{TE_j} \sim \alpha + \beta_1 SI + \beta_2 AT + \beta_3 RH + \epsilon_j$$

where j=1, ..., n, and $\epsilon_j \sim N(0, \sigma_\epsilon^2)$, such that $\epsilon_j \geq 1 - \alpha - Z_j\beta$, for j = 1, …, n. We estimate this by maximising the corresponding likelihood function. We employ the parametric bootstrap method for regression analysis to generate bootstrap confidence intervals for the parameter estimates δ and σ_ϵ^2. This approach integrates knowledge of the parametric structure and the assumed distribution, enhancing the accuracy of the confidence intervals. Please refer to Figure 1 for a summary of the research methodology followed.

Figure 1. Research Methodology



4. RESULTS AND DISCUSSION

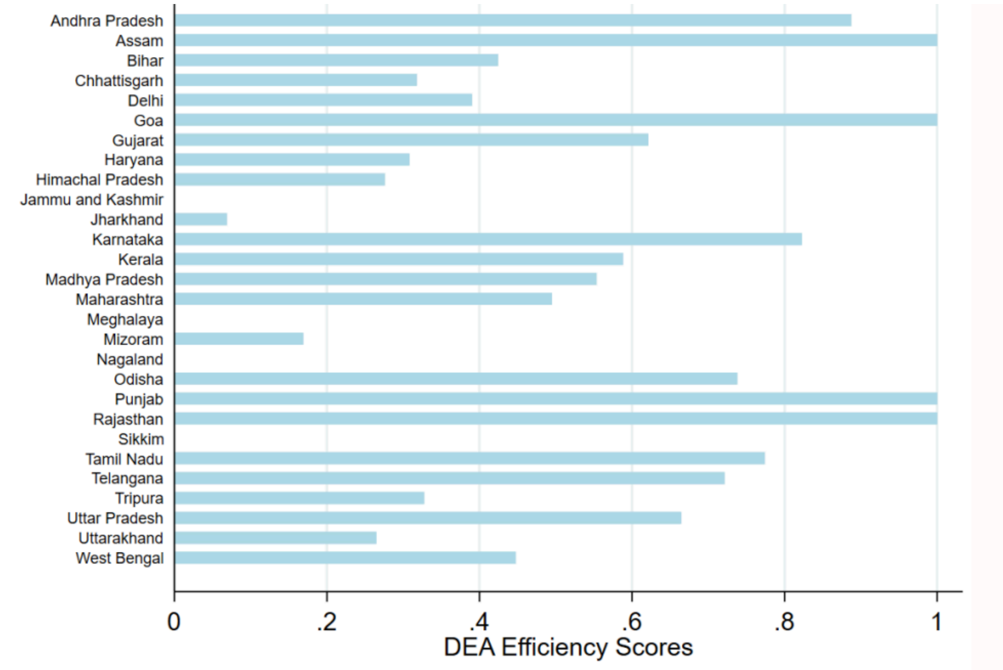
In this study, we performed an output-oriented, technically efficient (TE) DEA, assuming that plants aim to maximise solar electricity generated using the available resources. The efficiency scores obtained in the first-stage DEA analysis are presented in Table 2. The obtained results (VRS) are visualised in Figure 2.

Table 2. Results of first-stage Data Envelopment Analysis

S No.	State	Technical efficiency, CRS CCR model	Technical efficiency, VRS BCC model	Position on the obtained frontier
1	Delhi	0.378	0.385	IRS
2	Goa	1.000	1.000	-

3	Rajasthan	0.859	1.000	DRS
4	Karnataka	0.723	0.819	DRS
5	Assam	0.994	1.000	DRS
6	West Bengal	0.438	0.445	IRS
7	Odisha	0.707	0.707	IRS
8	Punjab	1.000	1.000	-
9	Bihar	0.412	0.419	IRS
10	Himachal Pradesh	0.260	0.279	IRS
11	Kerala	0.573	0.574	IRS
12	Haryana	0.306	0.308	IRS
13	Gujarat	0.545	0.614	DRS
14	Andhra Pradesh	0.797	0.882	DRS
15	Telangana	0.647	0.709	DRS
16	Uttarakhand	0.254	0.258	IRS
17	Tamil Nadu	0.684	0.768	DRS
18	Maharashtra	0.441	0.447	DRS
19	Mizoram	0.168	0.253	IRS
20	Uttar Pradesh	0.613	0.640	DRS
21	Arunachal Pradesh	0.321	0.525	IRS
22	Madhya Pradesh	0.506	0.525	DRS
23	Manipur	0.952	1.000	IRS
24	Tripura	0.319	0.434	IRS
25	Chhattisgarh	0.317	0.318	IRS
26	Jharkhand	0.066	0.089	IRS

Figure 2. BCC technical efficiency scores prior to bias correction in stage II.

