Performance evaluation and comparison of solar cell technologies based on historical data

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ABSTRACT: In the current work we study the performance of three photovoltaic (PV) cell technologies under real operating conditions and five years of observations. The measurements are in Saudi Arabia, a challenging place for solar panels' performance as they often operate at temperatures far beyond the Standard Test Conditions (STC). We perform statistical comparisons between the three solar cell technologies (Back-Contact, Hetero-Junction, and Aluminum Back Surface Field) and estimate each PV cell's efficiency. Towards this purpose, we employ statistical and machine learning tools. We use two approaches for cell technology comparisons. The first is non-parametric and depends only on the energy yield output. The second approach is parametric, and a linear model between the energy yield and the irradiance is learned, with stationary and time-varying coefficients. The energy output differences between the cell technologies were small but statistically significant. We conclude that the highest average power output is given by the BC technology, followed by the HJT and the AlBSF technologies. Additionally, we quantify the deterioration of the cell performance over time and the variations due to seasonal factors.

1 INTRODUCTION

The great majority of Saudi Arabia's landscape is located inside the sun belt resulting in a significant opportunity for renewable energy from solar panels [1,2]. However, the development of solar plants is quite limited, with the contribution to the national energy mix being about 0.5% for 2020. Given the high potential and the future need for renewable energy, this study aims to highlight the performance differences between various PV cell technologies located in Saudi Arabia. We furthermore elucidate their behavior over a long period of time under the challenging weather conditions of Saudi Arabia, such as the high operating temperatures and dust storms.

Specifically, the technologies we compare are the Aluminum Back Surface Field (AlBSF), the Hetero-Junction (HJT), and the Back-Contact (BC). AlBSF is one of the first solar cell architectures used in the PV industry. The BSF technology is used primarily for reducing the surface recombination velocity, thus increasing solar cells' performance. HJT solar cells combine two different technologies into one cell: a crystalline silicon (monocrystalline or polycrystalline) cell sandwiched between two layers of amorphous silicon. The main idea behind the BC solar cells is to move all or almost all of the front contact grids to the rear of the device. This results in larger surfaces exposed to light and reduced shading effects, thus increasing the efficiency of the solar cell [2,3].

In work [4], authors compare the cell architectures under realistic conditions based on a combination of numerical simulations and statistical correction. In the present work, we employ machine learning and statistical tools [5, 6] to explore further cell technologies' performance based solely on observations. results and conclusions rely solely on the observations. We first, in sec. 2, present the data and the pre-processing procedure, then in sec. 3, we discuss the methodology, in sec. 4, we present and discuss the results, and we conclude in sec. 5.

2 HISTORICAL DATA LOCATION AND PRE-PROCESSING

The location of the PV solar cells for which historical observations are collected is the New Energy Oasis (NEO) test field near the Red Sea coast (22.30 N, 39.10 E), KAUST, Thuwal, Saudi Arabia. The available historical data consists of irradiance (IR) and energy yield (EY) observations from the three cell technologies (AlBSF, HJT & BC) for the 2015-2019 calendar years. For each day, an observation is recorded every 10 minutes, starting at 6:00 and ending at 18:50. Thus, the maximum number of daily observations, at times $t_n > 0$, $n = 1,\ldots,T$, is $T = 78$; see, e.g., Fig. 1 for one day of observations.

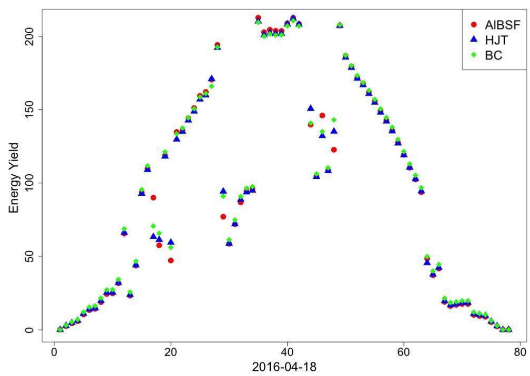

Figure 1: Daily Energy Yield and Irradiance

We initially performed an exploratory data analysis and visualization. We identified a small percentage of the records which did not follow the overall sample distributions. Irradiance and EY measurements had few problematic values, which we consider outliers, and we applied all the necessary data cleaning and preprocessing steps. Moreover, we further reduce the noise in the data by excluding measurements with an EY value below *10 W/m²*.

3 METHODOLOGY

We employ two approaches for comparing the three solar cell technologies. The first approach is a straightforward calculation of the EY difference between two technologies measured at the same time points. The second one is parametric in the sense that it incorporates the estimation of the efficiency coefficient for each architecture.

