

## Design of experiments approach for modeling the electrical response of a photovoltaic module

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### ABSTRACT

In the current paper, modeling and evaluation of the significant effect of independent variables on the behavior of the electrical response of a multi-crystalline photovoltaic (PV) module using design of experiments (DoE) approach is simulated. The main purpose of this contribution is to evaluate the maximum power response dependence within the indoor conditions of both variations of solar irradiation and surface temperature and checking the pertinent one on the defined response. The DoE approach is used for estimating both main and combined effect of the two independents considered variables. Multiple linear regression was been introduced to justify the relationship between the independent input variables and dependent output variable, also to determine which input factor is the most significant on the output variable. The DoE model can be used for predicting the response variable at different operating condition in a considered domain study. In addition, DoE approach based on statistical tool for analyzing the accuracy of the predictive model, then the significance of coefficients in the predictive model using statistical and graphical analysis. Therefore, an ANOVA Table can summarize the results, detect the parameters influences on responses variations and determine the best predictive model then reproduce the most possible the experimental data.

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## 1. INTRODUCTION

The recent increase of economic, industrial and environmental developments requires a huge use of clean energy resources and requires a rapid evolution of the material and technology in order to reduce pollution, to contribute positively to a smaller climate change allowing a sustainable development. In this context, solar photovoltaic energy has become an unavoidable and competitive secure of energy in all countries around the world. Photovoltaic energy production based in large scale on the crystalline silicon technology, it presents an important source widely presente in the earth. Several reseachs were carry out for modeling and predicting the behavior of photovoltaic module in operating conditions uses.

Some authors have presented in detail or in review form some modeling methods for PV systems as cells or modules. Nevertheless, generally, these methods require a deepned knowledge of the related PV electronics or physics properties or are based on datasheets providing by the manufacturers, not specific to the considered panel under evaluation [1-5]. By else, these methods are based on relatively complex and specific mathematical models [6-12]. With a view to considerable time, financial, and material resources savings that we can expect in development of performing new photovoltaic systems, the Design of Experiments (DoE) approach should be adapted to offers a practical upstream way for the study, the modeling and characterizations

of the influence of the pertinent parameters involved in the response of these systems. As mentioned by Antony [13], the DOE technique, based on simple graphical techniques, is an interesting tool for process improvement initiatives and can be applied for case studies in the context of different industry sectors, as it is an alternative to advanced statistical methods reducing time taken to design and to carry out tests. Usually, the DoE approach is mainly used to support the design of new industrial product or in statistical analysis process [14] as well as, to optimize the settings of a manufacturing process [8, 15] and to improve its performances [16] or to predict and to characterize its behavioral model [17-19].

The DoE is used as an alternative approach to assess the significant input parameters “factors” and their influences on the output parameters “response” of the considered system subject of experiments with the advantages that it does not require the knowledge of the physical model of the process to be studied. By cons, with the classical method [20-22], which can vary only one factor at a time, the modeling of the system is not easy if not possible and it is impossible to determine the correlation between the various parameters influencing the system response. Among these, its main advantage is its ability to predict the individual effects as well as the interactions between the various factors involved in the experiment [14, 23, 24]. By else, to characterize and model any system, the DoE approach significantly minimizes the number of experiments without degrading the response accuracy [25], i.e. it provides maximum of information on the response with a minimum of experimental trials. To model a phenomenon, the DoE is often concerned with a set of variables that can modify a specific response, noted “response of the system”. A systematic mathematical model of factorial design connecting between factors and response is then deduced.

In the current contribution, we focus on the modeling and evaluating with the DoE approach of the behavior of a multi-crystalline photovoltaic module. As input parameters of the established predictive model, factors, the solar irradiation and the surface temperature are considered. On the other hand, the maximum available power on the PV module is considered as output-response factor. These functional parameters of the PV modules are simply obtained from measurements carried out with a limited set of experimental trials. Experiments were performed at the laboratory. The experimental errors made on temperature and on electrical measurements, including irradiation measurements, are estimated to be of standard 10% values. They result to an estimated 10% error on the maximum power calculation. For a correct implementation of the DoE method applied to PV panels modeling, we have used statistical analysis, ANOVA and graphical analysis to allow the determination of the predictive model for the evaluation of any significant effect and the correlation between parameters affecting the response of the PV system.

