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Maintenance Scheduling by Means of Electrical Signature Analysis Technology

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***Abstract* – The increasing demand for efficiency and quality greatly influences the way in which assets and services are produced and managed. As a consequence, the maintenance of equipment is one of the key drivers for increasing the competitiveness in the market nowadays. This paper introduces ESA (Electric Signature Analysis), a technique that can act as a low cost and reliable tool for diagnostics and, for some applications, prognostics purpose. The effectiveness of the technique is discussed and, finally, demonstrated in a case study carried out for the monitoring of a Photovoltaic (PV) plant.**

I. INTRODUCTION

In modern industrial applications, the importance of quality, safety and reliability of systems and production processes is continuously growing [1]. A good maintenance program can greatly help to achieve these features and in the meantime to reduce the cost. In fact it aims to prevent malfunctions and deterioration and, ultimately, to preserve both the safety and desired quality levels. Among the possible approaches to diagnostics and maintenance of industrial plants, the choice should be a tradeoff among effectiveness, complexity and additional costs. The effectiveness of the method is related to its capability to estimate the state of degradation and to prevent malfunctions.

As well known, one of the most effective maintenance approaches is the Condition Based Maintenance (CBM). This kind of maintenance strategy directly evaluates the system's health condition with a periodic or, better, continuous monitoring system. If a continuous monitoring is performed, an on line diagnostic approach is obtained. Even more interesting is the so-called Predictive Maintenance (PdM) where a prediction of the future trend of the health of the system under consideration is performed. This approach starts from the consideration, often true, that in complex system faults are preceded by progressive degradation phenomena. The study of this trend can help to know the system degradation and its evolution obtaining both CBM and PdM policies.

As aforementioned, CBM can be based on uninterrupted evaluation of health status (health state) of the device or system under consideration that can be achieved performing a continuous monitoring activity. A maintenance activity is then planned on the base of signals indicating the good or degraded condition of the monitored system. When electrical systems or devices are considered, it is possible to use information obtained from the electrical signals of power supply, that are often simple to measure as described in the following, in order to identify the characteristics (features) associated with each state of operation, thus defining an electrical signature (signatures) for each working state. The analysis of this electrical signature (Electrical Signature Analysis, ESA) allows implementing both CBM and PdM policies.

The needed information can be achieved in two different ways. In the first case the signals acquired with additional appropriate sensors are used. It must be noticed that in this situation, it is necessary to take into account the cost and the necessary further space of the additional measurement devices and their installation. Moreover the complexity of the system tends to increase. A more convenient situation is when it is possible to exploit the signals and/or information already used for different purposes; for instance signals monitored for the normal operation of the system. Naturally this second approach is, when technically possible, very interesting and promising from the economic point of view. In both cases, the diagnostic problem is related to the extraction of features and signatures and, finally, their classification. The classification task is a problem in several fields and it has been widely studied in literature [2].

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One of the possible solutions, following the traditional engineering approach, is based on the study of a mathematical model that describes the behavior of the system and finds the mathematical relation between the inputs and outputs of the system under consideration. This approach is often known as the white-box approach and typically produces a mathematical model characterized by few parameters. These parameters are related to the physical domain of the studied problem and, therefore, they can be estimated from measurements performed on the system under consideration.

A more interesting approach is obtained applying non-traditional and more recent techniques, essentially based on statistical methods or soft computing techniques, or a combination of these methods. This approach is mainly known as black-box approach and it formalizes the correlation law between the inputs and outputs by a non-parametric model, which is characterized by a large number of parameters. The main advantage of such techniques is their ability to configure the model from the input data (learning from data), without requiring a thorough knowledge of the processes carried out by the system. Therefore, these techniques are extremely efficient in a wide range of applications in which the mathematical model of the system to be monitored is unavailable or excessively complex to achieve (this is very common in industry). Therefore the complexity of the problem is moved away from the study of the system, from the processes and from the physical phenomena involved in the configuration of the parametric paradigm.

