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Automatic fault detection for Building Integrated Photovoltaic (BIPV) systems using time series methods

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Abstract

Purpose – Faults in the actual outdoor performance of Building Integrated Photovoltaic (BIPV) systems can go unnoticed for several months since the energy productions are subject to significant variations that could mask faulty behaviors. Even large BIPV energy deficits could be hard to detect. The purpose of this paper is to develop a cost-effective approach to automatically detect faults in the energy productions of BIPV systems using historical BIPV energy productions as the only source of information that is typically collected in all BIPV systems.

Design/methodology/approach – Energy productions of BIPV systems are time series in nature. Therefore, time series methods are used to automatically detect two categories of faults (outliers and structure changes) in the monthly energy productions of BIPV systems. The research methodology consists of the automatic detection of outliers in energy productions, and automatic detection of structure changes in energy productions.

Findings – The proposed approach is applied to detect faults in the monthly energy productions of 89 BIPV systems. The results confirm that outliers and structure changes can be automatically detected in the monthly energy productions of BIPV systems using time series methods in presence of short-term variations, monthly seasonality, and long-term degradation in performance.

Originality/value – Unlike existing methods, the proposed approach does not require performance ratio calculation, operating condition data, such as solar irradiation, or the output of neighboring BIPV systems. It only uses the historical information about the BIPV energy productions to distinguish between faults and other time series properties including seasonality, short-term variations, and degradation trends.

Keywords Renewable energy, Time series analysis, Automatic fault detection, Energy performance, Operations and production management, Performance monitoring

Paper type Research paper

Introduction

Faults in the actual outdoor performance of Building Integrated Photovoltaic (BIPV) systems can go unnoticed for several months since the energy productions are subject to significant variations that could mask faulty behaviors (Leloux *et al.*, 2014). Even large BIPV energy deficits can be hard to detect (Drews *et al.*, 2007). BIPV systems could be manufactured in a wide range of sizes and installed in the most remote locations. In addition, the energy output of these systems is typically the only accurate information about them (Leloux *et al.*, 2014). These characteristics of BIPV systems make cost-effective and

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automatic fault detection of BIPV systems challenging (Leloux *et al.*, 2014). These faults could lead to safety issues and fire hazards (Zhao *et al.*, 2015). This study assesses the feasibility of using the historical energy productions of BIPV systems as the only source of information to detect faults.

This research introduces a new fault detection method that only uses the historical information about the BIPV energy productions. The new approach is cost-effective as the proposed method is capable of detecting the BIPV faults using only one source of information, the time series of historical energy productions. This innovative approach makes the automatic fault detection applicable to all sizes of photovoltaic systems integrated with any buildings, even those that are in most remote areas. The hypothesis of this research is that the rich information contained in the history of BIPV energy production provides invaluable information to detect these faults. The real-world performances of the PV systems contain valuable information that has not been fully utilized to evaluate the faulty PV systems (Leloux *et al.*, 2015). This research capitalizes on this opportunity by providing a cost-effective approach for fault detection that works with minimal information that is typically available.

Haeberlin and Beutler (1995) were probably among the first researchers that pointed out the possibility of online error detection if PV power and losses are normalized. Since 1995, several approaches have been proposed for the PV fault detection using normalized performance indicators. Existing approaches for fault detection are typically based on the calculation of a normalized performance indicator, such as performance ratio (PR), and operating condition data, such as solar irradiation (Woyte *et al.*, 2013; Drews *et al.*, 2007; Stettler *et al.*, 2006). For example, Drews *et al.* (2007) developed a fault detection approach working based on the difference between the simulated and actual energy yields. This approach uses the satellite-derived irradiance and a PV simulation model. Chouder and Silvestre (2010) also developed an automatic fault detection procedure for PV systems based on the comparison of the simulated and measured energy yields. It takes into account the environmental irradiance and module temperature evolution. This fault detection procedure was further extended by Silvestre *et al.* (2013) for grid connected PV systems. Firth *et al.* (2010) used performance data of 27 PV systems over a one- or two-year period to construct simple empirical models of the performance of PV systems during normal operation. This performance during normal condition was used as a baseline to identify faults. Bonsignore *et al.* (2014) developed a neuro-fuzzy fault detection method that identifies faulty behavior by comparing the value of six parameters along with the I-V curves in normal and faulty conditions. Hachana *et al.* (2015) developed a PV emulator for both normal and abnormal operating conditions. The amount of power losses along with the information extracted from this emulator was used to detect defects. Platon *et al.* (2015) developed a fault detection method based on the comparison between the measured and modeled AC power productions. The model predicts the AC power production using solar irradiance and PV panel temperature. Ghasempourabadi *et al.* (2016) combined real-time shading simulations with BIPV performance monitoring to detect faults. Dhimish *et al.* (2017) created a fault detection algorithm based on the analysis of the theoretical curves that describe the behavior of an existing PV system considering a given set of working conditions.