In the DoE approach theory, the variation of a given factor is limited between the low and the high levels of the actual or reduced centered values constituting the graduations of the axis thus delimiting the experimental study domain [26]. Two distinct ways are reserved to represent a factorial design: Draw the experimental domain and then add all experimental trial as points according to their coordinates, or summarize all trials by a Table [26, 27].

## 2. THEORETICAL METHODOLOGY

The DoE leads to deduce a mathematical model of complete factorial design of the response according to the factors that can vary in a bonded study domain limiting the input parameters variations [28-30]. In the absence of any experimental data connecting the response  $y$  to the factors  $x_i$ , the DoE method makes it easy to establish predictive mathematical relationships of the response as follows:

$$y = a_0 + \sum_{i=1}^k a_i x_i + \sum_{\substack{i,j=1 \\ i < j}}^k a_{ij} x_i x_j + \sum_{i=1}^k a_{ii} x_i^2 \quad (1)$$

where  $y$  is the measured response vector of the studied system,  $x_i$  is its input parameters or factors levels and  $a_i$  are the model coefficients.

The DoE methodology is based on the following steps:

- At first, we have posing the problem in order to find an answer to a question asked, this requires determining the objectives to be reached, we also define the responses, the factors that can affect the responses, then we build our experimental design.
- In the second step, we choose of the strategy of the experimental design, according to the objective of the study two possibilities are offered, either the screening technique or the response surface technique, endowed with mathematical modeling while using algebraic calculations.
- The last step is reserved for each of the two techniques, using statistical and graphical analyzes to analyze and interpret the obtained results.

In the present contribution, we model the behavior of the maximum power variation of a multi-crystalline photovoltaic module under simultaneous variations of solar irradiation and surface

temperature. In order to obtain a common representation of the units, the concept of the reduced centered value is commonly used. The standardized values are determined by a linear translation of the original coordinates of the system until a centered representation is achieved and a normalization of these axes yielding to the reduced representation with the upper and lower levels of the factors taking the values +1 and -1, respectively [13, 20, 26].

### 3. PRACTICAL IMPLEMENTATION OF THE METHOD

The experience was done on a multi-crystalline module is the BP Solar BP350J with a maximum power of  $P_m = 50W$  realized at voltage of  $V_{mp} = 17,5 V$  and a current  $I_{mp} = 2,9 A$ . Its open circuit voltage is  $V_{oc} = 21,8 V$  and its short circuit current is  $I_{sc} = 3,2 A$ . These values are extracted of the datasheet of the panels. This PV module is built within 72 cells in 4 rows of 19 cells, connected in 2 parallel strings of 36 in series, each row being bypassed by a diode.

Figure 1 shows the experimental bench, consisting of a multi-crystalline PV module, a dynamic load used to record the current and the voltage data of PV module, the measuring devices (ammeter, voltmeter), and scope for plotted I-V characteristics.

