ASSESSING PHOTOVOLTAIC PERFORMANCE USING LOCAL LINEAR QUANTILE REGRESSION

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ABSTRACT

The power generated by eleven different photovoltaic technologies and meteorological variables, such as irradiance and temperature, were recorded every half-hour at sites in the UK and Spain. These photovoltaic technologies included monocrystalline, multicrystalline and amorphous silicon, copper indium diselenide and cadmium telluride. Local linear quantile regression was used to determine the conversion efficiency of each technology as a function of the irradiance. This non-parametric technique also provides confidence intervals for the estimates. Monocrystalline silicon had the highest conversion efficiency, ranging between 10% and 13%.

KEY WORDS

Solar energy, Photovoltaic, Performance, Quantile regression

1 Introduction

Consumers are currently faced with a range of different photovoltaic technologies with varying costs and conversion efficiencies. In order to facilitate with the selection of an appropriate technology, manufacturers provide specifications such as the peak power rating, which describes the power output under "Standard Test Conditions" (STC). These conditions are defined as an irradiance level of 1,000 Wm^{-2}, an AM spectral distribution of 1.5 and a cell temperature of 25 ^{o}C. In practice, however, these ideal STC are unlikely to be met. In fact an irradiance level as high as 1,000 Wm^{-2} is representative of summer-time clear sky conditions; under such conditions, the cell temperature could reach 50 ^{o}C, thereby reducing the performance from that quoted under the STC (Table 1). The effects of combinations of temperature, cloud cover, elevation of the sun and other climatic conditions are not known. This lack of information complicates the process of choosing a photovoltaic technology to suit specific climatic conditions.

PV-Compare [1, 2], a project operated by the Environmental Change Institute, University of Oxford [3], tested eleven different photovoltaic technologies, situated both at Begbrook, near Oxford, UK (1W, 52N) and S'Alqueria, Mallorca, Spain (3E, 39N). The disparity in climate at the two locations provides a means of testing the robustness of the technologies to a range of meteorological conditions. The power generated by eleven sub-arrays were recorded every half hour. Meteorological conditions were monitored by taking half-hourly recordings of irradiance (insolation), three directional insolation measurements, the ambient temperature, and the temperature of the modules.

The aim of this paper is to use data from PV-Compare to quantify the proportion of energy which is actually converted to electricity, known as the conversion efficiency. The recordings obtained were extremely noisy, making it difficult to infer the functional form of the relationship between the power generated and the irradiance. Statistical estimation provides one approach for extracting the relationship and quantifying the conversion efficiency of each of the technologies. A nonparametric estimation technique known as local linear quantile regression is employed here.

The paper is structured as follows: Section 2 describes the different photovoltaic technologies; Section 3 explains the statistical technique employed for estimating the conversion efficiency; Section 4 provides the results of the analysis and Section 5 discusses the implications of the investigation.

2 Photovoltaic technologies

The eleven sub-arrays cover the range of present photovoltaic technologies: monocrystalline, multicrystalline and amorphous silicon, copper indium diselenide and cadmium telluride. Table 1 provides the names and details of these different photovoltaic technologies.

Monocrystalline silicon has the highest conversion efficiencies of around 14%. High temperatures are required to melt the silicon, and post-crystallisation processing involves sawing the crystals into wafers. This makes monocrystalline silicon both monetarily and energetically intensive to produce, and consequently, less viable for mass production. Multicrystalline silicon is better suited to mass-production, because although high temperatures are required to melt the post-crystallisation processing is minimised by casting the melt directly into the required shape without worrying about uniformity of the crystals. There is a loss of efficiency associated with processes occurring at grain boundaries between the crystals, which means that multicrystalline silicon only obtains efficiencies between

Table 1: *Description of the commercial products tested by PV-Compare.*

Product	Technology	Peak power, W	Area, m^2	STC efficiency	Field efficiency
Unisolar US64	Amorphous Si (Triple Junction)	512	8.1	6.32	5-6
ASE 30 DG-UT	Amorphous Si (Double Junction)	540	10.8	5	5-6
Intersolar Gold	Amorphous Si (Single Junction)	504	11.5	4.38	2-3
Solarex Millennia	Amorphous Si (Double Junction)	516	9.8	5.26	4-5
Evergreen ES 112 AC	Multicrystalline Si (Ribbon)	560	7.6	7.36	5-6
Siemens ST40	Copper indium diselenide	560	5.5	10.18	7-9
BP Solar Apollo	Cadmium Telluride	500	7.4	6.75	3-4
Astropower APX-80	Multicrystalline Si (APEX Si film)	640	8.6	7.44	4-5
BP Solar 585	Monocrystalline Si	595	4.4	13.52	10-13
Solarex MSX 64	Multicrystalline Si	640	5.6	11.42	7-9
ASE 300 DG UT	Multicrystalline Si (Edge Fed Growth)	600	4.9	12.24	8-10