Recently, Leloux *et al.* (2014) proposed an automatic fault detection method for BIPV systems that did not require solar irradiation data. They created a performance to peers indicator and used the temporal and spatial correlation between energy productions of neighboring BIPV systems to detect faults. They confirmed that it is possible to carry out automatic fault detection without solar irradiation data. Although Leloux *et al.* (2014) did not require solar irradiation data, their proposed fault detection method needs information about the performance of peer BIPV systems that do not necessarily exist.

In addition to the methods that detect faults at the PV system level, there are methods detecting faults in photovoltaic system components such as arrays (Takashima *et al.*, 2008; Vergura *et al.*, 2009; Kang *et al.*, 2012; Hu *et al.*, 2013; Zhao *et al.*, 2013; Jazayeri *et al.*, 2017; Kuo *et al.*, 2017). For example, Takashima *et al.* (2008) used the time domain reflectometry to detect faults in PV module strings. Hu *et al.* (2013) created a photovoltaic module fault detection using a parameter-based model that is coupled with an electrical model and energy balance equation. The key parameters in this model include the total effective solar energy, total heat exchange coefficient, and ambient temperature. Zhao *et al.* (2013) studied three fault detection rules (3-Sigma rule, Hampel identifier, and Boxplot rule) for solar photovoltaic arrays. They recommended Hampel identifier and Boxplot rule for PV array fault detection. Although these methods are capable of detecting faults in PV system components, they are not designed for automatic fault detection at the system level. Jazayeri *et al.* (2017) created an artificial neural network-based power estimation approach enabling fault detection in photovoltaic modules. Kuo *et al.* (2017) created a photovoltaic energy conversion system fault detection using fractional-order color relation classifier.

The proposed automatic fault detection approach for BIPV systems using time series methods departs from the findings of the literature survey. The proposed system-level approach does not require PR calculation, operating condition data, such as solar irradiation, and the outputs of neighboring BIPV systems. It uses historical information in the energy production time series of a BIPV system to detect outliers and structure changes. The objective of this research is to develop an approach to automatically detect two categories of faults (outliers and structure changes) in the energy productions of BIPV systems using time series methods. Net energy output is used to represent energy productions.

Methodology

Energy productions of BIPV systems are time series in nature. Therefore, time series methods are used to automatically detect faults (outliers and structure changes) in the monthly energy productions of BIPV systems. The research methodology consists of the following steps:

- automatic detection of outliers in energy productions; and
- automatic detection of structure changes in energy productions.

Figure 1 summarizes the methodology explained in the following sections. Figure 1 shows the components of two major steps (outlier detection and structure change detection) in the methodology and the inputs and outputs of each component.

Automatic detection of energy production outliers

An outlier is a BIPV energy production observation that is not consistent with the remainder of energy production observations. The outliers of BIPV energy productions could be related to momentary BIPV system faults, energy measurement errors, and file preprocessing errors. The outliers should be identified before detecting structure changes because they can cause significant bias in the analysis of BIPV energy productions (Tolvi, 2000; Chen and Liu, 1993). Since energy productions are dependent time series observations, statistical time series tests should be used to identify and characterize outliers (Tolvi, 2000). There are two types of outliers: additive and innovative outliers (Chang *et al.*, 1988). An additive outlier just affects a single observation whereas an innovative outlier also affects subsequent observations. The methods proposed by Chang *et al.* (1988) are used as the basis for identifying and characterizing additive and innovative outliers in the BIPV energy productions. The effect of an additive outlier