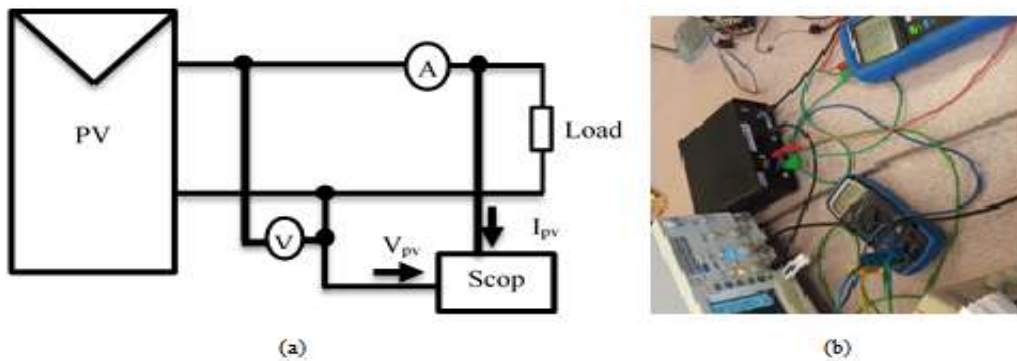


Figure 1. Experimental bench

Table 1, gives the experimental trials measurements and the observed responses: factors (solar irradiation  $I_r$  and surface Temperature  $T$ ) and response (maximum Power  $P_m$ ). It can be noted that solar irradiation levels and surface temperature were recorded during the same indoor experiments. Due to the artificial irradiation source (Hg lamps of Deltalab source), a significant increase of PV cell temperature is linked to the change in the irradiation level. In our case, a change in irradiation of  $494 W/m^2$  induced a change of  $2.9 ^\circ C$  at the surface of the PV cell. This experimental choice allows us to compare in the responses the relative effect of both factors.

The concerned parameters experimentally determined are:

- The solar irradiation  $I_r$  ( $mV$ ) using a pyranometer placed at the center of the PV panel, and can be converted in  $W/m^2$  according to its sensitivity  $S = 10,33 \mu V / W/m^2$ .
- The surface temperature  $T$  ( $^\circ C$ ) at the center of the PV panel using infrared thermometer, recorded within an accuracy of 1%.

Table 1. Experimental trials measurements and observed response

| N° | Factors           |                    | Response  |
|----|-------------------|--------------------|-----------|
|    | $I_r$ ( $W/m^2$ ) | $T$ ( $^\circ C$ ) | $P_m$ (W) |
| 01 | 842               | 31.8               | 16.79     |
| 02 | 842               | 43.7               | 16.25     |
| 03 | 1849              | 28.8               | 31.52     |
| 04 | 1849              | 47.4               | 30.29     |

From the DoE theory, after the defining the problem, we determine the objectives of the study to be achieved. Then, the choice of the strategy is used to carry out the experiments chosen by the experimenter in order to achieve the desired objective, in this paper it is enough to use the screening technique.

The screening technique makes it possible to determine, among the factors identified by the experimenter, those which have a statistically significant influence on the variations of the electrical response of the multi-crystalline PV module.

However, in (1) is simplified to a similar system as indicated in (2), which can be written:

$$y = a_0 + a_1x_1 + a_2x_2 + a_{12}x_1x_2 \tag{2}$$

Where:

$x_1$  and  $x_2$  are the solar irradiation and the surface temperature factors respectively,

$a_0$  is the coefficient representing the central value,

$a_1$ ,  $a_2$  and  $a_{12}$  are the coefficients associated to the respective contributions and interaction between them of the factors  $x_1$ ,  $x_2$ .

#### 4. RESULTS AND DISCUSSIONS

The full factorial design  $2^2$  (4 runs) is used for determining the main effect of factors and interaction effect that can varying the response, with precision of the more significant effect. Two ways to discuss and interpret the results as mentioned above are: graphical and statistical analysis. Figure 2 indicates the Pareto chart of effects, which presents factors and interaction effects in decreasing order as well as factor A, factor B and factor AB, so, we can see the most significant factor on the response variation how has presented by the important one.