7% and 12%. PV-Compare examined multicrystalline sub-arrays manufactured by different methods, such as ribbon and edge fed growth silicon. Amorphous silicon has no long-range crystal structure and low conversion efficiencies of between 4% and 6%. However, amorphous silicon is a thin film semiconductor, requiring small material inputs and lower production temperatures and costs, making it highly suited to large scale production. PV-Compare tested three different amorphous silicon technologies. Triple junction amorphous silicon has three different layers, each of which captures energy from a slightly different band of the incident solar spectrum. Single and double junction modules possess one and two layers respectively. Two sub-arrays made from non-silicon semiconductors were also investigated. Cadmium telluride and copper indium diselenide can both be used to make mass-produced thin film modules. These have higher efficiencies than amorphous silicon of around 7% and 10% respectively.

An increase in irradiance will augment the current generated by the photovoltaic cells, resulting from the increased number of electron-hole pairs that are produced. The proportion of energy which is actually converted to electricity depends on the conversion efficiency of the technology. The temperature of the modules also affects the amount of power generated. Despite the fact that increased temperatures decrease the band gap of the semiconductor and increase light absorption, thereby strengthening the current, a simultaneous decrease in the open-circuit voltage implies that such increases in temperature actually decrease the efficiency of the cell. On average, an increase of 1 ^{o}C decreases the power by 0.5%, but technologies with larger band gaps are less susceptible.

In summary, for a given level of irradiance, the performance depends primarily on the temperature of the module. This latter temperature is influenced by environmental factors such as the ambient temperature, wind speed and the cooling mechanisms incorporated in the design of the module. Details of other features, such as spectral responses are given elsewhere [4].

3 Methods

Quantile regression [5] is a technique for estimating the conditional quantile function, $q_p(x)$, $0 \leq p \leq 1$, of Y given $X = x$. For example, the median corresponds to $p = 1/2$. A pair of extreme conditional quantiles can be used to reflect a conditional confidence interval. The latter can be useful for conveying the range where one expects to find the majority of points, such as a confidence interval that reflects 95% of the distribution.

A nonparametric technique, known as local linear quantile regression (LLQR), provides estimates of the median and any other quantiles that are required [6]. An estimate for the quantile function, $\hat{q}_p(x)$, is calculated by minimising a local linear kernel weighted version of $E\left[\rho_p(Y-a)|X=x\right]$, where ρ_p is known as the *check* function,

$$\rho_p(z) = pzI_{[0,\infty)}(z) - (1-p)zI_{(-\infty,0)}(z), \qquad (1)$$

and p is the particular conditional quantile of interest.

Consider a set of n pairs of observations, $(X_1, Y_1), \ldots, (X_n, Y_n)$, from some underlying distribution, $F(x, y)$ with density $f(x, y)$. Suppose that the objective is to establish a description of the responses, Y_i given a particular value of $X = x$. A local linear fit is used to approximate the unknown pth quantile $q_p(x)$ by $q_p(z) = q_p(x) + q_p'(x)(z-x) = a + b(z-x)$ for z in a neighbourhood of x. The size of the neighbourhood and therefore the amount of smoothing is governed by a kernel, K, with bandwidth, h. This kernel is usually chosen to be symmetric. In the following, a Gaussian kernel is employed where h is the standard deviation.

The local linear estimator is defined by $\hat{q}_p(x) = \hat{a}$ where $\hat{a}$ and $\hat{b}$ minimise

$$\sum_{i=1}^{n} \rho_p(Y_i - a - b(X_i - x))K\left(\frac{x - X_i}{h}\right). \qquad (2)$$

As with any smoothing technique, the crucial step is the choice of bandwidth. The optimal bandwidth, $h_{1/2}$, for estimating the median was determined using cross-validation.

