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A Kriging-Based Partial Shading Analysis in a Large Photovoltaic Field for Energy Forecast

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Abstract. In this paper the use of the kriging estimation method for the study of partial shading in photovoltaic fields is investigated. Different cases of shadowing spatial distribution on the PV field surface, due to different relative positions between the plant and some clouds, are studied. The adopted method gives a spatial interpolation of the shadowing so that its distribution over all the surface can be obtained on the basis of a limited number of experimental data. In all cases the kriging estimates are nearly the same as the observed data, also when a strongly reduced experimental observations are available. The accuracy of the estimates is also confirmed by Q-1 and double kriging cross validation schemes. The followed approach allows a cheaper and simpler characterization of the PV plant output power allowing energy forecast.

Key words

Models and simulation of renewable energy sources; Photovoltaic array; Statistics; Kriging estimation.

1. Introduction

Photovoltaic (PV) generation systems represent an established technology. They have experienced a nearly exponential growth in the last decade and are currently playing an increasingly important role in supplying the growing global electricity demand [1]-[3]. From the PV systems operational point of view, different topics have to be taken into account, for example, the dependence of the output power from real weather conditions, the need for an inverter system for the ac power supply, the need for a maximum power point tracking (MPPT) control in order to extract as much power as possible, etc. [4]-[5]. In particular energy forecast and MPPT optimal design are necessary in order to improve the control of the power interface and the operation of the overall system [6].

In general PV arrays are composed of matrices of solar cells interconnected in series and parallel. Therefore the array performance is dependent on the behavior of the individual solar cells. This could be critical especially in non-ideal operating conditions [7].

An usual non-ideal operating condition that strongly affects PV arrays MPPT control and power generation is the partial shading. This problems is mainly due to passing clouds over a portion of the PV array and is particularly serious for large installations. Partial shading leads to a reduction of the output power. Moreover the occurrence of multiple local maxima, due to non uniform solar irradiation, can cause a failure of the MPPT control with a consequent considerable power loss due to the lack of the real MPP detection [8]-[10]. For this reason the correct experimental determination of solar irradiance distribution over a PV array is crucial both for the optimization of the MPPT strategies and for a correct prediction of the PV system energy capability.

The partial shading condition can be simply detected by a set of irradiance sensors suitably placed on the array surface. The higher is the sensor number the more precise is the evaluation of the irradiance distribution and the more costly is the overall installation.

In this paper a method for obtaining an accurate estimate of irradiance distribution over a large PV array by a reduced number of irradiance sensors is proposed.

The method is based on a kriging regressor that spatially interpolates the irradiance values obtained by the reduced number of available sensors over the whole array area. In this way a non-uniform or varying irradiance and the resulting power capability of the PV system can be identified in a cheaper way and managing a smaller amount of experimental data.

Different cases, corresponding to different dimensions of a shading cloud and to relative positions between the shading cloud and the PV array, are studied. In all cases the kriging-based estimate gives a good representation of the spatial irradiance distribution.

The paper is organized as follows. In Section II the features of the PV array are described, in Section III the fundamentals on the kriging estimation method are reported. In Section IV the distribution of solar irradiance on the PV array surface is given and finally in Section V the application of the kriging method to the cases under study is presented and the results of the estimate are reported.

2. Features of the PV array

The study is carried out on a PV field having the configuration described below. The total surface of the installation is of 240m^2 (10m×24m).

The field is composed of 120 modules (Solar world-Sunmodule Plus SW 160) each of them having a surface of 0.81m×1.61m and a rated power of 160Wp.

The total power of the plant is, therefore, about 20kWp. The strings are composed of 10 modules. Six single phase inverters are used for the grid connection of the PV field. Each inverter is supplied by two parallel connected strings, forming an array. In Fig. 1 a schematic representation of the PV plant is reported; bypass diodes and blocking diodes at the end of the strings are not drawn for simplicity.

