

# Identification of module replacements in US utility-scale photovoltaic installations

Chenyang Deng<sup>1</sup>, Jacob T. Stid<sup>2</sup>, Preeti Nain<sup>1</sup>, Annick Anctil<sup>1</sup>

<sup>1</sup>Department of Civil and Environmental Engineering, Michigan State University, East Lansing, 48824, MI, USA

<sup>2</sup> Department of Earth and Environmental Science, Michigan State University, East Lansing, 48824, MI, USA

**Abstract** — Including replaced modules is crucial to estimate PV waste generation. A new method is proposed to identify past module replacements, which could assist in estimating PV waste. The authors analyzed the variation in the capacity factor (CF) of the US solar plants from 2011 to 2020 to identify possible repowering. A sudden increase in CF is attributed to the possible replacement of old, less efficient modules with higher efficiency modules. The generation and construction data of major PV projects ( $\geq 1$  MW) is collected from US Energy Information Administration and converted into a statistical model to evaluate the capacity factor performance. An algorithmic program is generated that analyses and identify the plants with repowering. Multiple methods, including satellite image, machine learning, and data comparison, are applied to validate and optimize the program. Results show that the method can overall evaluate and monitor the trend of module replacement, although the identification accuracy of a single plant needs further validation. The model will use more parameters, including temperature, location, and irradiance, to improve the success rate.

**Keywords**—PV Replacement, PV Repowering, Solar capacity factor, End-of-life, photovoltaic modules

## I. INTRODUCTION

Solar photovoltaics (PV) has rapidly developed in the 21st century as an environment-friendly technology. It is considered one of the cleanest renewable energy sources meeting the challenges of increased energy demand with low environmental emissions. In 2021, a large capacity of solar plants was added to the US grids, and utility-scale (29%) and distributed (15%) solar accounted for a combined 45% of the all capacity added to US grids [1]. While the PV modules have low environmental emissions during their operational phase, they still have some environmental impacts during the entire life cycle. Production and end-of-life (EoL) stages contribute maximum to the environmental impacts and human health [2].

To better specify the material flow of the LCA, studies focused on the estimation of PV waste. One general methodology is to track the materials components in PV technologies [3]. The quantification of materials is used to forecast PV waste. The method relies mainly on references from related studies and accounts for crystalline technology and thus, doesn't account for new technologies. Related research typically uses the installation year as the baseline to forecast the

waste after 25-30 years [4]. However, the lifetime of the modules is not as long as manufacturers claim because operators prefer to replace the modules with new ones in the early years to achieve higher electricity generation for economic benefit. Therefore, the 'number/capacity of modules replaced per year' is a critical parameter in the PV waste estimation.

It is economically favorable to replace modules with more efficient ones. The critical condition is that the efficiency gain over installed modules must be large enough to justify the added replacement cost [5]. For crystalline silicon, an increase of 1% in cell efficiency would require the increase of cell production cost to be less than 25% for the process to be accepted [6]. PV manufacturers compete for higher efficiency, continuously developing better-performing modules at a reduced cost. For example, the manufacturer Longi has reached a 26.09% efficiency rate, claiming the materials applied are cheaper and more environmentally friendly [7]. JinkoSolar has released TOPCon solar modules with maximum efficiency of 23.23% [8]. Considering higher electricity generation and financial benefits, utility-scaled solar plant operators are motivated to replace less efficient modules with these new, more efficient ones. The suddenly increased efficiency has provided an excellent opportunity to identify the plants with module replacement.

## II. METHODS

The capacity factor (CF) refers to the ratio of the electricity output from a power plant over a particular time to the maximum possible output at its maximum capacity for the entire duration. Assuming that the annual difference of average sunlight time is ignorable for solar energy, the CF is representable for the performance of the solar module. Due to a series of factors, mainly module's degradation, the performance will decrease yearly, as represented by the CF. Since the CF represents the module's efficiency to some extent, an increase in CF from one year to the next is assumed as a replacement (old modules with lower efficiency are replaced with new modules with higher efficiency). The present study applies this approach to utility-scale solar plants ( $>1$  MW) to identify repowered plants.