The main feature of this approach is the ability to compensate the low a priori knowledge of the problem (or system) to be solved with the quantity of available data. In other words, the ability to correctly identify the behavior of the studied device or system depends on the availability of data related to situations in which the system can operate. Since the recent advances in technology have made economically attractive both high-capacity logical storage devices and high performance computer, this potential can be effectively used in order to capture, store and process several kind of signals (i.e. the electrical ones) to diagnostic purposes.

In this paper, after an overview on the classification techniques, a simple example of the use of ESA with black box approach, for a maintenance scheduling in a PV-plant, will be propose.

II. METHODS FOR THE HEALTH STATE IDENTIFICATION

The health identification task can be obtained by means of a number of different methodologies. In particular, for example, the following paradigm can be used:

- Statistical models;
- Cluster Analysis;
- Methods based on Soft Computing Approach (SCA);
- Artificial Neural Network (ANN);
- Fuzzy Logic System;
- Evolutionary Techniques;
- Feature Selection;
- Performance evaluation of the methodologies.

The aforementioned methods are well known in literature and will be not further discussed in this paper [3] - [11]. The theory necessary for the purpose of the proposed approach has been described in the next Section. However it is mandatory at this point, discuss about the performance evaluation of the aforementioned methodologies.

In the absence of a theoretical model, it is possible to estimate the ability of alternative instruments (described above) that can be opportunely configured in order to generalize the employed data set. This estimation can be performed by testing a group of data that were not used during model selection and configuration. The easiest way in order to estimate the performance can be the following. The set of available data is split into two subsets: the first one is used to configure the model (denoted as training dataset) and the second set is then used for the model validation (denoted as testing dataset). However, more complex ways for the performance evaluation can be adopted but these ways will be not further discussed.

If the choice of the model (*e.g.*, the number of neurons or the activation function) would be performed during the configuration phase, a part of the training dataset must be used for the model selection.

Generally, the available information are divided keeping in mind that more data are used during configuration (training), the greater the possibility of obtaining a model that well describes all possible situations. Unfortunately, it also means the greater the possibility that the adopted model structure adheres excessively to the used data (over fitting), incorporating also the noise present on them. However, if few data are used during the configuration phase, the resulting model may be not able to describe granularly the behavior of the considered system. Similar considerations can be observed on the testing dataset: a small set could not consider particular cases. By contrast, a very large data set could subtract valuable information from the configuration phase.

III. THE ESA APPROACH: AN EXAMPLE

The application of the ESA in industrial scenario has been already discussed [12] and in this paper an application devoted to the energy field is presented. In particular the ESA method has been applied to photovoltaic (PV) systems by following a “*black box*” approach and implementing a simple clustering process for the classification.

In recent years, problems related to the production of electrical energy are becoming more and more important. The rational use of energy resources and production from renewable sources, are the strategies currently adopted, worldwide, in order to reduce the emissions of pollutants and to limit environmental impact.

Between the different technologies that could play a role in creating sustainable and widespread energy production, the solar energy appears really promising. In fact, PV systems can be easily connected to the national grid, thus creating a network of distributed generation, or used for combined high-efficiency heat and power generation.

The basic element of these systems is the solar panel. This element is a device with high reliability even considering that the performance depends on many factors [13], of which the most important can be considered the environment [5], [6]: the presence of dust, for example, greatly influences the panel performance.

PV plants and panels reliability is an important aspect, especially in large systems, in which faster return on investment time horizon, in comparison with traditional systems, often does not consider the possible operational errors. Already in the early stages of design, both the reliability and the potential failures should be appropriately considered and evaluated in order to ensure appropriate responses in a more rapid and less expensive way.

The definitions of reliability and maintainability [1] can be easily rewritten when a PV panel is considered. It is clear that their assessment can be made only if the failure modes of the panel are known. Failure Modes, Effects and Criticality Analysis (FMECA) [13], [14] allows to identify the phenomena and causes, that lead to the PV system degradation and failures, as well as to determine their consequences and to devise methods for minimizing their occurrence as well described in [3], [4]. Following the FMECA approach, an analysis on the influence of dust on the performance of the PV modules has been proposed in a previous paper [13].