3. Kriging theory

Kriging is a statistical estimation technique for spatial interpolation of random quantities. The mathematic formulation of the method has been developed on the basis of the experiments performed by D.K. Krige to find out the distribution of minerals in the subsoil by punctual surveys. Its main application is in the field of geostatistics, and, thanks to its intrinsic features, it can be successfully used also when a small amount of sampled data are available.

The kriging method allows to obtain the quantity value at an unobserved location from observations of its value at nearby locations, being the unknown value obtained by a weighted mean of the available data. The spatial interpolation is based on the "autocorrelation" of the considered quantity, i.e., its property to vary in a continuous way. The weights are determined by using the semivariogram, a graphical tool that expresses the relation between the distance between two points and the variance between the measurements performed in such points. In the presented application the ordinary kriging algorithm is used, since it leads to a more accurate estimation [11]-[14]. In general kriging is applied to data which can be represented by an intrinsic statistical model (ISM). In an ISM the covariance function is only dependent on the separation of two data points, according to (1).

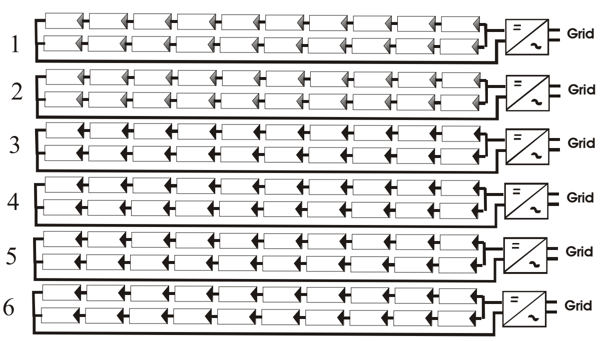

Fig.1. Schematic representation of the photovoltaic array.

$$E[\,(z(\mathbf{s})-m)(z(\mathbf{s}')-m)\,] = C(h), \qquad (1)$$

where m is the mean of z(**s**), i.e., the random quantity to be interpolated, and $C(h)$ is the covariance function with lag h, being h the distance between two samples **s** and **s'**, given by:

$$h = \|\,\mathbf{s}-\mathbf{s}'\,\| = \sqrt{(s_1-s'_1)^2+(s_2-s'_2)^2+(s_3-s'_3)^2} \qquad (2)$$

ISMs can be also characterized by a semi-variogram,

$$\gamma(h) = 0.5 * E[\,(z(\mathbf{s})-z(\mathbf{s}')\,)^2], \qquad (3)$$

where the relation between the covariance function and the semivariogram is:

$$\gamma(h) = C(0) - C(h). \qquad (4)$$

In the ordinary kriging the formulation of the estimator is the following:

$$\hat{z}(s_0) = \sum_{i=1}^{n} \lambda_i z(s_i) \qquad (5)$$

Eq. (5) means that kriging method finds a local estimate of the quantity at a specified location, s_0. This estimate is a weighted average of the N adjacent observations. The weighting coefficients λ_i can be determined on the basis of the minimum estimation variance criterion:

$$E\{[z(s_0)-\hat{z}(s_0)]^2\} = C(0) - 2\sum_i \lambda_i C(\|s_i - s_0\|) + \sum_i \sum_j \lambda_i \lambda_j C(\|s_i - sj\|) \qquad (6)$$

imposing the constraint of the normalization condition:

$$\sum_{i=1}^{n} \lambda_i = 1 \qquad (7)$$

It should be noticed that, in this way a predicted value, s_0, that provides the minimum estimation variance is obtained. The resultant kriging equations can be expressed as:

$$\begin{cases} \sum_{j=1}^{n} \lambda_j C_n(\|s_i - s_j\|) - \mu = C_n(\|s_i - s_0\|) \\ \sum_{j=1}^{n} \lambda_j = 1 \end{cases}, \qquad (8)$$

where μ is the Lagrangian coefficient. Equivalently, by using eq. (4), the kriging equation can also be expressed in terms of the semivariogram as follows:

$$\begin{cases} \sum_{j=1}^{n} \lambda_j \gamma_n(\|s_i - s_j\|) + \mu = \gamma_n(\|s_i - s_0\|) \\ \sum_{j=1}^{n} \lambda_j = 1 \end{cases}, \qquad (9)$$

