Solar Energy 174 (2018) 762–769

Contents lists available at ScienceDirect

Solar Energy

journal homepage: www.elsevier.com/locate/solener

Fault detection in a grid-connected photovoltaic system using adaptive thresholding method

Mustapha Ammiche[a], Abdelmalek Kouadri[a], Laith M. Halabi[b], Amar Guichi[c], Saad Mekhilef[b]

[a] Signals and Systems Laboratory, Institute of Electrical and Electronic Engineering, University M'Hamed Bougara of Boumerdes, Avenue of Independence, 35000 Boumerdès, Algeria

[b] Power Electronic and Renewable Energy Research Laboratory (PEARL), Department of Electrical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia

[c] Department of Electronic, University Mohamed Boudiaf, BP 166, 28000 M'Sila, Algeria

ARTICLE INFO

Keywords:
MWPCA
PCA
Grid-connected PV systems
Process monitoring
Data-driven methods
Adaptive thresholds

ABSTRACT

In this paper, an adaptive monitoring scheme with Fuzzy Logic Filter (FLF) is developed and applied to monitor a Grid-Connected Photovoltaic System (GCPVS). This method is based on Principal Component Analysis (PCA) and Moving Window Principal Component Analysis (MWPCA). It is designed to generate adaptive thresholds for its monitoring indices. The FLF filters the monitoring indices to reduce the number of False Alarms (FA) and increase the Fault Detection Rate (FDR). The application is carried out on the GCPVS of the Power Electronics and Renewable Energy Research Laboratory (PEARL) of Malaya University. The proposed technique is compared against PCA method in terms of FAR reduction. The detection ability of the adaptive thresholding with FLF monitoring scheme is tested first on simulated faults then it is applied to detect a real abnormal behaviour. The results show that the proposed method is effective in reducing the number of false alarms and in detecting different types of faults with high accuracy.

1. Introduction

Photovoltaic (PV) energy is considered to be the third most important renewable energy source after the hydro and wind power (Spataru et al., 2015). It can be used to generate heat and electricity and it can replace the unsustainable energies (fossil fuels) (Hassani et al., 2016).

The performance of a GCPVS and the energy production depends explicitly on the system monitoring which aims to report information about the energy potential and energy extracted. In addition, it permits the detection of different types of faults that may occur (Madeti and Singh, 2017, Harrou et al., 2018). Many methods have been developed to monitor a GCPVS, for instance, Firth et al. (2010) based on high resolution to investigate on a PV system performance and operational faults where monitoring data is used to develop a new empirical model of a GCPVS performance which then identifies the occurred faults. Spataru et al. (2015) proposed a method which takes advantage of the current-voltage (I–V) measurement for fault diagnosis. Kim (2016) used wavelet transform for online fault detection in a grid-connected PV system, Silvestre et al. (2016) developed a new approach based on OPC technology for automatic supervision and remote fault detection in a GCPVS. Dhimish and Holmes (2016) have reported some other techniques developed for a GCPVS monitoring. Many measured variables are involved in a GCPVS. These variables are mainly the solar radiations, panels temperature, the wind speed, the solar panels current and voltage values and the inverters current and voltage inputs/outputs, etc. Hence, a GCPVS can be seen as a multivariate process. Consequently, Multivariate Statistical Process Control (MSPC) approaches can be employed for fault detection purposes in this system.

MSPC methods have been widely used to monitor large-scaled dada processes. They are also named as data-driven or historical data techniques because only historical data are needed (Chiang et al., 2001). Particularly, Principal Component Analysis (PCA) is a well known multivariate statistical method (Ge and Chen, 2016; Liu et al., 2011; Russell et al., 2000; Zhu et al., 2017). The application of this method to a process monitoring raised some problems that led to extending it to Dynamic (DPCA) and Kernal PCA to include the dynamics and the nonlinear behaviours of the data in the statistical model (Deng et al., 2017; Ku et al., 1995; Rato and Reis, 2013). Moving Window PCA (MWPCA) and Recursive PCA (RPCA) were developed in order to track the system's changes in the operation setpoints (Rato et al., 2016; Elshenawy et al., 2010). Combined methods, such as Moving Window Kernel PCA (MWKPCA), were designed to deal with both nonlinear behaviour and operation setpoint changes (Fazai et al., 2016). To

E-mail address: a.kouadri@univ-boumerdes.dz (A. Kouadri).

https://doi.org/10.1016/j.solener.2018.09.024
Received 23 March 2018; Received in revised form 7 July 2018; Accepted 12 September 2018

handle the dynamic behaviour in both steady and unsteady states, Lou et al. (2017) proposed a two-step PCA. There are other techniques besides PCA have been also extensively developed and employed for system monitoring such that Canonical Variate Analysis (CVA) (Russell et al., 2000, Shang et al., 2017), Partial Least Squares (PLS) (Wold et al., 2001) and Independent Canonical Analysis (ICA) (Zhong and Deng, 2016).

