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Prognostic and diagnostic coupling framework based on osa-cbm strategy for photovoltaic generators

Fotovoltaik jeneratörler için osa-cbm stratejisine dayalı prognostik ve teşhis birleştirme çerçevesi

***Yazar(lar) (Author(s))**: Mohamed HASSAN ALI[1], Aamir MEHMOOD[2]*

ORCID[1]: 0000-0001-9820-9803

ORCID[2]: 0000-0002-0892-3972

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Prognostic and Diagnostic Coupling Framework based on OSA-CBM strategy for Photovoltaic Generators

Highlights

- *Framework*
- *Prognostic*
- *Diagnostic*
- *Corrected Performance Ratio*
- *Loess*

Graphical Abstract

This article proposes a prognostic and diagnostic coupling framework based on the OSA-CBM for photovoltaic generators (*PVG*).

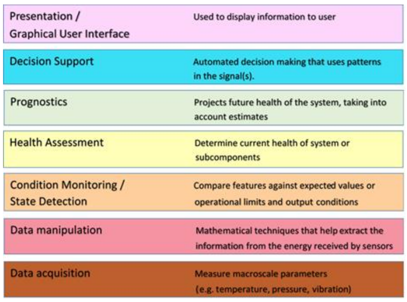

Figure. The seven layers of OSA-CBM architecture

Aim

This paper proposes a method for estimating the lifespan of photovoltaic modules using an OSA / CBM architecture.

Design &Methodology

For this, we apply a diagnostic - prognosis coupling strategy on the monitoring of real data from several power plants.

Originality

The real-time calculation of the lifespan of photovoltaic power plants facilitated by the diagnostic-prognosis coupling applied to real data.

Findings

The framework allows real-time knowledge of the performance of monitored photovoltaic plants.

Conclusion

Based on the test results, the OSA-CBM coupling algorithm effectively implements various prognostic, diagnostic and monitoring functions to present information and recommendations on the "Presentation" layer to the human user. However, the effectiveness of this framework depends on the functions involved (speed, robustness, precision.

Declaration of Ethical Standards

Theauthor(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Fotovoltaik Jeneratörler için OSA-CBM stratejisine dayalı Prognostik ve Teşhis Birleştirme Çerçevesi

Araştırma Makalesi / ResearchArticle

Mohamed HASSAN ALI[1*], Aamir MEHMOOD[2]

[1]MIS laboratory, University of Picardie Jules Verne, Amiens, France

[2]Department of Mechanical, Mechatronics and Manufacturing Engineering, University of Engineering and Technology, Lahore (FSD Campus-38000), Pakistan

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ÖZ

Bu makale, fotovoltaik jeneratörler (PVG) için OSA-CBM'ye (Koşul Bazlı Bakım için Açık Sistem Mimarisi) dayalı bir prognostik ve tanısal birleştirme çerçevesi önermektedir. İlk olarak, bu çalışma bazı PVG performans bozulma çalışmalarını ve temel bozulma göstergelerini sunar. Edinim sisteminden kaynaklanan sapmaları ve hataları önlemek için Loess veri analizi yöntemiyle ilişkili bozulma göstergesi olarak Düzeltilmiş performans oranını (CPR) seçiyoruz. Ardından, teşhis ve prognostik süreçleri birleştirmenin ana yöntemleri açıklanır: Watch Dog, Teşhis Sistemlerinde Prognostik İyileştirmeler (PEDS), Entegre Öngörücü Bakım Sistemleri (SIMP) ve OSA-CBM. Yedi özel katmana sahip bu son strateji, her iki sürecin birlikte çalışmasına izin verir. İzleme sistemi, PVG'lerin sağlık göstergelerini sağlar ve sonuçlar insan operatöre iade edilir. CPR'nin yıllık azaltma oranı ve azaltma oranı (Rd), önerilen birleştirme çerçevesini kontrol etmemize izin verir. Bu yaklaşım, IEA PVPS Task13 veritabanından dört fotovoltaik kurulumda toplanan deneysel verilerle doğrulanmıştır.

Anahtar Kelimeler: Çerçeve, prognostik, teşhis, düzeltilmiş performans oranı, loess.