Once obtained the weighting coefficients λ_j and the Lagrangian coefficient (μ) by solving either eq. (8) or eq. (9), the kriging variance, eq. (6), can be expressed as:

$$\sigma_0^2 = E\{[z(s_0)-\hat{z}(s_0)]^2\} = C(0) + \mu - 2\sum_i \lambda_i C(\|s_i - s_0\|) = \mu + \sum_i \lambda_i \gamma(\|s_i - s_0\|) - \gamma(0). \qquad (10)$$

4. Data generation

The presence of a cloud over a PV field causes a shadow in which the lightness decreases gradually going from the edges to the centre of the shadowed region. If the shadow surface is smaller than the PV field, only a portion of the PV field is interested by the reduced irradiance.

On the contrary, if the shadow surface is greater than the PV field extension, the whole field is interested by the reduced irradiance.

A function that gives a good approximation of the partial shading is the bidimensional Gaussian function [15]. Such a function is identified once two parameters, for each field dimension (x or y), are defined, i.e., the coordinates of the shading cloud centre and its width. Therefore the normalized shadowing, □over the PV field is described as:

$$Z(x,y) = exp\left(-\frac{(x-x_c)^2}{\sigma_x} - \frac{(y-y_c)^2}{\sigma_y}\right) \qquad (11)$$

where (xc,yc) represent the coordinates of the centre of the shading cloud and σx and σy are its dimensions, respectively along x and y axes. It should be noted that Z(xc,yc)=1 corresponds to the maximum shadowing.

The spatial distribution of the solar irradiance is given by:

$$G(x,y)=Gmax[1-Z(x,y)] \qquad (12)$$

where Gmax is the solar radiation without shadowing.

The following study cases are explored.

Case 1: One shading cloud on the PV field surface with coordinates of the center x=5, y=12 and dimensions σx=5 m and σy=12 m.

Case 2: Two shading clouds, partially superimposed, on the PV field surface. One cloud has the center coordinates x=5, y=6 and dimensions σx=10 m and σy=10 m, the other has the center coordinates x=7.5, y=12 and dimensions σx=5 m and σy=5 m.

In Fig.2 the spatial distribution of the normalized shadowing over the PV field surface, obtained by (11), in case 1 is reported. Fig.3 shows, for the case 1, the shadowing pseudocolor diagram, which represents a qualitative diagram where the smallest and largest elements of C are assigned the first and last colors. Case 2 is described by Figs 4 and 5 that show respectively the spatial distribution of the normalized shadowing over the PV field surface and the shadowing pseudocolor diagram.

5. Kriging processing

The kriging processing of the shadowing data, previously illustrated, is carried out by the EasyKrig© 3.0 software, developed by D. Chu. The EasyKrig program package uses a Graphical User Interface (GUI) to simplify the operation. It works in MATLAB environment and consists of five processing stages: data preparation, semivariogram computation, kriging, visualization and results saving.

A specific advantage of this software is the capability to automatically generate the required default parameters, overcoming the users' need to presume the initial parameters values. The kriging estimates of the shadowing distribution over the PV array are determined in the case 1 and in the case 2. These computations are done by considering firstly the configuration of the irradiance sensors, shown in Fig. 6. In this configuration, referred as full configuration, 120 sensors are used, one for each PV module.