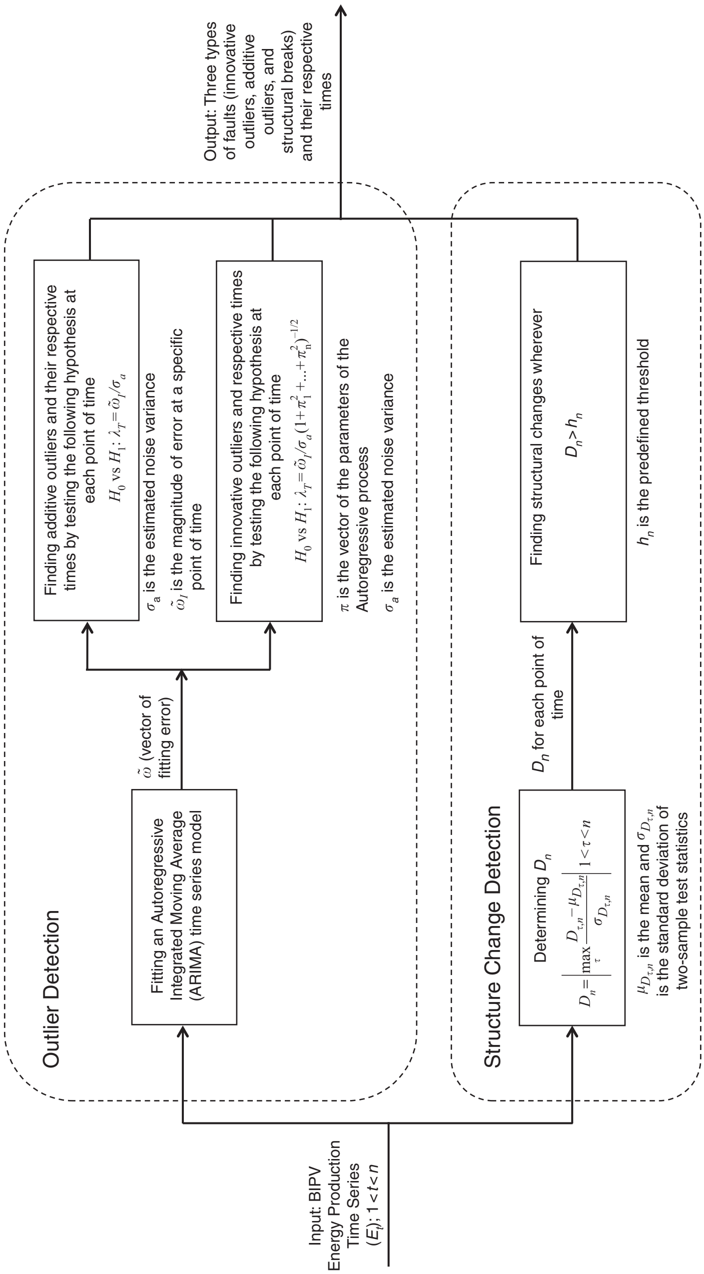

Figure 1.
Methodology flowchart

at time $t = T$, with magnitude of ω, on a BIPV energy production time series $\{E_t\}$ can be described using the following equation:

$$E_t = X_t + \omega I_t^{(T)} \tag{1}$$

where $I_t^T = 1$ for $t = T$ and $I_t^T = 0$ for $t \neq T$, and $\{X_t\}$ represents the BIPV energy production time series that follows autoregressive integrated moving average (ARIMA) model. ARIMA model is used to represent BIPV energy productions in Equation (1) because Jordan *et al.* (2010) recommended it for analyzing the outdoor performance of BIPV systems over time. A maximum likelihood test estimator is used to find additive outliers for a time series with unknown parameters based on the following hypothesis (Chang *et al.*, 1988):

$$H_0 \text{ vs } H_1 : \ \lambda_T = \tilde{\omega}_I / \sigma_a \tag{2}$$

where H_0 denotes the null hypothesis that $\omega = 0$ and H_1 denotes the alternative hypothesis that $\omega \neq 0$. In order to test the hypothesis, we utilized the maximum likelihood estimate method to find the unknown model parameters as if it contains no outliers. $\hat{\sigma}_a^2 = (1/n) \sum_{t=1}^{n} \hat{e}_t^2$ is the estimated noise variance and $\hat{\omega}_I = \hat{e}_T$, where $\hat{e}_t$ for $t = 1, 2, \ldots, n$ are the residuals computed from the estimated model. These estimates can be used to compute the test statistic $\hat{\lambda}_T = \hat{\omega}_I / \hat{\sigma}_a$. We scan through the sequence of $\hat{\lambda}_{1,t}$ for $t = 1, 2, \ldots, n$ to detect the additive outliers at unknown locations.