Prognostic and Diagnostic Coupling Framework Based on OSA-CBM strategy for Photovoltaic Generators

ABSTRACT

This article proposes a prognostic and diagnostic coupling framework based on the *OSA-CBM* (Open System Architecture for Condition Based Maintenance) for photovoltaic generators (*PVG*). At First, this work presents some *PVGs* performance degradation studies and the main degradation indicators. We select the Corrected performance ratio (*CPR*) as degradation indicator associated with the *Loess* data analysis method to avoid aberrations and errors from acquisition system. Then, the main methods of coupling diagnostic and prognostic processes are explained: Watch Dog, Prognostic Enhancements to Diagnosis Systems (*PEDS*), Integrated Predictive Maintenance Systems (*SIMP*) and *OSA-CBM*. This last strategy with its seven specialized layers permits the interoperability of both processes. The monitoring system provides health indicators of *PVGs* and results are returned to human operator. The annual reduction rate of the *CPR* and reduction rate (R_d), allows us controlling the proposed coupling framework. This approach is validated with experimental data collected on four photovoltaic installations from the *IEA PVPS* Task13 database.

Keywords: Framework, prognostic, diagnostic, corrected performance ratio, loess.

1. INTRODUCTION

Now-a-days the future of renewable energies insured and unchallenged. Among them, solar energy is based on photovoltaic panels (*PV*) whose performance has gradually increased. However, the electrical production of many photovoltaic panels has not been monitored with a prognostic function, or with diagnostic function, or a coupling of both to ensure better efficiency. Without this type of control function, the occurrence of faults will not induce only power losses, but it could also lead to safety risks, which would reduce the reliability of the *PV* system. The first maintenance strategies to optimize the availability of a system were based on conditional or preventive maintenance. The implementation of the monitoring allowed access to quantities informing permanently on the state of health of the system through indicators of degradation. With them, it becomes possible to evaluate the performance and monitor its degradation until the appearance of a failure.

If the diagnostic process allows the detection and localization of faults, the prognostic allows following the degradation to identify the moment of failure and to know the remaining life of the equipment. Linking diagnostic and prognostic processes is an innovative advancement in maintenance strategies.

Indeed, all information from the two processes on the state of health of the system is used to improve support for maintenance decisions. There are several approaches of coupling (WatchDog, *PEDS*, *SIMP*, *OSA-CBM* ...) allowing this interoperability; they are based on the

**Sorumlu Yazar (Corresponding Author)*
e-posta : mohamed.hassan.ali@u-picardie.fr

nature of the information available but also on the methods used by the two processes. These coupling methods will be developed with the respective features and advances. Then, a coupling strategy following the Open System Architecture for Condition Based Maintenance is proposed. In this strategy, the reduction rate R_d of the *CPR* degradation indicator is applied to control the coupling algorithm between the two processes. Our approach is tested on monitoring data from four *PV* plants of *IEA PVPS* task13 database.

2. EVALUATION OF PVGS DEGRADATION

The selection of degradation indicator representing the performance of a *PV* installation is treated by [3] [4] who implement the Performance Ratio (*PR*) indicator to know the evolution of the performance of a *PV* plant (equation 1). Moreover, the adapted form of *PR*, the *CPR* takes into account both the effects of temperature and irradiance (equation 2) [5]. Data acquisitions depend on multiple hazards that can interfere with data readability. It is important to correct acquisitions fluctuations without affecting measured data. For this purpose, there are number of statistical analysis methods used in process of data acquisition such as Linear Regression (*LR*), Classical Integrated Decomposition (*CSD*), or Locally Weighted Scatter plot Smoothing (*Loess*) [1]. Specially, this last technique, proposed by [2], makes it possible to extract a trend of the data at the local level due to a weighted polynomial fit. It provides an estimate closest to the trend that is not distorted by presence of aberrant or missing values [2]. Thus, it gives accurate results for data processing without denaturing them, in particular applied to *CPR* data according to [1].

$$PR = \frac{\sum_{i=1}^{M} P_{ACi}}{\sum_{i=1}^{M} P_{DC\_STC} \cdot \left(\left(\frac{G_{POAi}}{G_{STC}} \right) \right)} \tag{1}$$

$$CPR = \frac{\sum_{i=1}^{M} P_{ACi}}{\sum_{i=1}^{M} P_{DC\_STC} \cdot \left(\left(\frac{G_{POAi}}{G_{STC}} \right) \right)} \cdot \frac{1}{\left[1 + \alpha_{PM} \cdot (T_M - T_{STC})\right]} \tag{2}$$