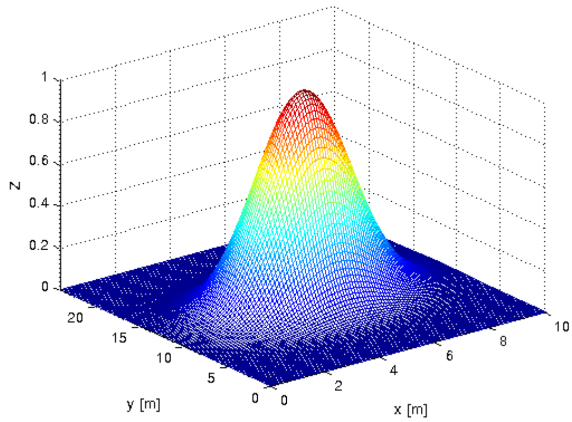

Fig.2. Spatial distribution of shadowing over the PV field surface in case 1.

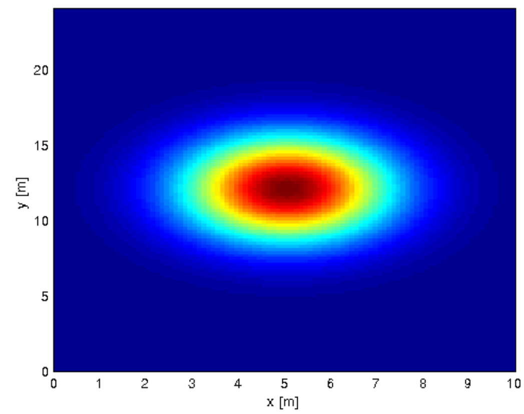

Fig.3. Pseudocolor diagram of shadowing over the PV field surface in case 1.

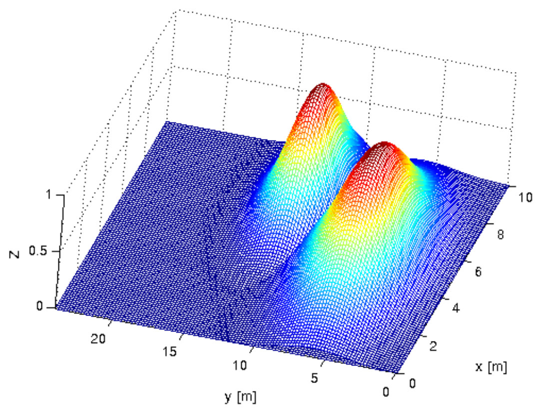

Fig.4. Spatial distribution of shadowing over the PV field surface in case 2.

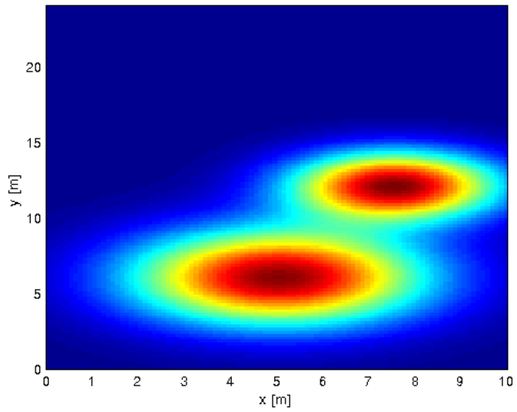

Fig.5. Pseudocolor diagram of shadowing over the PV field surface in case 2.

The sensors number is then progressively reduced up to the 25%. In this last configuration, referred as reduced configuration and shown in Fig. 7, the kriging estimate is performed again, in order to evaluate its accuracy with a reduced number of sensors. It should be observed that the x-y axes in Figs. 6 and 7 are not in scale.

A. *Case 1*

Fig. 8 shows the kriging map obtained by the processing of the shadowing data in the full sensors configuration. In Fig. 9 the kriging map obtained considering the sensors in the reduced configuration is given. The estimation of the shadowing distribution on the PV field surface is perfectly fitting with the given data when one sensor for each module is employed. A very good estimation is still obtained by using only the 25% of sensors, according to their disposition shown in Fig.7.

