The effects of sun-tracking on rooftop photovoltaic systems

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Abstract. Sun-tracking is an important mechanism to boost the electricity generation from photovoltaic systems by adjusting the orientation of the systems to receive more solar radiation. However, compared to the fixed-array systems, the use of the single-axis and dual-axis sun-tracking systems is usually impeded by increased cost, decreased reliability, and cumbersome maintenance. In this paper, we compare the performance of fixed-array, single-axis, and dual-axis rooftop photovoltaic systems in California using the data envelopment analysis method. For each system, an efficiency score is computed based on capacity, electricity generation, system cost, module use, solar irradiance and ambient temperature. We find the single-axis systems perform significantly better than the fixed-array and dual-axis systems. The fixed-array systems are more efficient than the dual-axis systems but the difference is not significant. The results imply the policymakers and solar installers should promote the single-axis sun-tracking and be cautious of using the dual-axis systems.

1. Introduction
The electricity generation from a solar photovoltaic (PV) system depends on the amount of solar radiation received by the solar panels. The solar radiation imparted on the panels is maximized when the sun lights hit the panels at a perpendicular angle. Since the position of the sun in the sky changes over time, the orientation of PV panels should be dynamically adjusted to produce the maximum power output. Sun-tracking is an important mechanism to boost the electricity generation by adjusting PV orientation [1,2]. The gain in electricity output from sun-tracking compared to the fixed-array system depends on many factors. Literature has reported that annual output gain of sun-tracking systems over the fixed-array systems lies in the range between 20% and 40% [1].

In terms of degree of freedom, there are two types of sun-tracking systems, i.e., single-axis and dual-axis. The single-axis system has one degree of freedom and usually tracks the sun’s east-to-west movement [3]. The dual-axis system follows the sun’s east-to-west movement and changing altitude angle [4]. While the sun-tracking can increase the electricity output compared to the traditional fixed-array systems, it suffers from cost, reliability, and maintenance problems as a result of more complex design [5].

In this paper, we would like to evaluate the performance of sun-tracking using data from the California Solar Initiative (CSI), the most prominent solar incentive program in the state. Specifically, we apply the data envelopment analysis (DEA) method to evaluate a dataset of 1,030 rooftop PV systems. DEA is a non-parametric mathematical programming approach that has been demonstrated as a powerful tool to evaluate the performance of electricity generation facilities, including hydro plants, thermal plants, and wind farms [6-9]. However, its application to solar PV systems is rather scarce.
except for a few recent papers [10-12].

2. Model

DEA constructs an efficiency frontier by fitting piecewise linear segments to enclose all the units to be evaluated. For each unit, DEA computes an efficiency score to capture the unit’s relative distance to the frontier. Units on the frontier are deemed efficient and assigned efficiency of one. Units within the frontier are deemed inefficient and assigned efficiency less than one. To apply DEA, it is important to discern discretionary inputs and non-discretionary inputs. The environmental factors are exogenous to the PV systems and hence are non-discretionary. To incorporate the non-discretionary inputs, we use the DEA model developed in Banker and Morey (1986). The model has been demonstrated to be useful for PV installation assessment [10,11].

We let \( j \) denote the index of the PV system for \( j = 1, \ldots, n \); \( k \) denotes the system under evaluation; \( \phi_k \) denotes the efficiency score for system \( k \); \( \lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n) \) is the vector of weights for the units; \( x_j = (x_{1j}, x_{2j}, \ldots, x_{mj}) \) denotes the vector of \( m \) discretionary inputs for system \( j \); \( z_l = (z_{1j}, z_{2j}, \ldots, z_{lj}) \) denotes the vector of \( r \) non-discretionary inputs for system \( j \); \( g_j = (g_{1j}, g_{2j}, \ldots, g_{sj}) \) denotes the vector of \( s \) outputs for system \( j \). The model is as follows.

\[
\text{Efficiency}_k = \text{Min} \quad \phi_k \\
\text{s.t.} \quad \phi_k x_{ik} - \sum_{j=1}^{n} x_{ij} \lambda_j \geq 0, \quad i = 1, \ldots, m \\
\sum_{j=1}^{n} z_{lj} \lambda_j \geq 0, \quad l = 1, \ldots, r \\
-g_{hk} + \sum_{j=1}^{n} g_{hj} \lambda_j \geq 0, \quad h = 1, \ldots, s \\
\sum_{j=1}^{n} \lambda_j = 1 \\
\lambda_j \geq 0, \quad \forall j = 1, \ldots, n; \quad \phi_k \text{ unconstrained}
\]

(1)

To capture the performance of PV systems, we employ the following inputs and outputs to capture the most salient features of solar installation performance. There are two variables for the non-discretionary inputs \( \{z_{ij}\} \) in model (1):

- Solar irradiance: Solar irradiance is the most important factor in PV electricity generation. We use the global horizontal irradiance (GHI), measured in kW/m²/day. GHI captures the solar resource available at the installation site.
- Ambient air temperature: This is the ambient air temperature measured in Celsius (°C) at the site of the system. Because the PV cell energy conversion efficiency decreases in temperature [13], ambient temperature can be regarded as an undesirable input and we employ the inverse of it in computing model (1). Using the inverse of an undesirable input is a common technique in DEA [14].