### A. Data collection and calculation

The construction data is extracted from EIA 860 forms [9], and the generated data is extracted from EIA 923 forms [10]. The location and other geological information are obtained from EIA Atlas [11]. The CF is calculated as per the following equation:

$$CF = \frac{W}{C \times 24hr \times 365d} \quad (1)$$

Where  $W$  refers to the annual generation, and  $C$  refers to the plant's total capacity. Though a solar plant cannot operate for 24 consecutive hours, it is still used to represent the maximum power output. For a plant with multiple arrays which was installed in a different year, the total capacity in a specified year could be represented as:

$$C(year) = \sum C_{1j} + \sum \left( C_{2j} \times \frac{m_j}{12} \right) \quad (2)$$

$C_{1i}$  refers to the module's capacity installed before the year;  $C_{2i}$  refers to the module's capacity installed this year;  $m_j$  refers to the entire operating months. Notably, the newly installed modules may not be entirely operated in the initial year, but the overestimation will not impact the results.

### B. Identification and correction

The total number of utility-scale solar plants reported by EIA is 4581, and the number of newly operated plants since 2013 is listed in TABLE I.

TABLE I. SUMMARY OF NEWLY INSTALLED PLANTS SINCE 2013

| Year   | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|--------|------|------|------|------|------|------|------|------|
| Plants | 243  | 310  | 370  | 469  | 526  | 473  | 487  | 534  |

The solar plant data includes many abnormal values, including 0 values, negative generation, and non-zero values before the operation year. It is addressed by initial data cleaning and organizing. Also, it is assumed that the fluctuation in annual irradiation has a negligible impact on the CF; therefore not considered. The three considered factors contributing to the yearly variation in capacity factor are:

- i) Degradation of the PV modules
- ii) Module alteration
- iii) Grid fluctuations

A code is developed to detect the variation in capacity factor and reduce the impact of the degradation and grid. Further, a three-class criterion is applied to rank the replacement: i) no replacement, ii) average probability of replacement, and iii) high replacement probability. To reduce the error, the yearly evaluation will depend on the performance for 3 to 5 consecutive years.

### C. Validation

To validate the results for the identified replacement in Arizona, satellite images from National Agriculture Imagery Program (NAIP) are used to identify module replacements.

## III. RESULTS

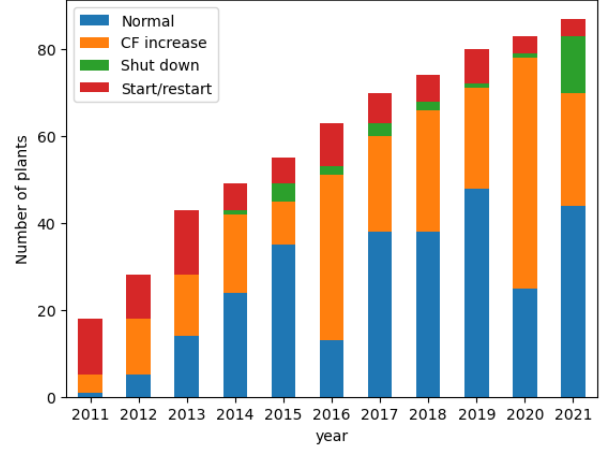


Figure 1: Operation Condition of solar plants in Arizona

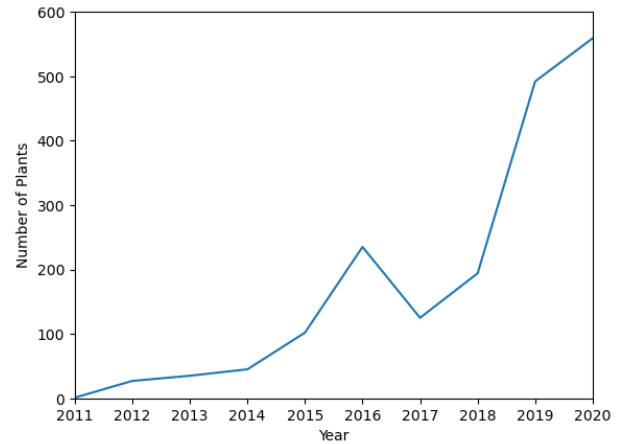


Figure 2: Number of identified repowered plants by year based on the CF change.