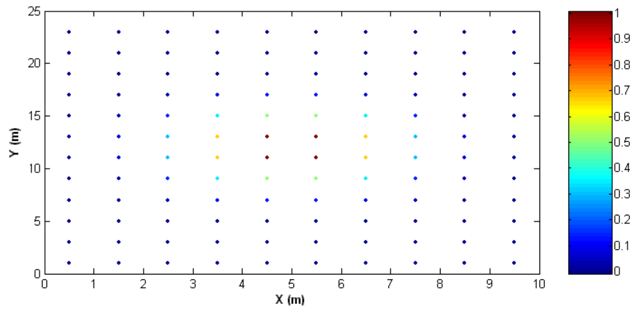

Fig.6. Sensors configuration with one sensor for each PV module (measured data are referred to case 2; the colour bar indicates the shadowing).

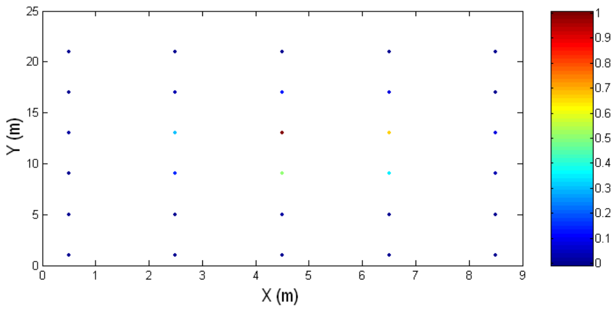

Fig.7. Configuration with sensors number reduced to the 25%. (measured data are referred to case 2; the colour bar indicates the shadowing).

B. *Case 2*

Fig. 10 shows the kriging map obtained by the processing of the shadowing data in the full sensors configuration. In Fig. 11 the kriging map obtained with the sensors reduced configuration is represented. Also in this case the shadowing distribution on the PV field surface, due to the contemporary presence of two clouds partially superimposed, is perfectly estimated, when one sensor for each module is employed. Moreover the estimation is very satisfactory also in the reduced configuration, except for a slight overestimation in the area of the superposition between the two clouds.

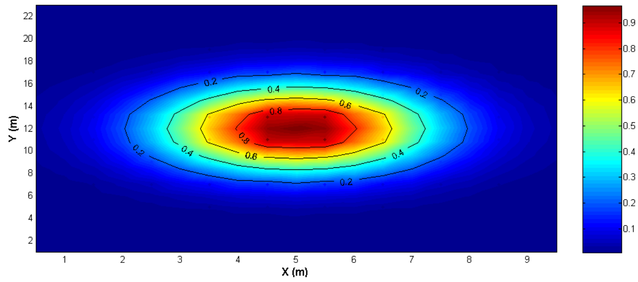

Fig.8. Kriging map of the shadowing in case 1 with full configuration of sensors.

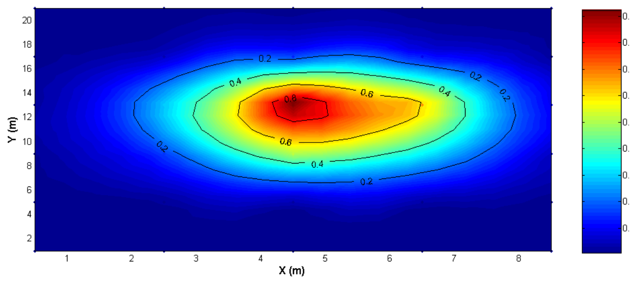

Fig.9. Kriging map of the shadowing in case 1 with reduced configuration of sensors.

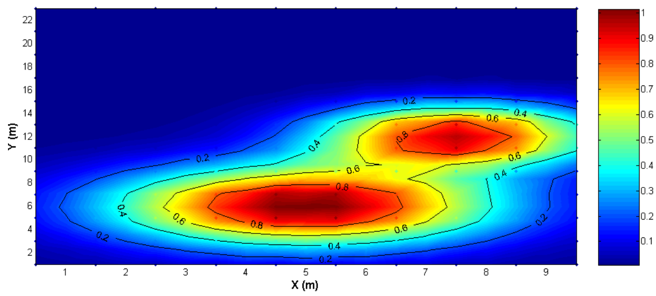

Fig.10. Kriging map of the shadowing in case 2 with full configuration of sensors.