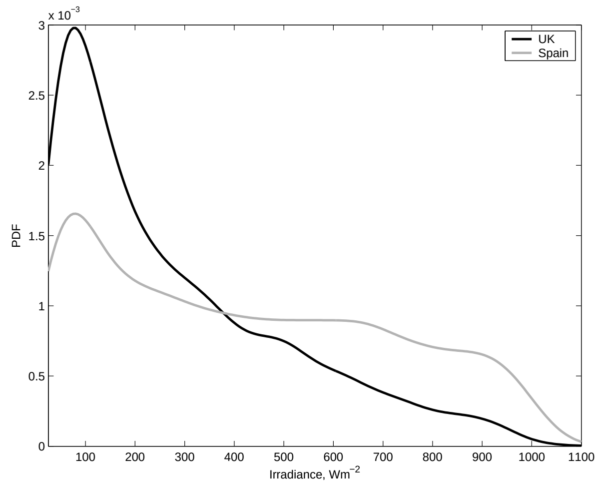

Figure 1: Probability density function of irradiance in the UK and Spain.

An alternative approach is to employ an automatic bandwidth selection technique [7]. Following [6], the value of $h_{1/2}$ was then used to determine suitable bandwidths, h_p for different quantiles p from

$$h_p = h_{1/2} \left[\frac{2}{\pi} \frac{p(1-p)}{\phi(\Phi^{-1}(p))^2} \right]^{1/5}, \qquad (3)$$

where ϕ and Φ are the standard normal density and distribution functions.

4 Results

The varying amounts of light intensity experienced in the UK and Spain due to their different climates may be seen from Fig. 1, which shows the probability density function of irradiance levels (greater than 25 Wm^{-2}). This illustrates that the cloudy conditions in the UK reduce the intensity of the light such that there is a larger probability of receiving light with irradiance levels less than 400 Wm^{-2} than in Spain. In contrast, the much clearer conditions generally experienced in Spain admit light with a high level of irradiance. The problem with using the STC irradiance level of 1,000 Wm^{-2} for measuring performance is apparent since such ideal conditions are rarely present in the UK.

In order to compare the different photovoltaic technologies, it is necessary to include the effect of different cell sizes, given in Table 1. The cell efficiency is defined as the power generated per unit area divided by the irradiance. This dimensionless ratio is then expressed as a percentage and reflects the ability of the photovoltaic cell to convert solar energy into electricity.

Comparing the efficiencies of the photovoltaic technologies in the UK (Fig. 2) and Spain (Fig. 3) demonstrated that the *BP Solar 585* (monocrystalline silicon) was a clear winner in both locations, although there was a larger decrease in performance at the higher levels of irradiance in Spain. The second best performance was given by *ASE 300 DG UT* (multicrystalline silicon) for irradiance levels greater than 200 Wm^{-2} and the *Solarex MSX 64* (multicrystalline silicon) for irradiance levels less than 200 Wm^{-2}. The *Siemens ST40* (copper indium diselenide) and the *Solarex MSX 64* (multicrystalline silicon) came third and fourth for irradiance levels greater than 200 Wm^{-2}. The *Intersolar Gold* (amorphous silicon, single junction) generally had the lowest cell efficiency in both countries. Efficiency levels of the crystalline technologies decrease at low irradiance due to spectral effects [4]. Overall the results of the comparison were relatively robust to the disparate climatic conditions in the two countries, suggesting that the analysis could be generalised to other climates.

The multicrystalline and monocrystalline silicon technologies all displayed evidence of reduced performance due to increasing temperature; this was particularly apparent for the efficiencies in Spain (Fig. 3). The increase in temperature that is associated with higher levels of irradiance may be seen from Fig. 4.

Figure 5 shows how the distribution of efficiency varies with the level of irradiance for one technology, the *BP Solar 585* in the UK. Although the distribution is relatively symmetrical for irradiance levels above 500 Wm^{-2}, between 100 and 500 Wm^{-2} the distribution is skewed such that it is also possible to observe efficiencies much less than the median value. This change in the distribution of efficiency with irradiance can be explained by considering the meteorological conditions in the UK. Cloudy conditions typically dominate in the UK giving rise to low irradiance, low temperatures and blue light, which decreases efficiency. Clear skies in the morning and evening are also associated with low irradiance and temperature but the redder light increases the efficiency level. It is the presence of these distinct spectral conditions that causes the spread in efficiency levels shown in Fig. 5 for low irradiance. As the sun gets higher in the sky, on clear days the irradiance increases, the light becomes bluer and the temperature increases. While the initial increase in irradiance improves efficiency, the blue light and hot temperatures eventually reduce efficiency.