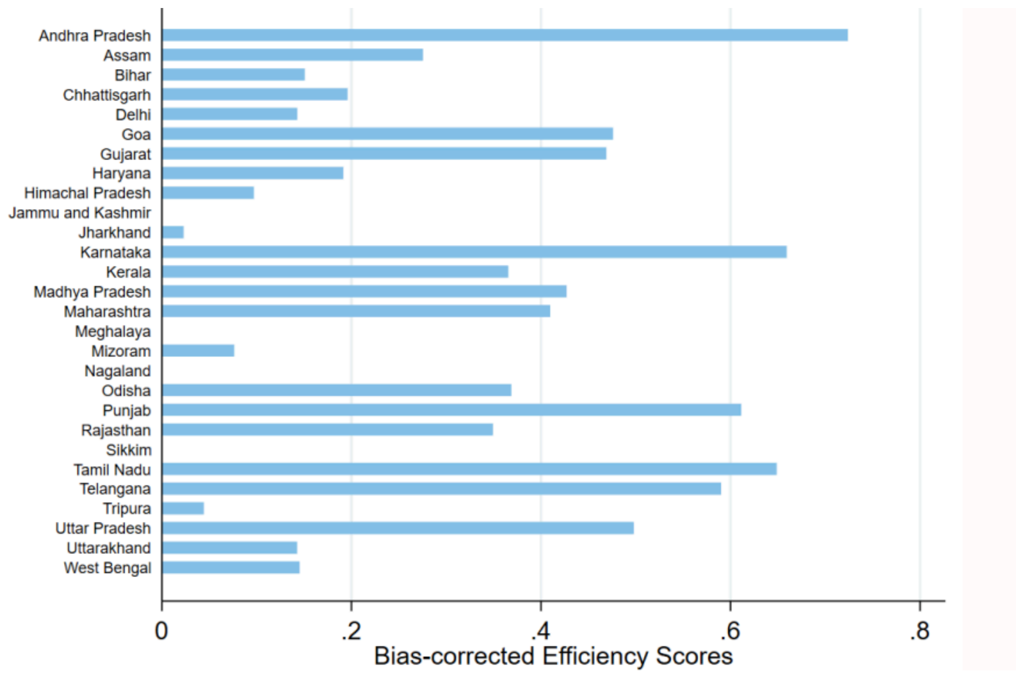


In the second stage, we perform a truncated bootstrapped two-stage regression following Simar & Wilson (2007), where the dependent variable is the CCR efficiency scores obtained in stage I. The results are presented in Table 3 below. The efficiency scores obtained post-bias-correction in stage II are visualised in Figure 3.

Table 3. Results of truncated bootstrapped regression. *Note: *** $p < 0.01$, ** $p < 0.05$*

Variable	**Model 1 (Algorithm 1)**	**Model 2 (Algorithm 2)**
Constant	-2.934***	-3.098***
Solar insolation	0.519***	0.526***
Air temperature	0.027**	0.034***
Relative humidity	0.003	-0.001
Variance	0.165***	0.166***
No. of observations	20	24

Figure 3. BCC technical efficiency scores post-bias correction in stage II.



The truncated regression model with a bootstrap approach seems to provide a good fit to the data, as evidenced by positive t-statistics. These statistics are statistically significant for variables such as solar irradiance and air temperature, indicating their strong influence on the model. However, humidity does not exhibit statistical significance in this context. We also observe that Andhra Pradesh displays the highest technical efficiency, followed by Karnataka, Tamil Nadu and Punjab. In our analysis, we obtained a mean efficiency score of 0.610 prior to bias correction for the solar power generation industry in India. It adjusts to 0.336 after bias correction in the second stage.

5. CONCLUSION

In conclusion, our study utilised Data Envelopment Analysis (DEA) followed by a truncated regression model with a bootstrap approach introduced by Simar & Wilson (2007) to analyse the factors influencing solar power generation efficiency in India. Our findings indicate that variables such as solar irradiance and air temperature significantly impact efficiency, while humidity does not show statistical significance.

Furthermore, our analysis reveals regional disparities in efficiency, with Andhra Pradesh exhibiting the highest technical efficiency, followed by Karnataka, Tamil Nadu, and Punjab. Prior to bias correction, the mean efficiency score for the solar power generation industry in India stood at 0.610, which adjusted to 0.336 after bias correction in the second stage.

These results underscore the importance of considering regional variations and the need for bias correction in efficiency evaluations within the solar power sector. Policy recommendations stemming from our study include:

a) *Investment in Solar Infrastructure:* Governments should prioritise investments in solar infrastructure, especially in regions with high solar irradiance and favourable climatic conditions, to enhance efficiency.

b) *Research and Development*: Continued research into innovative technologies and practices to improve solar power generation efficiency, particularly in areas with lower efficiency scores, is crucial.

c) *Data Collection and Monitoring:* Establishing robust data collection mechanisms and monitoring systems to track efficiency trends over time and across regions will facilitate evidence-based policy decision-making and targeted interventions.

Moving forward, targeted efforts should be directed towards regions with lower efficiency scores to unlock their full potential in solar electricity generation. By addressing regional disparities and enhancing efficiency, India can accelerate its transition towards a more sustainable and resilient energy future.

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