Similarly, a maximum likelihood test estimator is used to find innovative outliers for a BIPV energy production time series with unknown parameters based on the following hypothesis (Chang *et al.*, 1988):

$$H_0 \text{ vs } H_1 : \ \lambda_T = \tilde{\omega}_I / \sigma_a \left(1 + \pi_1^2 + \ldots + \pi_n^2\right)^{-1/2} \tag{3}$$

where π_i ($i = 1, \ldots, n$) are the parameters of the autoregressive process.

Automatic detection of energy production structure changes

Structure changes in the energy productions of BIPV systems are the result of changes in the structure of time series, such as variance changes and level shifts. Tsay (1988) provided excellent general discussions about structure changes in time series. In particular, the structure changes in BIPV energy productions could be related to system failure or maintenance. The timing of these failures and maintenance activities are not necessarily known and easy-to-identify. The change point model framework introduced by Hawkins *et al.* (2003) and Hawkins and Zamba (2005) and extended by Hawkins and Deng (2010), Ross *et al.* (2011) and Ross and Adams (2012) for non-parametric change detection (with no knowledge requirement about the distributional form of the data) are used in this study for identifying and characterizing various structure changes in the time series of energy productions.

The basic idea is to test whether each energy production time series follow multiple distributions. The test hypothesis involves evaluating a sequence of n energy production observations $e_1, e_2, \ldots, e_n$ with a structure change after some time τ and comparing the distribution f_0 prior to the change point, and distribution f_1 afterwards. The hypothesis that should be tested is provided in the following equation:

$$H_0 : E_i \sim f_0(e; \theta_0), \quad i = 1, 2, \ldots, n \tag{4}$$

$$H_1 : E_i \sim \begin{cases} f_0(e; \theta_0), & i = 1, 2, \ldots, \tau \\ f_1(e; \theta_1), & i = \tau + 1, \tau + 2, \ldots, n \end{cases}$$

where θ_i is the potentially unknown parameter of each distribution.

Since the change point is not known in advance, a two-sample test has to be applied at every possible split point τ for $1<\tau<n$. Mann-Whitney statistic is selected as the two-sample test statistic (D_n) in this study. The test statistic is presented here:

$$D_n = \left| \max_{\tau} \frac{D_{\tau,n} - \mu_{D_{\tau,n}}}{\sigma_{D_{\tau,n}}} \right| \quad 1<\tau<n \tag{5}$$

where $D_{\tau,n}$ is the two-sample test statistic for different values of τ, $\mu_{D_{\tau,n}}$ is the mean and $\sigma_{D_{\tau,n}}$ is the standard deviation of two-sample test statistics, and D_n is the maximum standardized statistic. The null hypothesis of no structure change is rejected if $D_n > h_n$ for a predefined threshold h_n.

This approach for detecting a change point is extended to detect multiple change points. Whenever a change point is detected, the above approach needs to be restarted from the following observation in the sequence and the data before the identified change point should be ignored (Ross, 2012). This extended approach is used in this study to detect multiple structure changes in the BIPV energy production time series.

Results

Data set description

The monthly energy production data of 89 BIPV systems are used in this study. The data are collected from Florida Solar Energy Center. Most of BIPV energy production time series (76 percent of energy production time series) have a length more than one year and less than five years. The average length of BIPV energy production time series is 39 months. Figure 2 shows the histogram of the lengths of the BIPV energy production time series in the database.

Long-term trend in the data set. The time series of energy productions of these 89 BIPV systems are subject to long-term trends. Linear regression is used to characterize long-term trend in the longitudinal energy productions. Linear regression is consistent with the literature for characterizing long-term trend. It is found that the average of degradation in the BIPV systems is 1.36 percent (where degradation exists and the slope of linear regression is negative).