The combination of these two techniques, *Loess* and *CPR*, makes it possible to evaluate results of photovoltaic installations installed on different locations, according to [5]. In each case, we extract from the monitoring, the *CPR* data. Then with *Loess* statistical analysis, we obtain a trend for calculating annual reduction rates R_d of *CPR*, as seen in figures 3 to 6, under the assumption of constant linear degradation from [3][4]with equation 3:

$$R_d = \frac{CPR_{Least} - CPR_{First}}{CPR_{First}} \times \frac{1}{\Delta t} \times 365 \tag{3}$$

Loess method applied to the *CPR* indicator makes it possible to evaluate the performance of *PVGs* in the coupling processes.

3.COUPLING METHODS

Coupling methods can use prognostic and diagnostic functions. The prognostic evaluates residual lifespan of a component or a system and diagnostic process is about detecting, identifying and locating faults. Moreover, there is a large number of diagnostic methods adapted to *PVGs*[6]. There are several architectures for maintenance strategies that support a set of processes for maintenance decision as according to [7], the four main architectures are: WatchDog[8], *PEDS* (Prognostic Enhancements to Diagnosis Systems) [9], *SIMP* (Integrated Predictive Maintenance for Systems) [7], *OSA-CBM* (Open System Architecture for Conditional Maintenance) [10].

- **WatchDog Method**

The WatchDog system, proposed by [8], makes it possible to combine a physical component and a software by gathering all necessary knowledge (model, methodology) on a dynamic system. Its architecture, based on the measurement and filtering data, performs the evaluation of the health system for diagnostic and prognostic. Actual data measurements and decision support activities are done outside the WatchDog. This method of prognostic does not explicitly use the results of diagnostic process. It mainly represents statistical models of prognostic.

- **PEDS Method [9]**

This approach permits to link two prognostic functions, one vertical based on statistics of failures data, and the other horizontal, that is following faults detection by a diagnostic function

- **SIMP Method [7]**

This method is a strategy of global integration of prognostic and preventive maintenance in the company's information systems and its various internal and external processes. The SIMP method implements a suite of three sequential sub-processes: surveillance, prognostic and decision support.

- ***OSA-CBM Method (Open System Architecture for Condition Based Maintenance)***

The *OSA-CBM* (Open System Architecture for Condition Based Maintenance) method [10] defines a coupling architecture for the diagnostic and prognostic to implement *CBM* processing in an open architecture. In this method, the seven layers are well defined, creating a linear succession of specialized internal processes. The first three layers make it possible to acquire the measurements and to process them in order to obtain appropriate indicators. The diagnostic layer determines faults and their locations. Then, the prognostic layer defines the future state of the system by considering the prior knowledge and the future environment of the system (solicitations, environmental conditions) and it contributes to the process of decision support. A final layer manages functions of human-machine interfaces.