We construct the following two variables for discretionary inputs \( \{x_{ij}\} \) in model (1):

- Modules: This is the total number of PV modules used in the system. The module quantity can affect capacity and electricity generation. We note that number of modules has been used as an input in PV assessment in literature [10,11].
- Cost of the system: It is measured in thousand dollars and usually includes the module, inverter, labor and overhead costs.
We construct the following two variables for the outputs \( \{ g_{hl} \} \) in model (1):

- **Capacity**: We use the CSI rating as capacity of the system, measured in kW. The CSI rating is measured upon 1,000 W/m² solar irradiance, 20°C ambient temperature and 1 m/s wind speed. It also factors in inefficiency of inverter and design factors (e.g., shading, mounting, orientation). The CSI rating is on average 85% of the nameplate capacity.
- **Electricity generation**: This is the total electricity generated by the PV system measured in MWh for a designated time period.

In computation, we adjust for inflation for system costs by converting the costs of installations at different times to January 2013 value, using the monthly consumer price index for all urban consumers from the US Bureau of Labor Statistics (http://www.bls.gov/cpi/data.htm).

### 3. Data and variables

From the PV system data, we obtain the CSI working dataset and the production dataset (both datasets are available at https://www.californiasolarstatistics.ca.gov/data_downloads). From the data, we can identify four tracking types, i.e., fixed-array (no tracking), single-axis, dual-axis, and mixed-array. Because the CSI does not specify what tracking methods the mixed type is exactly using, we delete all mixed systems in data. For each system, we can observe the location (city, county and ZIP code), the capacity, the cost, and the quantity of the modules. For a subset of systems, CSI reports the monthly production data. By January 2016, a total of 157,802 system-month observations have been entered into the production dataset. Following previous literature that evaluates the sun-tracking performance in one annual period [1], we assess the impact of sun-tracking from January 1st 2013 to December 31st 2013. PV systems without production data have to be removed. Finally, we obtain a sample of 1,030 PV systems.

We obtain the solar irradiation data from NREL (http://www.nrel.gov/gis/data_solar). The data provides monthly average daily solar irradiation at 10-kilometer resolution for the entire United States. The ZIP code for each 10x10 kilometer grid cell is also given in the data. Therefore, we assign the irradiance (converted from irradiation) to a PV system by matching the ZIP code. Note that higher irradiation leads to higher electricity generation and among the three types of PV systems, on average the dual-axis systems are installed at sites with the highest irradiation of 5.35kWh/m²/day. We obtain the ambient air temperature data from the National Climatic Data by the National Oceanic and Atmospheric Administration (NOAA, https://www.ncdc.noaa.gov/cdo-web/datasets). The NOAA records the temperature at a group of weather stations in California. For each PV system, we use the inverse distance weighting interpolation to derive the ambient temperature from weather station data [15]. Table 1 shows the descriptive statistics of all variables. There are 959 fixed-array systems, 56 single-axis systems, and 15 dual-axis systems. Based on table 1, the average cost-to-capacity ratios are 6.59$/W for fixed-array, 5.22$/W for single-axis, and 5.89$/W for dual-axis. Hence, by simple economic analysis, single-axis is the most cost-effective tracking method in terms of capacity expansion. This is further validated by the DEA results.