Seasonality in the data set. The time series of energy productions of these 89 BIPV systems are also subject to seasonality. Seasonality is the periodic behavior in BIPV energy productions over time. BIPV energy production seasonality is highly correlated with external factors, such as weather. Autocorrelation function (ACF) (Box and Jenkins, 1976) is used to evaluate the cyclical behaviors of energy production time series. ACF of the energy productions are plotted to assess the lag-dependent cyclical behaviors. Figure 3 shows the seasonality behavior of energy production of a BIPV system and Figure 4 shows the corresponding ACF plot of the energy production recorded for this BIPV system. The apparent seasonality and the

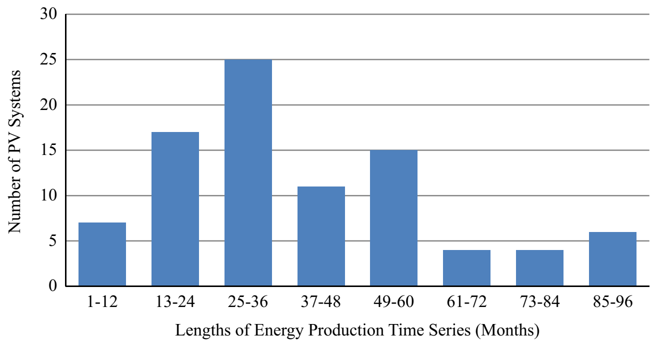

Figure 2. The histogram of the lengths of the BIPV energy production time series

lag-dependent cyclical behavior of the energy productions are evident from the ACF plot. Similar seasonality behaviors were evident in the time series of energy productions of all BIPV systems studied in this research. The seasonality makes the fault detection challenging.

Automatic detection of energy production outliers

The outlier detection method is implemented to identify outliers in the data set. It is found that the energy productions collected from 59 systems (out of 89) include at least one outlier. The average number of outliers per system is 1.5. This result shows the importance of outliers. Therefore, these outliers cannot be ignored in fault detection. Figure 5 shows an outlier in energy productions of a BIPV system. This outlier could be easily identified by looking at the energy production time series. However, outliers are not always easy to detect, since they could be masked by short-term variations, seasonality, and trend. Figure 6 shows an example of a hard-to-detect outlier that is successfully detected using the time series approach proposed in this study.

Automatic detection of energy production structure changes

The energy production time series collected from 55 systems (out of 89) include at least one structure change. The average number of structure changes per BIPV system is 1.1. Figure 7 shows an example of a structure change in the energy productions of a BIPV system. As it can be seen, there is an obvious structure change happened in early 2004. However, similar to outliers, structure changes are not always easy to detect since they could be masked by short-term variations, seasonality, and trend. Figure 7 shows an

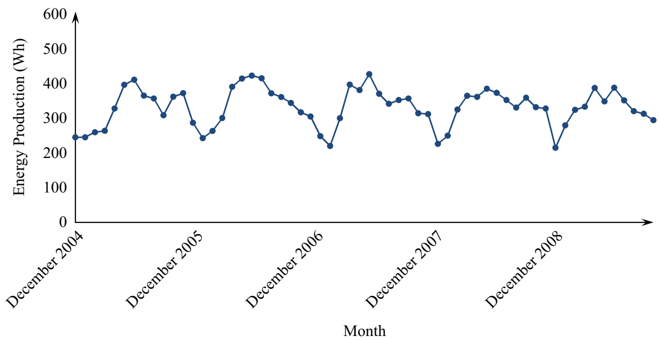

Figure 3.
Seasonality in the time series of energy productions of a BIPV system

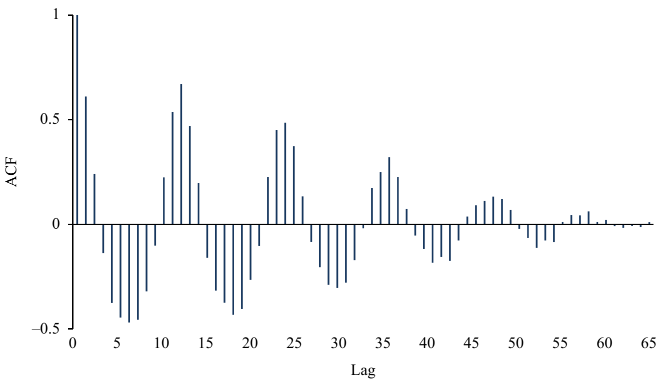

Figure 4.
ACF plot of energy productions time series of the BIPV system shown in Figure 2