These seven layers of the *OSA-CBM* are, as seen in Figure 1

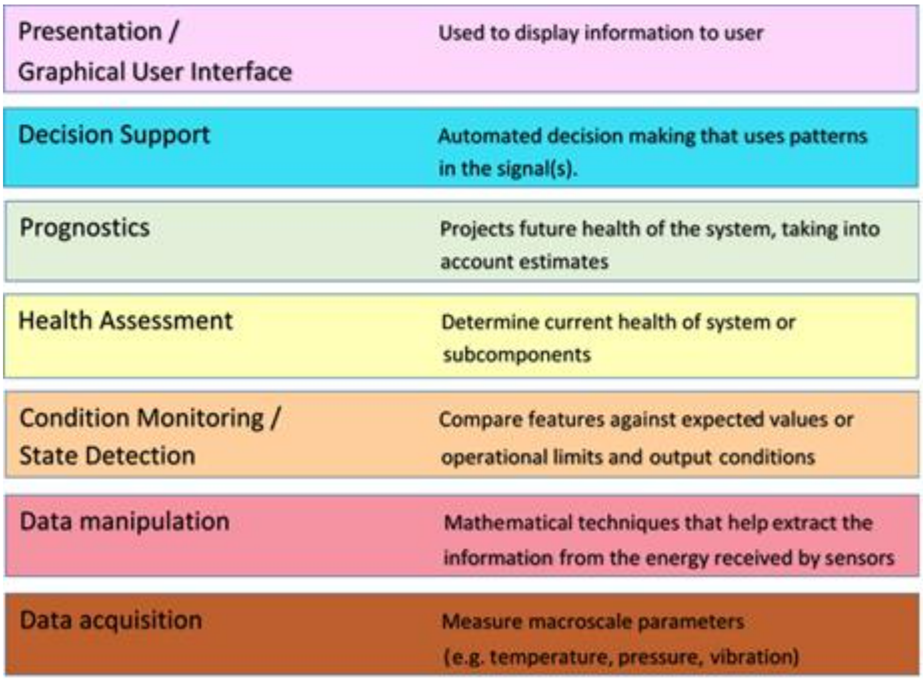

Figure 1. The seven layers of OSA-CBM architecture

- **Layer 1**: data acquisition (Data layer)

Acquisition layer transforms physical quantities into electrical signals by using adapted sensors.

- **Layer 2**: Data manipulation (Data Manipulation layer)

This layer processes the signal of acquisition layer in order to extract representative quantities of the system health state.

- **Layer 3**: Data Monitoring (Condition Monitoring / State Detection layer)

This layer extracts data from previous layers to compare them to limit values. When boundaries are crossed, this layer can generate alarms.

- **Layer 4**: Diagnostic (Health Assessment layer)

This layer receives data from the monitoring layer and others from the diagnostic to determine if health of monitored system, subsystem, or component is degraded. This layer generates a diagnostic on one or more faults associated with a level of confidence. It can take into account the evolution of the trend based on health history, load, operating status and maintenance history.

- **Layer 5**: Prognostic (Prognostic layer)

This layer receives data from all previous layers. Its main purpose is to project the current state of system health in the future by providing information on its residual lifespan.

- **Layer 6**: Decision Support layer

This layer provides recommendations and alternatives to keep the system in good shape. For this, it uses results from diagnostic and prognostic layers. Recommendations can be planned maintenance actions, a change in the operational configuration of the system or other.

- **Layer 7**: Presentation (Presentation / GUI layer)

Last layer provides the interface between the system and one or more human operators. It serves in particular to present collected information's results.

The specialization of these seven layers allows a better interoperability of different processes in next proposed coupling.

4. PROPOSED COUPLING FRAMEWORK

In this work, we propose a prognostic-diagnostic coupling flow-chart according to aging evolution. This is to realize efficient faults diagnostic and to calculate residual lifetime. For this, we use the monitoring of meteorological parameters and power signals of *PV* plants. These data are processed to ignore errors from monitoring system or sensors. We propose to use the *Loess* method from [2], which allows extracting a trend of the data at the local level with weighted polynomial adjustments [4].

Subsequently, the values of the degradation indicator (*CPR*) are continuously extracted to inform on occurrences of degradation and its evolution. The reduction rate R_d of the *CPR* indicator is used here as defined in [4], with the linear annual degradation assumption. It is admitted according to [1], that a limit of R_d of 1% per year defines effects of only aging without extrinsic faults. As long as R_d is below this limit, the search for extrinsic faults is irrelevant. Indeed, aging predominates and we can quantify its evolution with the prognostic function. Below this limit, the effects of aging and extrinsic faults are simultaneous, with greater attenuation of system performance.

The diagnostic and prognostic functions are used simultaneously for the determination of the service life and the identification of faults. Only in case of determination of this one, one resets the surveillance because the intervention of maintenance (replacement) changes the state of the system. The set of steps is shown below with the correspondence to the 7 layers of the *OSA-CBM* architecture according to [10][11]. Indeed, we propose a coupling framework with:

- Layer 1 is constituted by data monitoring of: T_i ; G_i; P_{DC}; P_{AC}
- Layer 2 includes data processing by *Loess* analysis [2] followed by determination of *CPR* (degradation indicator) and then its annual reduction rate R_d according to [4].
- Layer 3 presents the test of R_d rate with the average threshold of 1%/year considered as limit of the effects of aging for polycrystalline Silicon technology according to [1].
- Layer 4 concerns the diagnostic function allowing detection, discrimination and localization of faults.
- Layer 5 corresponds to prognostic function, which evaluates *PVGs* lifetime.
- Layer 6 groups together recommendations related to system situation.
- Layer 7 serves as an interface informing human operator of diagnostic results, faults effects on lifespan and maintenance recommendations to be made.