5 Conclusion

The variety of photovoltaic technologies, with different efficiencies and financial costs, and different meteorological conditions means that selecting an efficient technology is not straightforward. Furthermore, the standard test conditions that are supplied by the manufacturers rarely provide sufficient information to facilitate decision-making.

PV-Compare provided half-hourly recordings of meteorological conditions and the power generated by eleven different technologies at sites in the UK and Spain. A non-parametric statistical technique was employed to calculate the cell efficiency of these photovoltaic technologies. This technique uses a local linear version of quantile regression

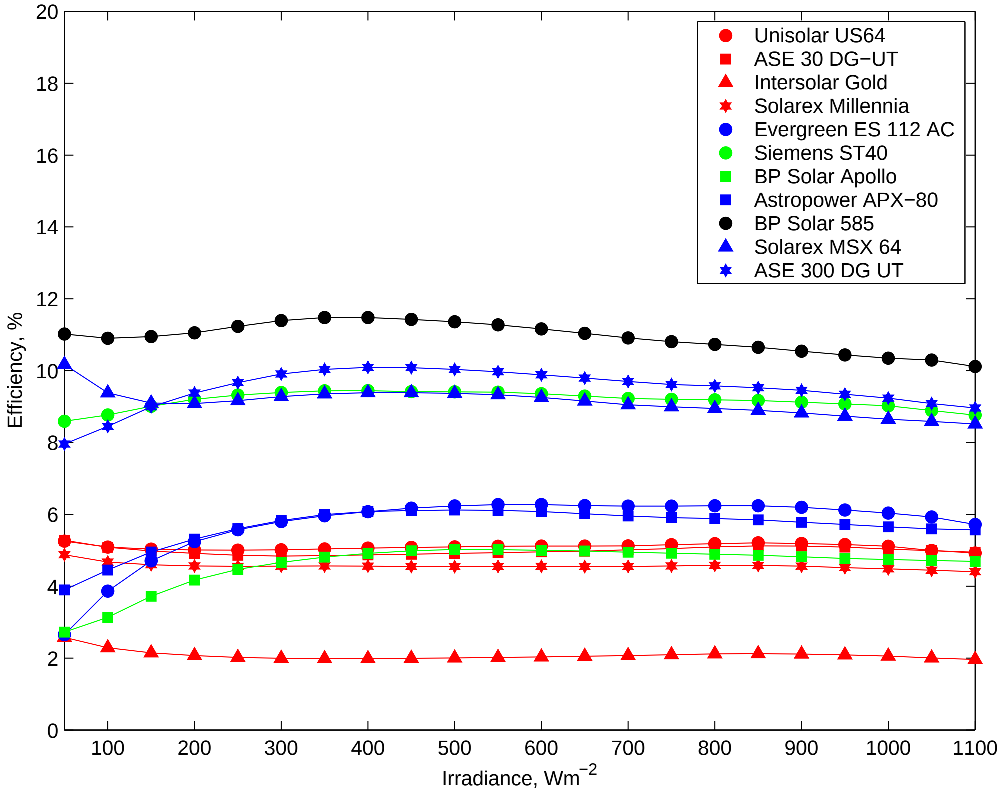

Figure 2: Efficiency of the eleven photovoltaic technologies situated in the UK. See Table 1 for further details.