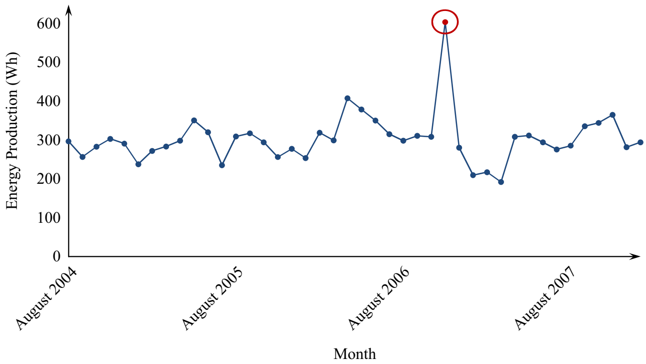

Figure 5.
Easy-to-detect outlier in the time series of energy productions of a BIPV system

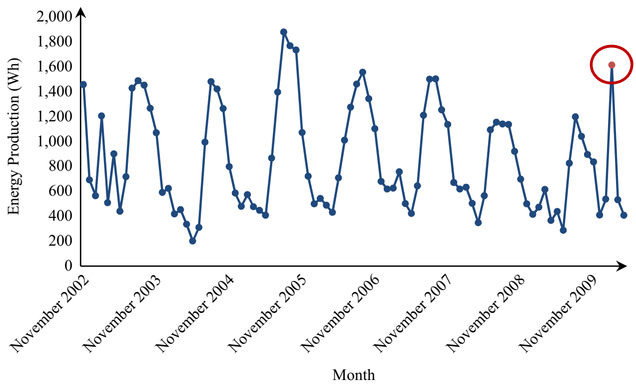

Figure 6.
Hard-to-detect outlier in the time series of energy productions of a BIPV system

example of a hard-to-detect structure change happened in early 2006. This structure change is successfully detected using the time series approach.

Figure 8 shows the frequency of observed structure changes in the BIPV energy production systems in the data set. These results represent the significance of structure changes and importance of detecting these faults in the BIPV systems.

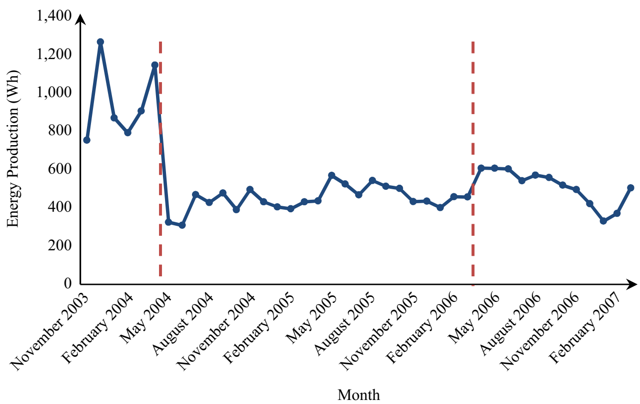

Figure 7.
Structure change in the time series of energy productions of a BIPV system

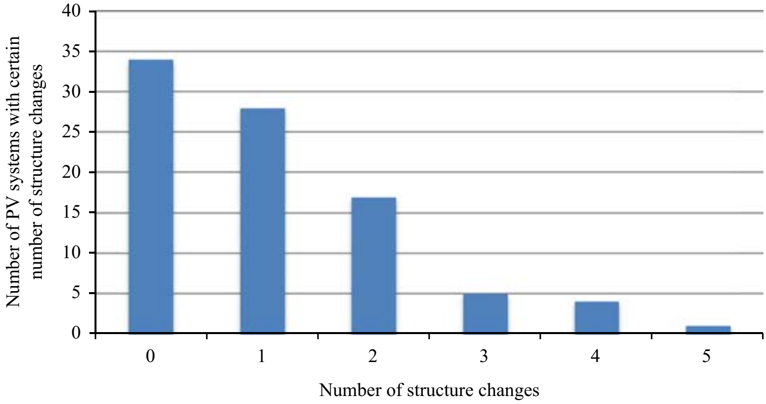

Figure 8. Frequency of observed structure changes in BIPV energy production systems

Conclusions

The results of this study show that time series methods can take advantage of historical information in PV energy production time series to distinguish between faults and the other time series properties including seasonality, short-term variations, and degradation trends. In other words, it verifies the hypothesis that the rich energy production history provides invaluable information to detect faulty behaviors. Development of the proposed cost-effective approach to detect faults using the historical energy production could make the automatic fault detection applicable to all sizes of BIPV systems integrated with any buildings, even those that are in most remote areas. In the future, cost-effective prototype equipment should be developed to automatically detect faults using the proposed methodology detailed in this manuscript.

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