The main problem that one can face when applying linear data-driven techniques, such as PCA, to a process monitoring with fixed control limits is constantly the high number of false alarms. These false alarms may be due to the presence of random noise in the system, dynamics, nonlinear behaviours, the operation setpoint changes and the mathematical formulas by which the control limits are calculated. To address this problem, adaptive thresholding technique with Fuzzy Logic Filter (FLF) is developed. The monitoring scheme combines both PCA and MWPCA to result in an adaptive and robust technique to false alarms. The use of PCA allows the construction of a statistical model that properly fits the process. This model is kept constant during the monitoring task. The constructed model is then used to evaluate the monitoring indices of each new testing sample. A moving window of fixed size allows the generation of the adaptive thresholds for the evaluated monitoring indices after they have been filtered by FLF. Both adaptive thresholds and FLF involve in the number of false alarms reduction besides to the PCA performance enhancements. The application of the proposed method has been performed on the grid-connected PV system of the Power Electronic and Renewable Energy Research Laboratory (PEARL) at Malaya University, Malaysia. The adaptive scheme with FLF has been tested first to evaluate its detection ability of random sudden changes, and incipient fault. These faults are associated with short circuits, an abrupt increase or decrease of currents and voltages, sensors failure, and slow temperature augmentation. The monitoring scheme has been then used to detect a real abnormal operation of the GCPVS. The obtained results demonstrate the effectiveness of the proposed technique in promptly and correctly detecting different types of faults.

The remaining sections of this paper are organized as follows. Section 2 is dedicated to the mathematical formulation of the PCA-based fault detection method. In Section 3, the proposed adaptive thresholding scheme with FLF has been provided and explained. Section 4 shows the application results and discussions. The last section, Section 5, is restricted to some conclusions and findings.

2. Backgrounds

2.1. Principal component analysis

2.1.1. Definition and mathematical formulation

Principal Component Analysis (PCA) is a dimensionality reduction technique able to capture the most dominant variances in the data (Chiang et al., 2001). PCA defines the principal component subspace and the residual subspace by means of a linear transformation (Chiang et al., 2001). Given a process data of m measured variables $x_1, x_2, \ldots, x_m$ and n observations. These data can be stored in a zero mean and unity variance matrix $X_s = [X_{s1}^T, X_{s2}^T, \cdots, X_{sm}^T]$. The linear transformation, that projects the data onto the subspaces, is provided by the following equation

$$T = X_s P \tag{1}$$

Where T is the score matrix. P is an m by m orthonormal matrix consists of the covariance matrix of X_s eigenvectors. The covariance matrix of X_s is given by the Singular Value Decomposition (SVD) as

$$cov(X_s) = P^T \Lambda P \tag{2}$$

Eq. (1) permits to rewrite X_s as

$$X_s = TP^T \tag{3}$$

Once the number of principal components, a, is selected, X_s becomes as

$$X_s = \widehat{X}_s + E \tag{4}$$

Such that

$$\widehat{X}_s = \widehat{T}\widehat{P}^T \tag{5}$$

$$E = \widetilde{T}\widetilde{P}^T \tag{6}$$

where $\widehat{P} \in R^{mxa}$, $\widetilde{P} \in R^{mx(m-a)}$, $\widehat{T} \in R^{nxa}$ and $\widetilde{T} \in R^{nx(m-a)}$

2.1.2. The number of principal components

In the literature, many methods are used for the number of principal components, a, selection. These methods mainly include the parallel analysis, cumulative percentage of variances, scree plot and cross-validation (Chiang et al., 2001, Sheriff et al., 2017). In this work, the parallel analysis criterion has been used. So, the number of retained principal components, a, is defined as the point at which the eigenvalue profile of the original data crosses the eigenvalue profile of generated data assuming independent observations (Chiang et al., 2001).

2.1.3. PCA-based fault detection

Two monitoring indices are associated with PCA-based fault detection method, the Hotelling's T^2 and Q statistics (Ramahaleomiarantsoa et al., 2012). These indices are provided by

$$T^2 = x^T \widehat{\mathrm{P}} \widehat{\Lambda}^{-1} \widehat{\mathrm{P}}^{\mathrm{T}} x \tag{7}$$

$$Q = \|(I - \widehat{\mathrm{P}}\widehat{\mathrm{P}}^{\mathrm{T}})x\|^2 = x^T (I - \widehat{\mathrm{P}}\widehat{\mathrm{P}}^{\mathrm{T}})^2 x \tag{8}$$

The control limits, which correspond to each monitoring index, are given by

$$T_\delta^2 = \frac{a(n-1)(n+1)}{n(n-a)} F_\delta(a, n-a) \tag{9}$$

$$Q_\delta = \theta_1 \left(\frac{C_\delta \sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right)^{\frac{1}{h_0}} \tag{10}$$

where n is the number of observations and a is the number PCs. $F_\delta(a, n-a)$ is an F-distribution of a, n-a degree of freedom evaluated at given confidence level $(1-\delta)$.

$$\theta_i = \sum_{j=a+1}^{m} \lambda_j^i, \qquad i = 1, 2, 3 \tag{11}$$

$$h_0 = 1 - \frac{2\theta_1\theta_2}{3\theta_2^2} \tag{12}$$

C_δ is the normal deviate corresponding to $(1-\delta)$ percentile.

3. Proposed adaptive monitoring scheme with FLF

The performance of PCA based fault detection with fixed control limit is poor in terms of false alarms rate reduction due to the random noise in the process measured variables and the process dynamics. In addition, the mathematical formulas used to develop the thresholds always allow some normal samples to violet the limits which correspond to the type I error. The false alarms rate with this technique can be reduced by increasing the confidence interval, δ. However, high values of δ decreases the PCA monitoring indices sensitivity and hence some of the faults may not be detectable. The proposed monitoring scheme aims to overcome this problem and improve the PCA based fault detection technique. It is a combination of both PCA and Moving Window PCA (MWPCA) schemes. The monitoring indices are being evaluated using a fixed constructed PCA model while the adaptive thresholds are being updated through a fixed length moving window. The sensitivity enhancement is handled by the adaptive thresholds