The correspondence between the *OSA-CBM* architecture is thus established for each layer, as shown in Figure 2

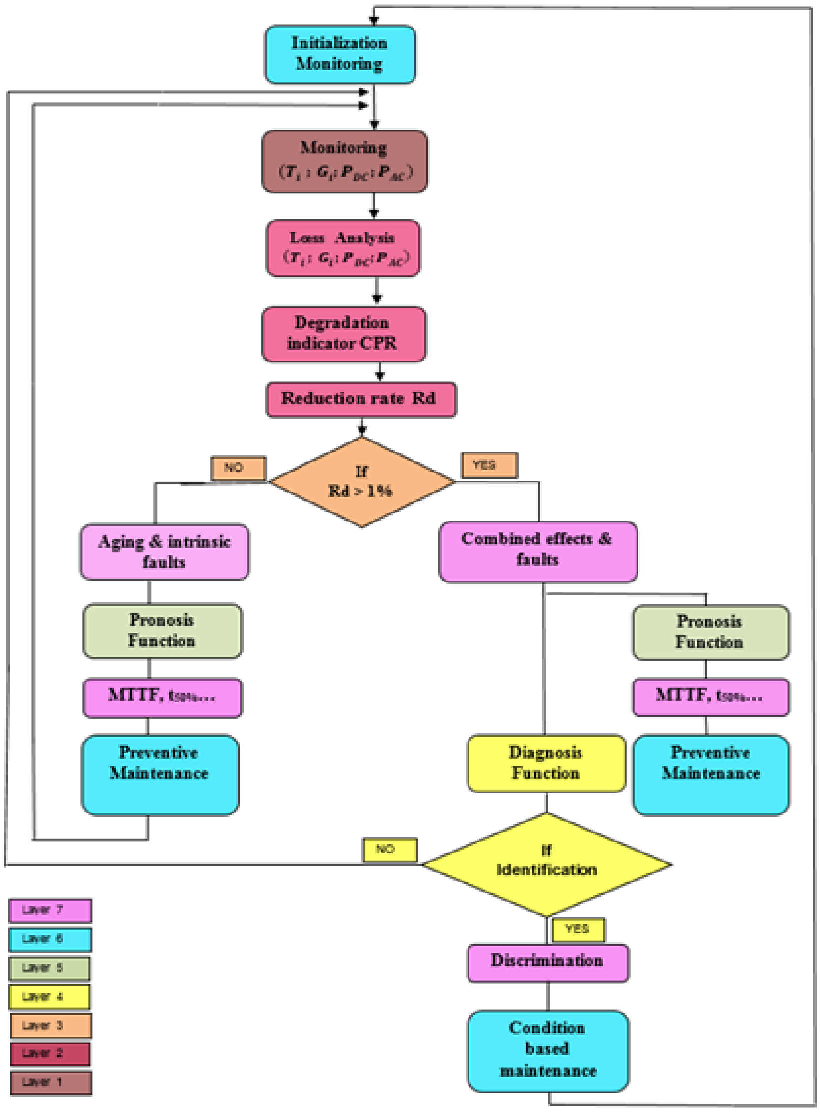

Figure 2. Prognosis-diagnosis coupling flow chart

5. APPLICATIONS AND RESULTS

The implementation of the proposed coupling depends on the degradation indicator, *CPR*, and in particular its reduction rate R_d. Indeed, R_d is continuously tested with a limit of 1% to identify fault beginning acting in addition to aging effects. Using monitoring data of four PV plants: Mont Soleil, Joch, Gfeller and Birg from the *IEA PVPS* task 13 database (Table 1), we were able to calculate *CPR* indicators curves and those for associated reduction rates R_d. The acquisitions are dependent on multiple hazards that may interfere with the readability of data. It is important to correct the fluctuations of the acquisitions without affecting the measured data. For this, *Loess* statistical analysis is applied to the data (i.e. *CPR*) of four plants. We obtained *CPR* trend curves allowing us to determine the reduction rates R_d by equation 3 according to [4]. This makes it possible to follow the degradation of the four photovoltaic power plants below installed on different operating sites. R_d evolution controls coupling algorithm (Figure 2) in the implementation of diagnostic and prognostic functions respectively. The evolution of reduction rates R_d for each site, is illustrated in Figures 3-6. The degradation due to aging can be monitored in the case of Mont Soleil and Birg *PV* plants, where the gradual decline of the *CPR* is more visible. The *PV* plants of Gfeller and Joch show occurrence of more identifiable faults with significant variations of their respective, reduction rates R_d. Differences in results are consequence of the variety of operating environments. In