Figure 1 shows the capacity factor variation from 2011 to 2020 for plants over 1 MW capacity in Arizona. The total number of solar plants with over 1 MW capacity in Arizona gradually increases. The period from 2011 to 2013 is the fastest growing time, where most plants have more than five years of operation. For increased CF in 2016, the chance of replacement could be anticipated (the overall tendency for all states also happened in 2016).

Figure 2 shows the number of identified repowered plants from the initial algorithm, where the plants are only divided into non-replacement and replacement categories. To reduce the impact of the annual sunlight time, the algorithm detects the replacement based on the performance in a 5-year overall performance to, and the abnormal capacity factor change is

excluded. The peak in 2016 is already observed and recorded. This proves the validity of the present method and approach.

Figure 3 shows the solar plant distribution with no replacement, the average probability of replacement, and the high probability of replacement in the Mainland of the US, Hawaii, and Alaska not included. The figure shows that in 2016 most replacements happened in the coastal, and in 2020 northern areas have more replacement than 2016. This could be explained by the start year and location of the solar plants. In coastal regions like California and North Carolina, they have a very early solar plant start, while the north area has a late start following the trends in 2014-2017. Considering the economic benefits, most operators will replace the modules with higher efficient modules for more electricity generation for modules operated over 5 years. Another factor, the location/region, could impact the motivation for replacement. In the northern area, the modules are more frequently impacted by bad weather conditions, mainly the snow. Under such conditions, the modules are easier to be damaged or degraded, causing a shorter lifetime of the module with more frequent replacement.

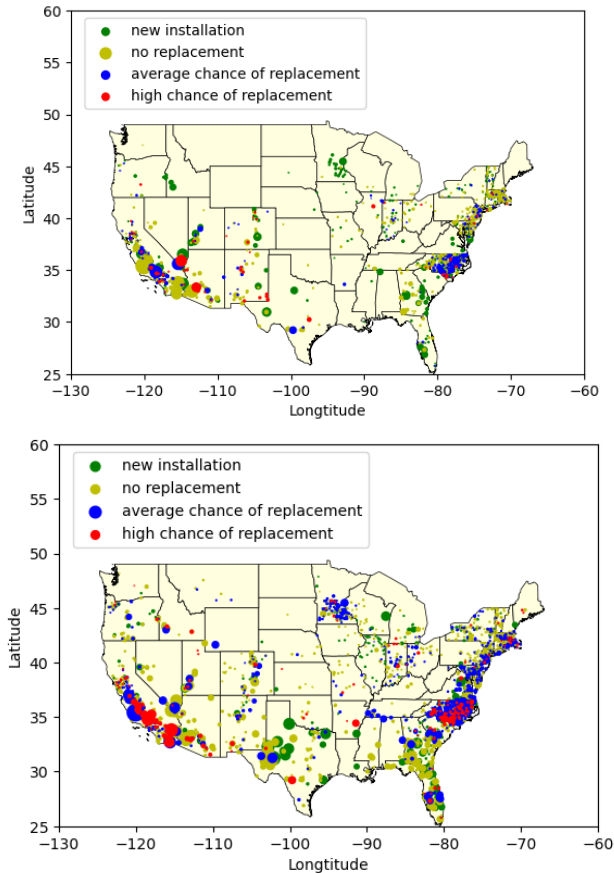


Figure 1: Replacement distribution map of US solar plants in a) 2016; b) 2020.

From the figure, there are some patterns about the module replacement related to the location and operation year. If the correlation of the replacement with those parameters could be

thoroughly understood, it is possible to build a model covering all the parameters, to explore the relationship between the replacement trends with time, location, temperature, and generation, furtherly predict the capacity of replaced modules. In addition, the machine learning methods could be applied to optimize the algorithm, using the plant information and CF as input and the results from relative studies for training, which is expected to increase the accuracy for the identification.

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