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Analysis of photovoltaic system performance time series: Seasonality and performance loss

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A B S T R A C T

In this work, the seasonality and performance loss rates of eleven grid-connected photovoltaic (PV) systems of different technologies were evaluated through seasonal adjustment. The classical seasonal decomposition (CSD) and X-12-ARIMA statistical techniques were applied on monthly DC performance ratio, R_P, time series, constructed from field measurements over the systems' first five years of operation. The results have shown that the R_P of crystalline silicon (c-Si) technologies was higher during winter. This was also the case for the copper–indium gallium-diselenide (CIGS) and cadmium telluride (CdTe) technologies but with lower seasonal amplitude. The amorphous silicon (a-Si) technology exhibited a different seasonal profile, with high R_P during summer and autumn and low during winter. In addition, the trends extracted from the application of CSD and X-12-ARIMA on three-year, four-year and five-year R_P time series were used to estimate linear performance loss rates. A comparison between standard linear regression (LR), CSD and X-12-ARIMA has shown that CSD and X-12-ARIMA resulted in higher rates overall for c-Si, 1.07 and 0.93%/year respectively, but with significantly less uncertainty than LR. Lastly, it was shown that X-12-ARIMA provided statistical inference in the presence of outliers and produced model residuals that were uncorrelated, in contrast to CSD.

1. Introduction

Various studies of the outdoor performance of photovoltaic (PV) systems have shown that both crystalline silicon (c-Si) and thin-film PV technologies operate under a strong seasonal profile [1–4]. The seasonality of c-Si technologies is mainly attributed to meteorological conditions such as the total irradiance, its spectral content, the angle of incidence, the ambient temperature and the wind speed and features a prominent annual seasonal pattern, with slight variations due to meteorological events [5,6].

Similarly, the performance of thin-film technologies such as amorphous silicon (a-Si), copper–indium gallium-diselenide (CIGS) and cadmium telluride (CdTe) is also affected by the irradiance, spectrum, angle of incidence, ambient temperature and wind speed, although the temperature dependence is weaker in comparison to c-Si technologies [2]. The spectral effect is more pronounced in a-Si technologies due to the different spectral response of a-Si [7]. Previous studies on a-Si have reported seasonal variations with peak performance during the summer [8–10]. This behavior was partly explained by the Staebler–Wronski effect [11,12], its reversal through thermal annealing [13] and spectral effects [1].

Although the seasonal profile is discernible from monthly energy yield and performance ratio, R_P, time series, further insight into the seasonality of each PV technology can be obtained by extracting the seasonal component using statistical methods. More specifically, seasonal adjustment techniques originating from econometrics, such as classical seasonal decomposition (CSD) [14,15] and regression modeling with Auto-Regressive Integrated Moving Average (ARIMA) [16,17] errors (regARIMA) [18], are used to decompose a seasonal time series into the seasonal component, the trend and the residual or irregular component. Generally, CSD is regarded as a simple method of seasonal adjustment [19] as the decomposition is performed with minimal effort and computational needs. This technique also forms the basis for most of the

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modern decomposition methods [14]. CSD and other statistical methods have been used in the past to model grid-connected PV power production [20] and to determine degradation rates of PV modules [21,22]. Despite that and due to the fact that the particular technique fits a predefined model, it doesn't take into account the particular characteristics of each time series and therefore, cannot optimally model each different PV system technology. Additionally, since the technique requires the assumption that the model residuals are uncorrelated, it could not provide statistical inference and this was proven by the presence of autocorrelation in the model residuals.

On the other hand, the X-12-ARIMA modeling method allows the calculation of the optimal regARIMA model for each PV system time series and uses robust statistics to decompose the time series into the seasonal, the trend and the residual components. The method was applied through the X-13ARIMA-SEATS software package [23], developed by the U.S. Census Bureau and used extensively in econometrics and time series analysis by institutions such as the Deutsche Bundesbank [24], the European Central Bank [25], the Australian Bureau of Statistics, Statistics Canada, Office of National Statistics UK and many others. The first seasonal adjustment method where regARIMA was derived from, was released in 1967 as the X-11 procedure [26], enhanced in 1983 with ARIMA forecasts and backcasts by the X-11-ARIMA procedure [27], further enhanced in 1998 by adding regARIMA, outlier identification and a plethora of diagnostics into X-12-ARIMA [28] and most recently in 2012 by X-13ARIMA-SEATS [23,29], which incorporates the X-12-ARIMA method and the TRAMO (Time Series Regression with ARIMA Noise, Missing Observations and Outliers) – SEATS (Signal Extraction in ARIMA Time Series) method of the Bank of Spain [30,31]. TRAMO is used to pre-adjust a series, while SEATS is used to seasonally adjust it.