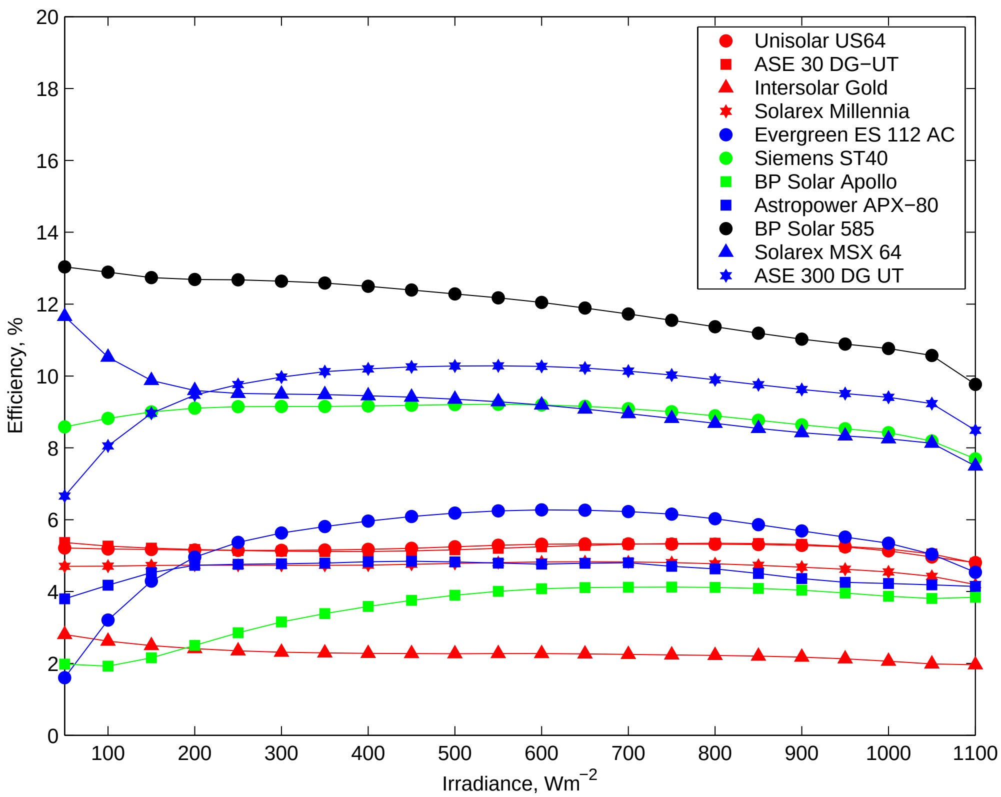

Figure 3: Efficiency of the eleven photovoltaic technologies situated in Spain. See Table 1 for further details.

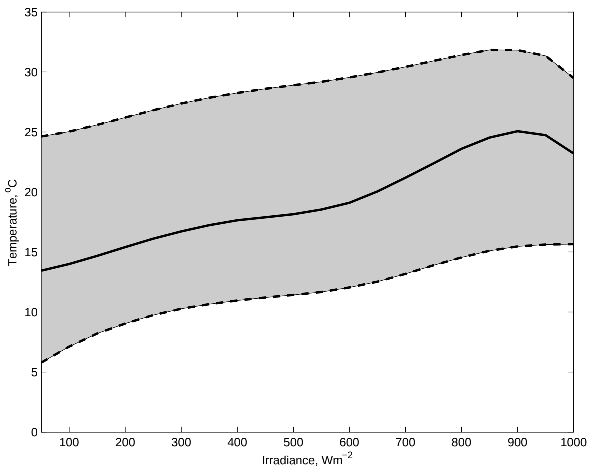

Figure 4: Median (solid), 5% and 95% (dashed lines) temperature versus irradiance in Spain.

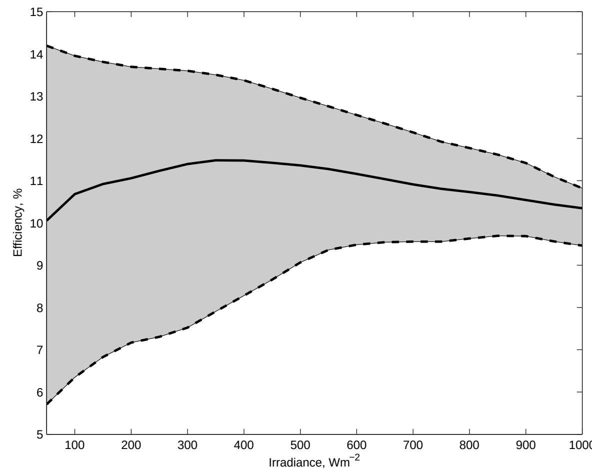

Figure 5: Median (solid), 5% and 95% (dashed lines) conversion efficiency of the BP Solar 585 *located in the UK.*

to establish different conditional quantiles and is also capable of providing confidence intervals for the conversion efficiency given a specific level of irradiance.

Table 1 presents the field conversion efficiencies for each technology. The technique offers a robust approach to comparing the different technologies and can provide consumers with additional information about specific operational characteristics. This would allow the consumer to collect site-specific observations of irradiance throughout the year and to use this time series to forecast the likely performance of each of the different technologies. Such site-specific metrics would be of great use to aid the consumer in selecting the most appropriate technology.

The ability to quantify the risk imposed by uncertainty in the estimation of the conversion efficiency (Fig. 5) is of great utility when attempting to operate within the newly deregulated electricity markets where failure to supply may lead to financial penalties.

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