3.1 Direct, non-parametric comparisons

The first approach is a straightforward calculation of the EY difference between two technologies measured at the same time points. This "synchronous" comparison is required because the variability in the EY values stemming from weather or maintenance factors or simply the existence of missing data could affect the statistics of the quantity of interest.
The quantity of interest is the *relative performance difference* between architectures *A* and *B*, defined by

$$d_{AB}\,(t_n) \;=\; \frac{EY_A(t_n) - EY_B(t_n)}{1/2[\,EY_A(t_n) + EY_B(t_n)]} \qquad (1)$$

for instant times $t_n > 0$, n=1,2,... .
Here A (and B) denotes the type of the architecture being AlBSF, HJT, or BC. We study the relative performance d_{AB} statistics on a monthly and annually basis and for all the available observations.

3.2 Indirect, parametric comparisons

The parametric approach is defined via a linear model

$$EY_A(t_n) \;=\; c_A IR(t_n) \;+\; z(t_n),\;\; t > 0 \qquad (2)$$

where c_A is the slope and $z(t)$ the residual error.
The linear model is motivated by the estimated correlation coefficient between irradiance and EY is above 92%, even when we consider all records.
The linear irradiance model (2) has only one parameter, the slope c_A, and it is directly interpretable as the efficiency of the solar cell. Given that the relationship between irradiance and energy yield is not stationary for the whole five-year period, we slice the data monthly. Then, we compute the slope using two estimation methods: Ordinary Least Squares (OLS) and Robust Least Squares (RLS) with Huber weights [5].
We then compare the estimated slopes and utilize statistical testing to assess the significance of the differences.

4 RESULTS AND DISCUSSION

The EY differences between cell technologies were small but distinctive. The BC technology achieved the highest average power output, followed by the HJT and the AlBSF technologies. We next report the results supporting this conclusion while we quantify the differences. Also, we present the relative performance results for non-parametric (NP) and parametric (P) approaches.

4.1 Results on the non-parametric comparisons

Tables I and II report the average relative performance gain (or loss), $E[d_{AB}]$, between the three solar cell technology pairs per year and in total, respectively. We observe that the BC outperforms the other two technologies for each year from 2015 to 2019 and, on average for 2015-2019. Moreover, the relative performance difference between the BC and AlBSF has increased over the years. Similar is the behavior for the BC and HJT, except for 2018. Table II also verifies that HJT has better performance than AlBSF.

Table I: Average relative performance difference, $E[d_{AB}]$, between the three cell technologies. Positive values imply that the first cell technology is better.

Year	2015	2016	2017	2018	2019
BC vs AlBSF	0.5	4.4	15.6	13.2	18.8
BC vs HJT	1.5	2.4	5.4	3.0	4.8
HJT vs AlBSF	-1.0	2.1	12.4	-	-

Table II: Relative performance difference for 2015 - 2019

d_{AB} 100% / A vs B	$E[d_{AB}]$	95% C.I.
BC vs AlBSF	5.84	(5.75, 5.94)
BC vs HJT	3.11	(3.06, 3.16)
HJT vs AlBSF	2.53	(2.42, 2.64)

Figs. 1 and 2 compare the EY average value for the BC vs. the HJT and AlBSF technologies yearly and monthly. The BC technology achieved the highest average power output for all years and months. Similar is the behavior for the HJT and AlBSF pair, which we do not report here for ease of presentation.
The mean average difference of deviations for the EY output is 0.9 W/m² for the BC vs. HJT and 5.1 W/m² for the BC vs. AlBSF. These measurements ensure that the HJT performance is closer to the BC than the AlBSF.

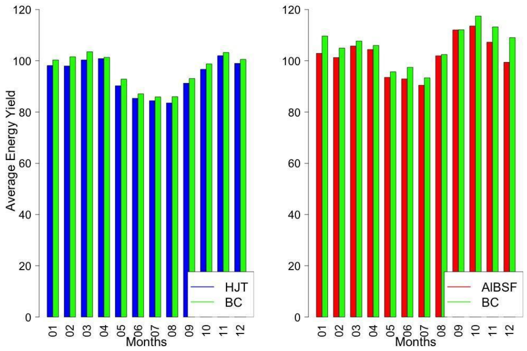

Figure 2: BC vs. AlBSF, monthly average EY.

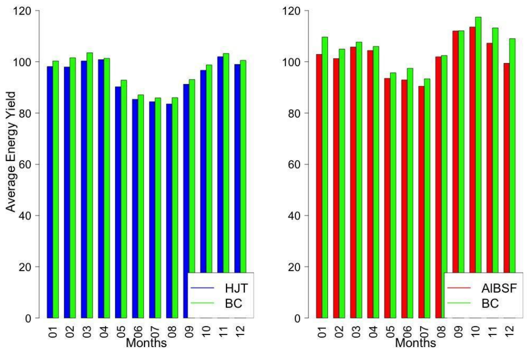

Figure 3: BC vs. HJT and AlBSF, yearly average EY.