The X-12-ARIMA method is more flexible than classical methods since it can effectively deal with seasonal variations, random errors, outliers and level shifts and, most importantly, it was developed to eliminate all autocorrelation in the model residuals. Previous investigations showed that multiplicative ARIMA could be used to model monthly PVUSA metrics [20], estimate PV degradation on a relatively short time series, reduce the impact of outliers and other errors on the degradation rate [21] and improve the forecasting of the R_P of c-Si technologies [32]. Due to the complex nature of ARIMA and regARIMA, they are entirely implemented in software [33]. This study used one of the most widely used software packages in econometrics, X-13ARIMA-SEATS [23], to apply the semi-parametric X-12-ARIMA method on PV performance time series in order to fit the optimal regARIMA models, quantify the seasonality of the R_P time series, estimate the performance loss rate from the noise-less extracted trend and detect additive outliers and level shifts in the data, ensuring low uncertainty and robustness to outliers.

The objective of this paper is to present a direct comparison of the seasonal profiles and an estimation of the performance loss rates of different PV technologies installed side-by-side, using robust seasonal adjustment of time series of field measurements. The CSD and X-12-ARIMA methods were applied on three, four and five-year long R_P time series from 1 kW_p grid-connected PV systems of different technologies, installed at the PV Technology test site of the University of Cyprus in Nicosia, Cyprus in 2006. The results showed that the seasonal profiles and performance loss rates were mostly dependent on the PV technology under study, followed by the outdoor exposure duration and the choice of seasonal adjustment technique. The estimated performance loss rates also included PV array loss factors such as module degradation, mismatches, initial power stabilization and, at a smaller part, partial shading and soiling, as the modules were regularly cleaned.

Lastly, this paper demonstrates the importance of using a robust workflow of statistical data analysis for reporting the performance loss rate of PV systems in operation. In this regard, the workflow was comprised of accurate measurement collection, data qualification and outage correction, robust statistical modeling through X-12-ARIMA, model validation, statistical inference and correct interpretation of the results by taking into account the uncertainty of the estimation.

2. Outdoor PV test site

The PV Technology test site of the University of Cyprus in Nicosia, Cyprus was commissioned in June 2006 along with the installation of 12 grid-connected PV systems, ranging from monocrystalline silicon (mono-c-Si), multi-crystalline silicon (multi-c-Si), Heterojunction with Intrinsic Thin layer (HIT) to a-Si, CdTe, CIGS and other PV technologies from different manufacturers, such as BP Solar, Atersa, Sanyo, Solon, Suntechnics etc. [34].

The rated power of each PV system is approximately 1 kW_p. The systems are grid-connected using identical inverters (SMA Sunny Boy SB 1100) in order to eliminate the side-effects of using different maximum power point tracking (MPPT) algorithms. All PV systems were installed facing South at a tilt angle of 27.5° for optimum annual energy yield in Cyprus and were ground mounted on metal frames [35]. Table 1 provides manufacturer datasheet specifications for each PV module technology including maximum power, P_{MPP}, and efficiency, η_{STC}, at standard test conditions (STC: 1000 W/m^2 irradiance, AM1.5 air mass, 25 °C cell temperature), open circuit voltage, V_{OC}, short circuit current, I_{SC}, array area, A, and others [36].

It is worth noting that during the evaluation period the Schott Solar ASIOPAK-30-SG a-Si system had suffered a broken module in October 2006, was ultimately dismounted in January 2011, and thus has not been taken into account in this study, while the performance of the BP Solar mono-c-Si and Solon multi-c-Si systems had been affected by partial shading starting from the second year.

The PV system monitoring started in the beginning of June 2006. Both meteorological and electrical PV array and system measurements were acquired and stored through an advanced data acquisition platform. The platform comprises of weather sensors and electrical transducers connected to a highly reliable central data logging system that stores instantaneous measurements every 1 s. The measurements are also averaged every minute and every 15 min and stored in the database. In accordance to the international guidelines for measurement, data exchange and analysis, IEC 61724 [37], the monitored meteorological parameters include the total irradiance in the plane of array (POA), G_I, wind direction, a_w, wind speed, S_w, as well as ambient, T_{am}, and module, T_m, temperature. The electrical parameters measured include array DC current, I_A, DC voltage, V_A, and AC power to the utility, P_{TU}, all at the maximum power point (MPP). The experimental infrastructure is summarized in Table 2 [38].

Periodic calibrations and inspections of the sensors were performed to ensure top quality measurements and to account for any sensor drifts [35]. Additionally, all sensor cabling and connection terminals were periodically checked for moisture intrusion, damage and loose connections.

3. Methodology

3.1. PV performance analysis

The analysis of the performance of the PV systems was based on monthly DC R_P time series, constructed from the 15-min average measurements. The array DC power was preferred over the system AC power in order to exclude the influence of the inverter from the