addition, the interpretation of R_d signal requires knowledge of history of maintenance interventions that followed faults detection. Indeed, these interventions induce a restoration of performances towards nominal values where positive rebounds observed on R_d signals can hide aging impact.

6. APPLICATIONS AND RESULTS

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Table 1. Locations and technologies for the four PV plants

PV plants	Joch	Birg	Mt Soleil	Gfeller
Location (Latitude Longitude Height Angle of inclination)	46.54 7.98 3454 90°	46.56 7.86 2677 90°	47.15 7 1250 50°	47.62 7.62 530 na
Technologies	Siemens M75 multicrystallin silicon		Siemens SM55 Monocrystallin silicon	

The acquisitions are dependent on multiple hazards that may interfere with the readability of data. It is important to correct the fluctuations of the acquisitions without affecting the measured data. For this, *Loess* statistical analysis is applied to the data (i.e. *CPR*) of four plants. We obtained *CPR* trend curves allowing us to determine the reduction rates R_d by equation 3 according to Phinikarides et al. (2013). This makes it possible to follow the degradation of the four photovoltaic power plants below installed on different operating sites. R_d evolution controls coupling algorithm (Figure 2) in the implementation of diagnostic and prognostic functions respectively. The evolution of reduction rates R_d for each site, is illustrated in Figures 3-6. The degradation due to aging can be monitored in the case of Mont Soleil and Birg *PV* plants, where the gradual decline of the *CPR* is more visible. The *PV* plants of Gfeller and Joch show occurrence of more identifiable faults with significant variations of their respective, reduction rates R_d.

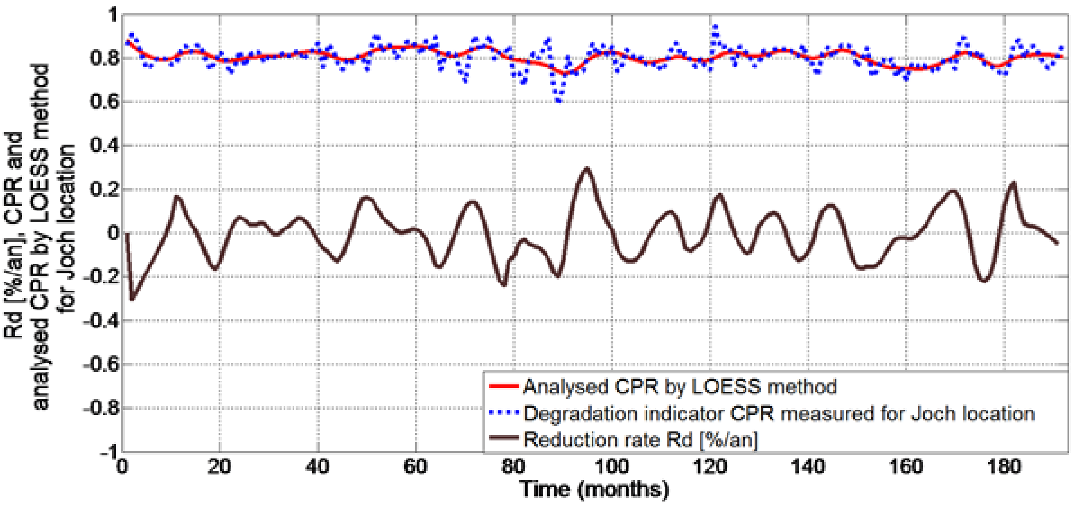
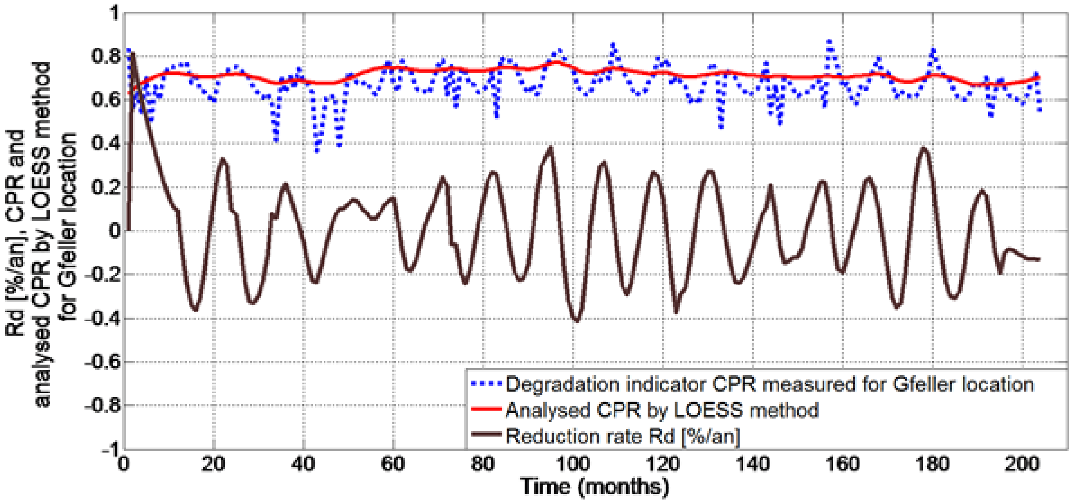