Few, but interesting, studies analyze the efficiency reduction due to the presence of dust and debris on the PV modules [6], [8], [9], [10], [11], [15]. Powder deposition is influenced by environmental, weather conditions and, finally, design criteria. In fact, its accumulation depends on many factors like: inclination of the PV panel, wind direction, humidity, kind of installation (stand alone or on tracker), *etc*. In particular, both weather and design factors influence the dust accumulation process and related effects. A brief schematic representation of the factors that determine the settling of dust on the PV panels is shown in [7].

A. Feature Definition

It is well known that a grid-connected PV plant works with a kind of regulation that maximize, in assigned climatic conditions, the power generation (Maximum Power Point, MPP). MPP represents the second important feature (after the energy produced by the plant) that characterizes the signature of a PV system. Environmental parameters (such as humidity, temperature of the air and of the panel, wind and, in particular solar radiation) represent other useful features for ESA application. A possible way to operate is to observe the generated power and to relate this value not only to the climatic conditions (solar radiation and temperature) but also to the presence of dust on the surface of the PV module. By a theoretical point of view, this MPP reduction evaluation can be considered as a mono-dimensional Euclidean distance. In order to explain this property a brief recall of the used method can be here very useful.

MPP is mainly influenced by two parameters: the temperature of the panel and the solar radiation. The behaviour of the panel can be evaluated taking into consideration the MPP index (such as the Maximum Power - MP) versus the solar radiation and the temperature. In a previous paper a qualitative chart of the MP versus solar radiation curve has been discussed [14]. It has been also shown that the estimation of the performance loss of the PV panels can be evaluated using these MP curves. At this aim it is sufficient to select the MP ideal value in clean status and to evaluate the difference between the actual value, limited by the presence of the dust for example and the former. The obtained difference is the index of the performance reduction.

However the correct way to consider the MP is to recognize that it is also a temperature dependent parameter. Definitively, MP can be considered as a function:

$$MP = f(SR, T) \tag{1}$$

where *SR* is the solar radiation and *T* is the panel temperature.

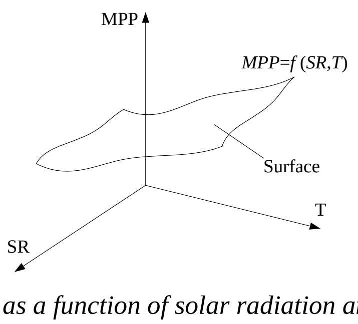

Fig. 1 – MP as a function of solar radiation and panel temperature.

Now we recall that our goal is to apply a method based on the signature. At this aim it is necessary to identify the reference condition in which the Reference

Signature of the clean panel can be defined (it can be drawn as a surface in the three dimensional coordinates: MP – Radiation – Temperature as depicted in Fig. 1). The working point of the clean panel lies on this surface.

In normal operating conditions, the actual signature is a surface and could be different from the aforementioned Reference Signature. The distance between these two surfaces can be considered as a measure of the presence of dust.

Even if the distance between two surfaces is evaluable from the mathematical point of view, in actual situation, a simplification is possible. In fact, assuming that temperature and solar radiation are known, a mono-dimensional distance could be evaluated.

The performance decrease can be evaluated by analyzing the MP evolution and comparing its value with the expected one, previously obtained by means of a dataset selected with the criterion discussed in Section II. By integrating the power produced by the plant in MPP condition, it is possible to evaluate and compare the expected energy value with the actual one. This suggests a new interesting ESA approach: MP reduction helps to obtain information concerning the plant efficiency and the decrease of the energy produced in MPP condition can be considered as a strategic information in the maintenance policy.

B. Feature Qualification

In order to quantify the robustness of the proposed method it is important to verify the capability of the selected feature to track the evolution of the panels of the plant from cleaned to the dirty condition. To this purpose, experimental tests have been performed on a 10 PV panels in presence of dust depositions. In particular, the PV modules have been exposed to different environmental conditions over the time and the corresponding efficiency degradations have been monitored. The experiments have been designed and conducted in laboratory using a sun simulator and a test chamber [13].