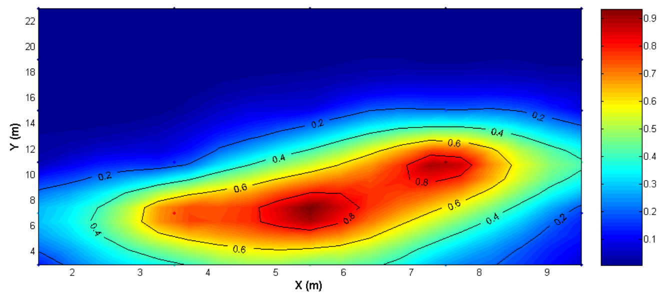

Fig.11. Kriging map of the shadowing in case 2 with reduced configuration of sensors.

C. Cross validation

In order to assess the accuracy of the kriging estimations, when 25% of sensors are available, some cross validation methods are employed.

Cross-validation is a statistical technique consisting in the partitioning of data into subsets such that the analysis is initially performed on a single subset. Subsequently the other subsets are used in confirming the initial analysis [16]-[17].

The main cross validation methods are: Q-1, Q-2, double kriging and leave one out cross validation (LOOCV).

Q-1 and Q-2 cross validations are used to check the statistical distribution of the residuals between the observed data and kriged values at the original observation locations by using the same kriging parameters and variogram model parameters.

To perform Q-1 and Q-2 cross validations, a normalized residual array (E_r) needs to be constructed [18].

In detail, Q-1 checks the statistics of the mean of the residual E_r and approximately follows the normal distribution. Q-2 checks the statistics of the variance of E_r. while (Q-2)*(n-1) approximately follows the chi-square distribution with parameter n-1.

The acceptable region defined in the Easykrig program (two black vertical lines) is the 0.025 and 0.975 percentiles. The double kriging cross-validation scheme is to evaluate the level of agreement between the kriged or predicted values and the original observations at all observation locations. The predicted data at grids obtained from the kirging (first stage) are served as 'input data'.

The mean value at the original observation locations are estimated by kriging (second stage) with the same kriging parameters and variogram model parameters.

The results from the second kriging are then compared with the original observed data in a separate plot. Finally the LOOCV works as ' Double Kriging' except that, for each location, all observed data but the one at that location are served as 'input data' in performing second kriging computation.

In Fig. 12 the Q1 cross-validation plot, for case 1 with 25% of sensors, is shown. Fig 13 shows the double kriging cross validation plot, for case 1 with 25% of sensors. Figs. 14 and 15 show the analogous cross validation plots for case 2 with 25% of sensors.

In all studied cases a very good matching between observed and estimated data is observed.

This results confirms the suitability of the kriging approach to study partial shading in large PV installations.

Kriging method allows to give a good prediction of the shadowing spatial distribution on the PV plant surface with a reduced number of irradiance sensors.

This has the great advantage of a cheaper realization of the PV field and of the possibility to manage a smaller amount of experimental data.

Moreover a simpler and less expensive computation of the PV plant real output power is possible and this can be used for energy capability forecast.

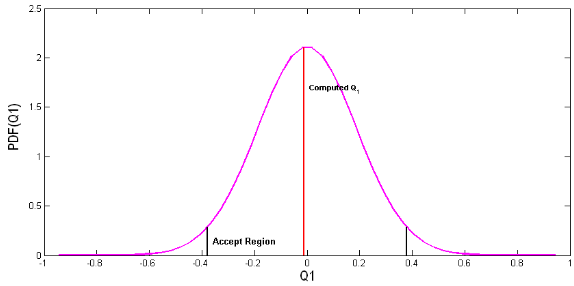

Fig.12. Q-1 cross validation plot for case 1 and 25% of sensors.