Figure 3. Evolutions of R_d, *CPR* and the *Loess* analysis of CPR for Joch *PV* plant

Differences in results are consequence of the variety of operating environments. In addition, the interpretation of R_d signal requires knowledge of history of maintenance interventions that followed faults detection. Indeed, these interventions induce a restoration of performances towards nominal values where positive rebounds observed on R_d signals can limit aging impact observation



igure 4. Evolutions of R_d, *CPR* and the *Loess* analysis of *CPR* for Gfeller *PV* plant

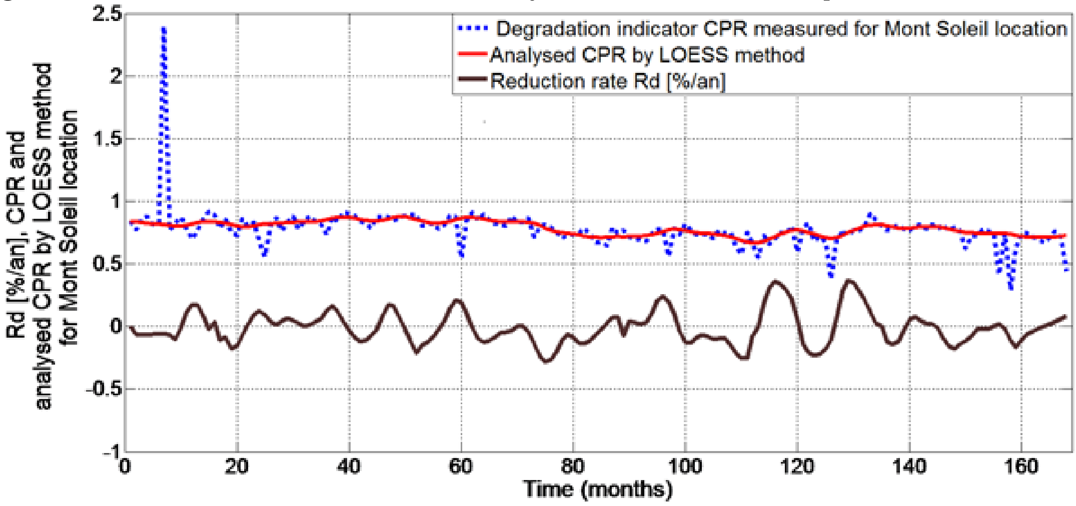


Figure 5. Evolutions of R_d, *CPR* and the *Loess* analysis of *CPR* for Mont Soleil *PV* plant