Since the selected PV panels belong to the same production process and to the same production lot, the panels can be considered as a homogeneous sample and the evaluation of the collected MP data is possible from a statistical point of view. Furthermore, the conditions of exposition have been randomly assigned to the panels. In other words, MP value can be considered as measurements of a character on individual samples from a large population. In Fig. 2 the computed values of generated MP by the PV modules in dirty condition and after cleaning are shown. The experimental setup has been designed and implemented in order to assure that the power variations, in any conditions, are bigger than the measurement system resolution [14].

These aspects are discussed and proved in [6], [13], [14], [16], [17]. Obviously, all the panels show a reduction of the generated power in presence of dust.

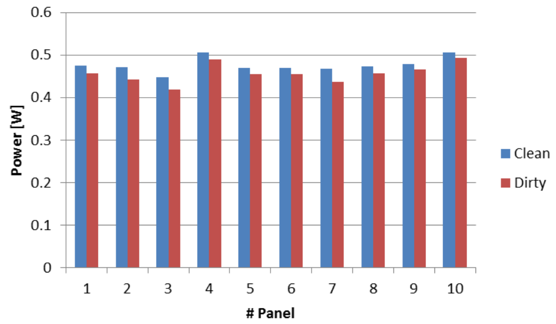

Fig. 2 – Power reduction due to dirty surface in a PV panel.

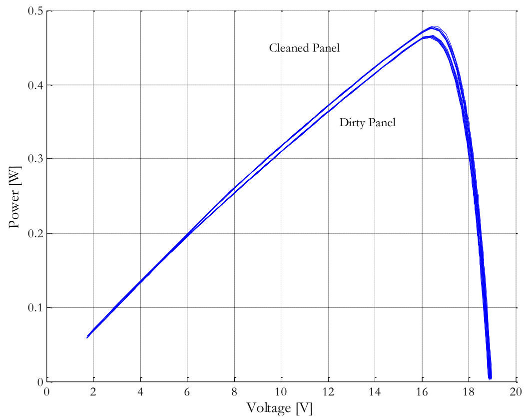

Fig. 3 – Typical chart for Power vs Voltage for cleaned and dirty panel.

In Fig. 2 an example of MPP decrease is depicted. As aforementioned, electrical signals have been acquired with a resolution good enough to state that the evaluated MP variations are actually due to the studied phenomenon. Measurements have been repeated many times in order to verify that the repeatability conditions are met. In fact, Figure 3 reports many P-V characteristics which can be easily classified in two separate groups (Cleaned and Dirty panel respectively).

C. Feature versus Maintenance Activity

It is well known that a frequent cleaning allows increasing the plant efficiency. However, this strategy can be difficult or not cost-effective to be implemented.

In [15], an economical method that allows choosing the optimal maintenance interval for a PV plant has been presented and discussed. The method, starting from the costs related to the cleaning of the panels, compares them to the economic losses due to the decrease of the efficiency. The output of the model is the optimum maintenance interval: it allows to plan the maintenance interventions and to define the most suitable maintenance and monitoring policy for a specific plan.

In fact, following the approach presented in [15], the maintenance time (T_M) can be obtained by the following equation:

$$T_M \le \frac{C_{MA}}{\frac{P_{gen}}{\eta_{corr\ irr}} \cdot \eta_{ineff} \cdot \left(R_S + R_{inc}\right)} \qquad (2)$$

where P_{gen} is the generated power by a clean panel (in kW), η_{ineff} is the percentage of efficiency reduction due to soiling, η_{corr_irr} is the correction factor related to the mean value of the radiation in the period under examination (if the term P_{gen} is divided by η_{corr_irr}, it is possible to define the power generated in reference conditions in that period), R_s is the value of saving (in Euros) for each produced kWh, R_{inc} is the value (expressed again in Euros) of the economic incentives for each produced kWh and T_M is the worthwhile moment to do maintenance activities. The percentage of efficiency reduction due to soiling is supposed to be constant during monitoring interval.