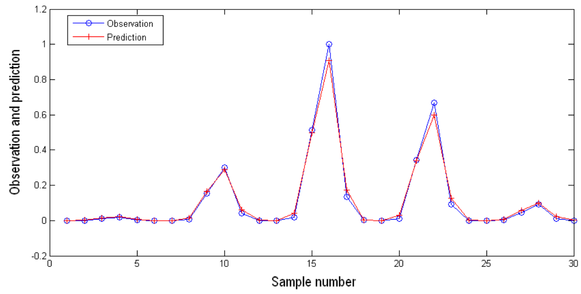

Fig.13. Double kriging cross validation plot for case 1 and 25% of sensors.

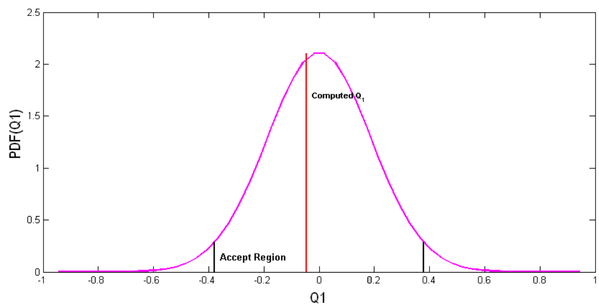

Fig.14. Q-1 cross validation plot for case 2 and 25% of sensors.

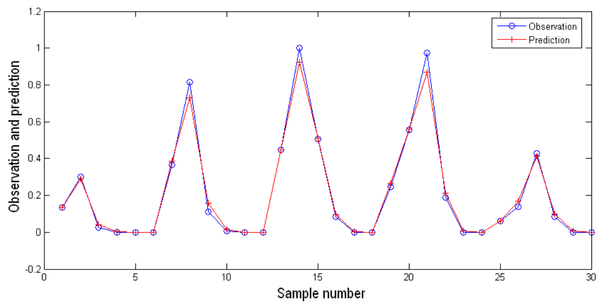

Fig.15. Double kriging cross validation plot for case 2 and 25% of sensors.

6. Energy forecast

In this section the results, obtained both by measurements (one sensor for each module) and kriging interpolation (one sensor every four modules), are used for the evaluation of energy supplied by the PV field under partial shading conditions. This analysis is carried out with reference to the case 1. Fig. 16 shows the plant partially shaded, according to the configuration of the case 1. It should be noted that the array 1 is uniformly illuminated by a solar irradiance of 800W/m^2, while the array 4 is partially shaded. In particular its upper string has the central modules completely darkened. Therefore the array 1 can deliver the maximum power according to the characteristics depicted in Fig. 17. The electrical characteristics of the PV modules are obtained by a modelling and a parameter identification technique, described in [19]-[20]. Under uniform irradiance condition the power vs. voltage (P-V) curve exhibits a unique maximum. On the other hand the P-V characteristics, that represent the electrical behaviour of the upper and lower strings of the array 4, are composed by different curves due to different solar irradiance on series connected modules.

These curves will exhibit multiple local maxima. As a consequence, the available power is reduced respect to array 1. In this case, because the voltage of upper string is considerably reduced respect to the voltage of the lower string, the former will be disconnected by its blocking diode.

The electrical characteristics of the strings in array 4 are illustrated in Fig. 18, for the current vs. voltage (I-V) curves and in Fig. 19, for the P-V curves.

Figs. 18 and 19 include the electrical characteristics obtained: a) with solar irradiance measured with one sensor for each module; b) with solar irradiance measured with one sensor every four modules and interpolated by kriging in the other modules.

By a comparison it is verified the goodness of the interpolating technique for identifying the actual irradiance on each module and therefore to find out the actual maximum output power, under partial shading conditions. The differences observed for the lower string are due to the extension of the deeply shaded zone that is comparable with the distance between two sensors. This represents the worst case for any spatial interpolation method. Anyway this does not affect the correct estimation of the maximum power.