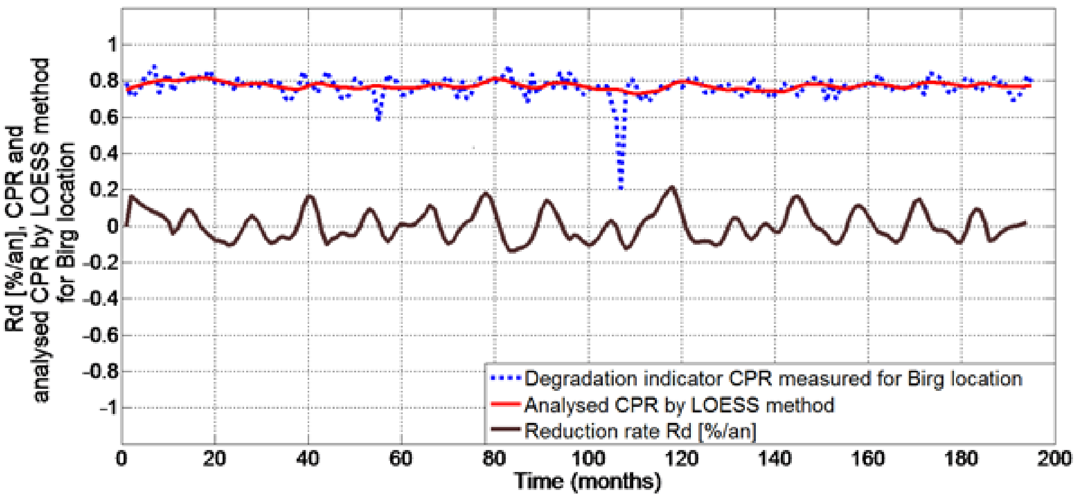


Figure 6. Evolutions of R_d, *CPR* and the *Loess* analysis of *CPR* for Birg *PV* plant

7. CONCLUSION

The prediction of the lifetime of a *PV* system depends on many parameters. The knowledge and the modeling of the degradation of photovoltaic installations have been treated in numerous publications. In this article, we present a synthesis work on the different coupling strategies that can improve reliability of *PV* systems. We have reviewed main existing approaches coupling strategies (WatchDog, *PEDS*, *SIMP*, *OSA-CBM*) and we proposed a strategy based in *OSA-CBM* with seven layers allowing interoperability of diagnostic, prognostic and monitoring. The proposed framework regulated by a threshold test on the annual reduction rate, R_d of the *CPR* degradation indicator is applied to four studied *PV* system. According to test results, the *OSA-CBM* coupling algorithm implements various prognostic, diagnostic and monitoring functions to present informations and recommendations on the 'Presentation' layer to human user. However, effectiveness of this framework depends on involved functions (speed, robustness, precision).

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Mohammed Hassan Ali: Mohammed Hassan was performed the experimental studies, analyzed the results and wrote manuscript.

Aamir MEHMOOD: Aamir was performed the experimental studies, analyzed the results and wrote manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study

NOMENCLATURE

OSA-CBM	Open System Architecture for Condition Based Maintenance
PVG	Photovoltaic generator
CPR	Corrected Performance Ratio
Loess	Locally Weighted Scatterplot Smoothing
PEDS	Prognostic Enhancements to Diagnosis Systems
SIMP	Integrated Predictive Maintenance Systems
PR	Performance Ratio
R_d	Reduction Rate
IEA	International Energy Agency
PVPS	Photovoltaic Power Systems Program
LR	Linear Regression
CSD	Classical Integrated Decomposition
R_d	Annual reduction rate
STC	Standard test condition of the PV cell; T_{STC} = 25°C and G_{STC} = 1000 W/m^2
T_M	Photovoltaic module temperature (°C)
T_{STC}	Temperature at STC (°C)
G_{STC}	Solar irradiation at STC (1000W/m^2)
G_{POAi}	Solar irradiance on the plane of array (W/m^2)
P_{ACi}	AC power (W)
P_{DC}	DC power (W)
P_{DC_STC}	DC power in STC (W)
α_{PM}	Maximum power temperature coefficient (%/°C)
R_d	Annual degradation rate
Δt	Number of days in evaluation period
$CPR_{INITIAL}$	Initial CPR value in evaluation period
CPR_{LEAST}	Least CPR value in evaluation period
CPR_{FIRST}	First CPR value in evaluation period

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