#### Table 1. Descriptive statistics for the variables.

|                      | Unit        | Fixed-array | Single-axis | Dual-axis |
|----------------------|-------------|-------------|-------------|-----------|
| No. of systems       | No.         | 959         | 56          | 15        |
| Irradiation          | kWh/m²/day  | 5.30        | 5.34        | 5.35      |
| Temperature          | °C          | 17.66       | 16.06       | 18.76     |
| Modules              | No.         | 986.97      | 2038.29     | 362.20    |
| Cost                 | thousand$   | 1294.80     | 2792.53     | 573.49    |
| Capacity             | kW          | 196.40      | 534.49      | 97.36     |
| Generation           | MWh         | 367.33      | 1015.55     | 159.90    |
4. Results
The DEA results obtained from model (1) are summarized in table 2 with the mean, standard deviation, minimum, maximum, 25th quartile and 75th quartile of the efficiencies reported for each sun-tracking type. Overall, the fixed-array systems attain a mean efficiency score of 0.58. The dual-axis systems have a mean efficiency of 0.54, the lowest among the three tracking types. The single-axis systems have a substantially better mean efficiency of 0.75, which is 29.24% higher than the fixed-array performance and 38.77% higher than the dual-axis performance. The maximum efficiency is 1.00 for both fixed-array and single-axis systems, while the highest efficiency for dual-axis is only 0.89. The efficiency scores of the single-axis systems strictly exceed the fixed-array and dual-axis at the minimum, 25th quartile and 75th quartile. The results seem to indicate that single-axis sun-tracking is the best tracking mechanism, while dual-axis is the worst one.

| Table 2. Sun-tracking methods and efficiency measures. |
|--------------------------------------------------------|
| Fixed-array | Single-axis | Dual-axis |
| No. of systems | 959 | 56 | 15 |
| Mean | 0.58 | 0.75 | 0.54 |
| Std. Dev. | 0.17 | 0.20 | 0.14 |
| Min | 0.20 | 0.42 | 0.28 |
| Max | 1.00 | 1.00 | 0.89 |
| 25th quartile | 0.47 | 0.57 | 0.47 |
| 75th quartile | 0.65 | 0.98 | 0.60 |

Since the DEA results do not provide statistical inference, we resort to statistical methods to test the differences. To compare the performance of the sun-tracking methods, we run the nonparametric Wilcoxon rank sum test and the t-test. The Wilcoxon rank sum test does not need the normality assumption and serves to complement the t-test. The test results are reported in table 3. The efficiency gain of the single-axis systems over the fixed-array and dual-axis systems is strongly significant in both t-test (p<0.001) and Wilcoxon rank sum test (p<0.0001). The difference between the fixed-array and the dual-axis systems turns out to be insignificant. The reason may be that the increased generation from a dual-axis system is compromised by the complexity and cost of the system compared to fixed-array. The results imply that adding one degree of freedom to the orientation of fixed-array PV system through the single-axis mechanism can substantially improve the PV performance. However, compared to the single-axis design, the PV performance deteriorates after a second degree of freedom is introduced through the dual-axis system. This is because compared to the single-axis system, the increment in solar radiation by adding a second degree of freedom is not sufficient to compensate for the increased cost from complex design and installation procedure [16].

| Table 3. Test of differences. |
|-------------------------------|
| Single-axis vs. Fixed-array | Dual-axis vs. Fixed-array | Single-axis vs. Dual-axis |
| t-test | 7.1855 | 0.0000 | -0.9022 | 0.3672 | 3.8250 | 0.0003 |
| Wilcoxon rank sum test | 5.9539 | 0.0000 | -0.5402 | 0.3672 | 3.8250 | 0.0003 |

* The table reports the t-statistics and z-statistics followed by the p-value in parentheses.

An intriguing problem to explore is how the efficiencies of different sun-tracking methods have evolved over time. The CSI dataset does not specify the installation date but we can proxy it using the interconnection application date. It turns out all the systems in sample were installed in 2008-2012. We plot the annual mean efficiencies of the three tracking types in figure 1 over time. The single-axis
tracking is substantially better than the fixed-array and the dual-axis for every single year in 2008-2012, and the gap has been widening from 2010 to 2012. Therefore, as time goes by, single-axis has been an increasingly favorable tracking method. The fixed-array is slightly better than the dual-axis in 2008 and 2009. But from 2010 onwards, the fixed-array and dual-axis have almost identical mean efficiencies.

![Figure 1. Change of performance of sun-tracking methods over time.](image)

5. Conclusions
In this paper we study the performance of different sun-tracking mechanisms by applying the DEA method to rooftop PV systems in California. After factoring in capacity, electricity generation, cost, module use, solar irradiance and ambient air temperature, we find the single-axis systems perform significantly better than the fixed-array systems with a roughly 30% gain in efficiency. The dual-axis system does not show significant improvement over the fixed-array system. Moreover, the efficiency gap between single-axis and other tracking methods has been enlarging from 2010 to 2012. Our results imply that policymakers and solar installers should promote the use of the single-axis sun-tracking and be cautious of using the dual-axis systems. Finally, we would like to point out that the aforementioned results are derived from California data. In other regions with different climate and installation cost, the validity of the results should be examined through further tests [17]. However, the methodology developed in this study is general and can be adapted for different scenarios.

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