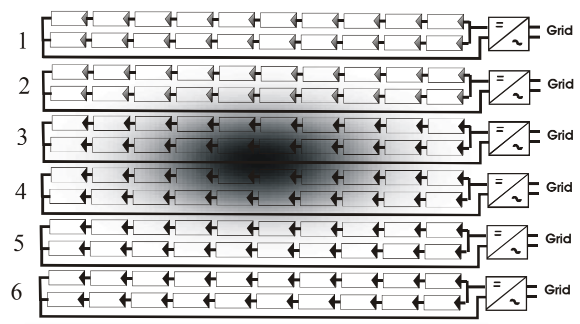

Fig.16. Partially shaded plant: case 1.

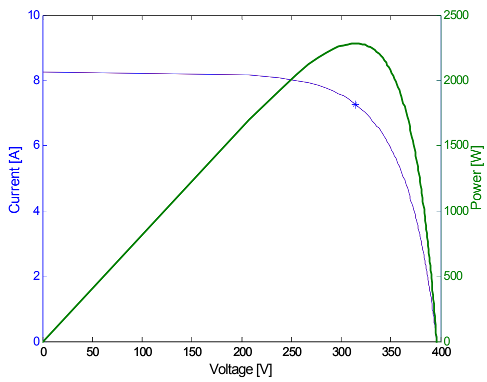

Fig.17. I-V and P-V characteristics of the array 1, under a uniform solar irradiance of 800 W/m^2.

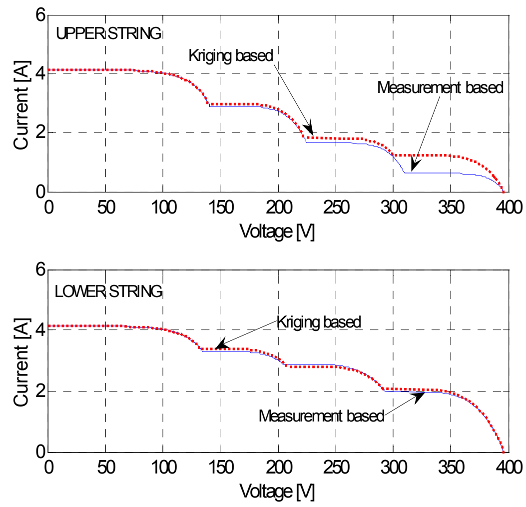

Fig.18. I-V characteristics of the upper and lower strings in array 4.

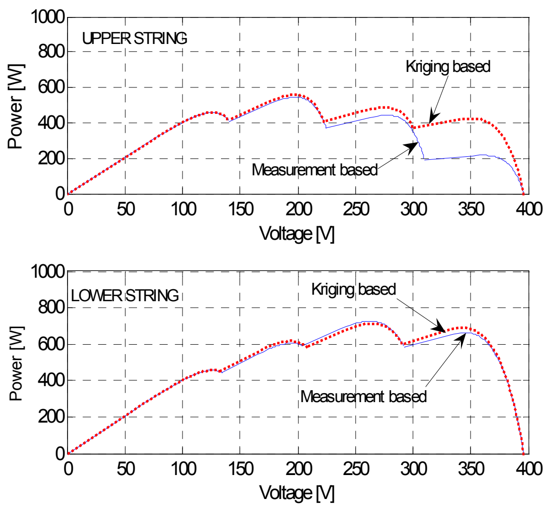

Fig.19. P-V characteristics of the upper and lower strings in array 4.

7. Conclusions

The spatial distribution of the shadowing over the surface of a large PV field is computed by means of the kriging interpolation method.

Thanks to the proposed approach, the accurate estimation of the partial shading is possible by using a very small number of experimental observations, coming from solar irradiance sensors mounted on the PV field modules. The reliability and accuracy of the method are evaluated by testing configurations where different relative positions between shading clouds and PV field surface have been considered.

The very good matching between observed and estimated data is also confirmed by Q-1 and double kriging cross validation schemes.

The proposed method allows a less expensive characterization of the PV plant output power, including possible local maxima due to partial shading. Therefore the kriging estimation method represents a useful tool for PV plants energy assessment.

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