In order to experimentally verify the effectiveness of the model, a photovoltaic test plant has been considered. It is a plant placed on a roof with a rated power of 20 kW (in STC condition). The plant is regularly monitored and works in MPP condition. During the year considered for the qualification of the maintenance method, the MPP variation due to the surface condition has been estimated: the mean reduction value of 4% has been assigned to the efficiency reduction coefficient η_{ineff} . The correction factor η_{corr_irr} has been considered equal to one (this assumption is possible assuming that the evaluation considers the actual energy produced by the plant).

In order to compute the maintenance time, typical maintenance costs have been considered: an average cost for cleaning the considered plant has been estimated to be € 170.00 for each intervention, defined considering this activity as an additional task of a regular maintenance contract. By considering R_s + R_{inc} equal to 0.443 €/kWh it is possible to evaluate the losses in economic terms.

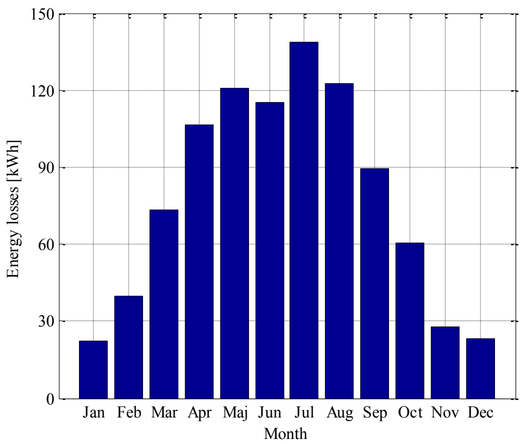

Fig. 4 – Energy losses vs month.

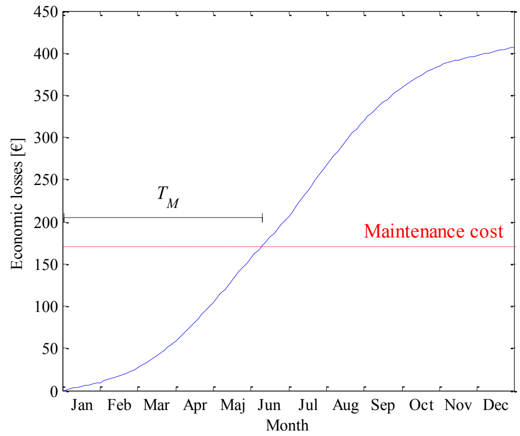

Fig. 5 – Economical losses vs months.

Fig. 4 shows the total energy losses for each month while Fig. 5 shows the results obtained using the proposed model.

The performed analysis demonstrates that, supposing to begin the simulation in January, the optimum maintenance interval is five months. It is clear that, since the generated power is not constant during the year, the maintenance time interval depends on the month in which the cleaning process has been performed.

It is interesting to highlight that considering MP value as a statistical parameter [14], it is possible estimate energy losses characterizing and monitoring only one panel; in this way the term $P_{gen}\ \eta_{ineff}$ can be replaced with the actual estimation.

IV. CONCLUSIONS

The use of ESA as a technique of diagnosis allows to easily identifying the decrease of the performances of a PV plant. A second important feature that has been highlighted in this research is the low economic investment required to implement this approach to the diagnostic task. Often it is sufficient to use sensors, signals and information already available for other purposes. In fact, an energy monitoring activity is always implemented in this kind of plant. MPP evaluation is in fact required and computed by the inverter devoted to the DC/AC conversion. In addition to this information, only the knowledge of the environmental parameter is required.

The advantages of such approach are: substantial reduction in inspections of equipment/facilities under the automatic monitoring that is inherent in the method; efficient planning of maintenance programs; implementation of improved environmental sustainability plans thanks to the automatic waste reduction and resource (change and intervenes when necessary); improvement of the quality levels of production because the plant tends to work more effectively or at least under conditions planned and managed.

Finally, it is interesting to highlight that the proposed method could be used to identify possible malfunctions (diagnostic purpose) and/or, evaluate, the residual life time of the plant (for this purpose the MP reduction can be considered as a prognostic index).

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