4.2 Results of the parametric approach

In this section, we present the results of the parametric approach; see section 3.2. We note that both OLS and RLS estimators provided similar results; thus, we only present the results with OLS. Table III depicts the relative performance difference corresponding to the parametric approach. Comparing the results reported in Tables I and III, we observe that both approaches report qualitatively similar results. However, the parametric indirect approach is more conservative than the direct non-parametric approach. One possible explanation for this difference is that the parametric approach puts more weight on measurements with high irradiance values, while the non-parametric approach treats all measurements equally. Given that more power output is produced when irradiance is higher, the parametric approach is expected to provide more consistent comparisons. Despite being indecisive for 2015, it is evident that BC technology outperforms the other two for the subsequent calendar years.

Table III: Parametric approach. The relative performance between the three cell technologies.

Year / $E[d_{AB}]$	2015	2016	2017	2018	2019	All
BC - AlBSF	-1.8	1.9	12.8	9.0	18.3	5.5
BC - HJT	-0.4	0.6	4.8	1.0	3.5	2.1
HJT - AlBSF	-1.4	1.3	4.6	-	-	3.2

The upper plot of Fig. 3 shows the estimated slopes for the three cell technologies on a monthly basis. The time-varying behavior of the slope, hence, the solar cell efficiency, is evident. The lower panel of Fig. 3 shows the efficiency difference between pairs of solar cell technologies. This plot is a higher resolution presentation of the efficiency differences relative to Table III. These differences in performance are statistically significant as quantified by the p-values of the t-test reported in Table IV.

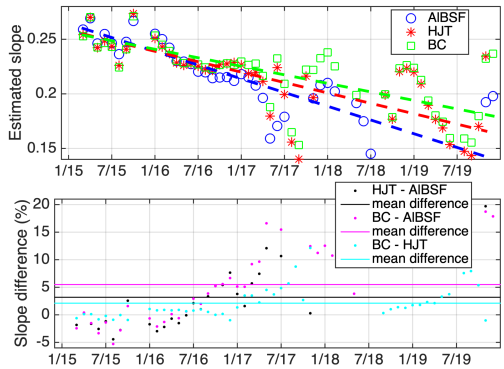

Figure 4: Upper panel: Monthly estimated slope for the three cell technologies. The slope is a direct estimator of cell efficiency. Thick dashed lines correspond to the linear trend of the slopes for each cell type and reveal the drop in efficiency over time. Lower panel: the efficiency difference for each pair (dots) and the respective average difference (solid lines).

Table IV: p-values for the t-test.

	BC–AlBSF	BC–HJT	HJT–AlBSF
p-value	0.000362	0.000008	0.027369

Moreover, it is evident from the upper panel of Fig. 3 that there is an annual performance deterioration in all cell technologies, which is different for each technology. We model this decay with a linear regression model, and the inferred model corresponds to the dashed lines in the upper panel of Fig. 3. For BC, the *average rate of deterioration* was 5.6%, for HJT, the rate was 6.9%, and for AlBSF, was 8.4%. To put these values into perspective, given that AlBSF and BC cells started with the same efficiency at the beginning, the efficiency of BC after 3 years will be the same as the efficiency of AlBSF after only 2 years!

Finally, we model the temporal evolution of the efficiency with a linear regression model that not only incorporates the decay trend but also the seasonal variation of the efficiency. It is obvious from Fig. 5 (dashed lines) that there are strong seasonal phenomena. Moreover, the efficiency is, on average, about 25% lower during the summer months relative to winter ones. This large difference shows the adversity of the weather conditions in desert environments which directly impact the production of solar energy.

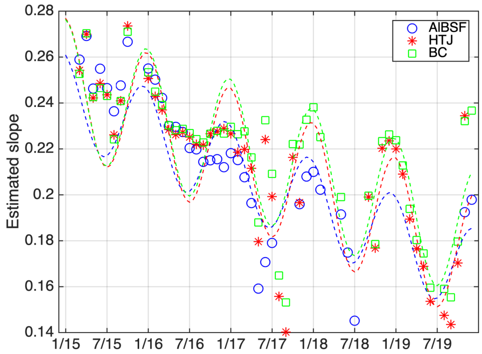

Figure 5: Same as the upper plot of Fig. 4 but with a regression model that considers the efficiency's seasonal trend.

5 CONCLUSIONS

BC was, on average, 5.5-5.8% more efficient than AlBSF and 2.1-3.1% more efficient than HJT. Interestingly, for 2015 the ranking is different (see Tables I and III). The deterioration over time is also evident: we estimated a 5.6-9% annual drop in power output efficiency depending on the cell technology. Data also revealed that the most dramatic performance difference was observed during seasonal alteration. The relative efficiency drop in summer relative to winter is up to 40%, eliminating the gains from increased irradiance. Therefore, informed decision-making for PV installation projects should take into special account the temperature coefficient of the PV cells. At the same time, mitigation measures such as cooling may be financially viable and worth considering.

We observe a temporal variation in the cell performance (the slopes). We attribute it to the heat; since the temperature in the afternoon (when the sun falls from its azimuth) is higher than in the morning (when the sun rises towards its azimuth).

6 ACKNOWLEDGMENTS

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