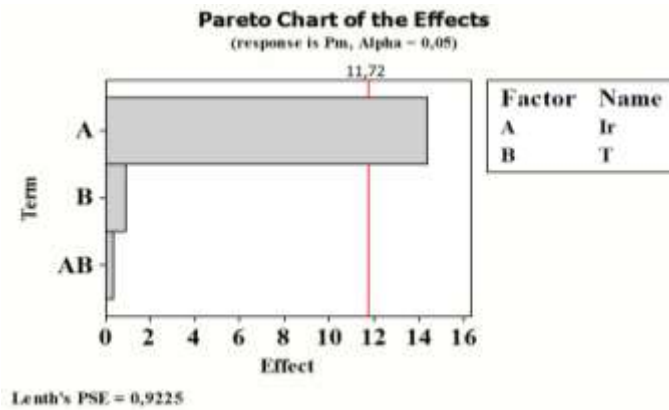


Figure 2. Pareto chart of effect factors

Therefore, the signification and direction of the variation of response due to the direction of the factors is clear from the centered response value as mentioned by Figure 3. However, it is to be noted that, the influence of the solar irradiation factor growth in the same direction and it is more significant than the surface temperature factor. By cons, and as expected, the temperature factor influence inversely on the direction of the power response. The response at the center of the study domain corresponds to the central value  $a_0 = 23.7$  at the operating point ( $Ir = 1346 \text{ W/m}^2$  and  $T = 38.1 \text{ }^\circ\text{C}$ ).

When the factors are in reduced centered values, the effects are represented by the slopes of the corresponding regression line segments. However, the global effect of factor is the variation between the sum of responses at the high level of factor and the sum of responses at the low level of the same factor, then, the mean effect of factor or effect factor is the half of the global effect. In our case, when the solar irradiation passes from  $1346 \text{ W/m}^2$  or level 0 to  $1849 \text{ W/m}^2$  or level 1, the maximum power increases and passes from  $23,7 \text{ W}$  to  $30,9 \text{ W}$ , within an increasing of  $7,2$ . Moreover, when the surface temperature passes from  $38,1 \text{ }^\circ\text{C}$  to  $47,4 \text{ }^\circ\text{C}$ , the maximum power decreases and passes from  $23,7 \text{ W/m}^2$  to  $23,18 \text{ W/m}^2$ , so a decrease of  $0,44$ .

The global effect of factor 1 is the grown up of the maximum power from  $16,5 \text{ W/m}^2$  to  $30,9 \text{ W/m}^2$ , when the solar irradiation raised from  $842 \text{ W/m}^2$  to  $1849 \text{ W/m}^2$ . The global effect of factor 2 is the push down of the maximum power from  $24,22 \text{ W/m}^2$  to  $23,18 \text{ W/m}^2$ , when the surface temperature raised from  $28,8 \text{ }^\circ\text{C}$  to  $47,4 \text{ }^\circ\text{C}$ .

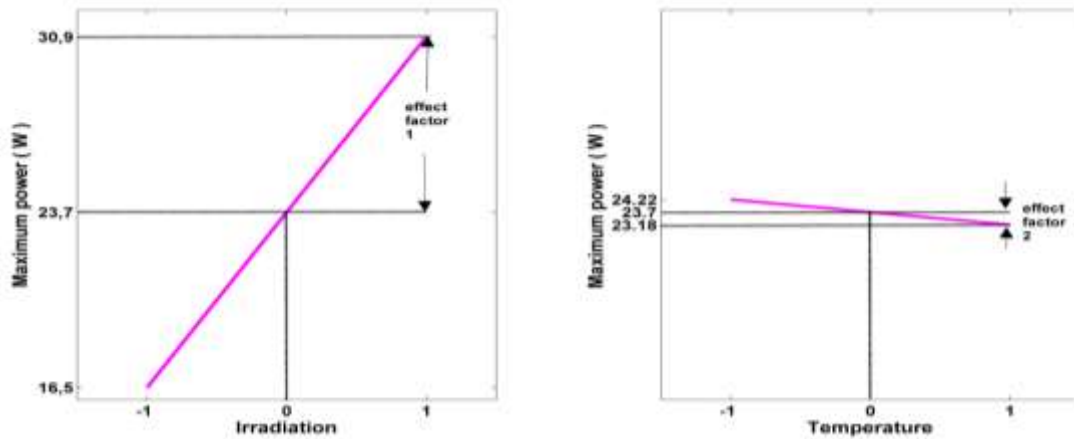


Figure 3. Illustration of effect factors of the maximum power response

Additionally, we analyze the interaction effects between solar irradiation and surface temperature of the maximum power response. Indeed, following the DoE theory, the difference between the two slopes of the factor responses indicates the presence of an interaction between these two factors. The interaction is even stronger as slopes are different. In the current study, the results are modeled and represented in Figure 4.

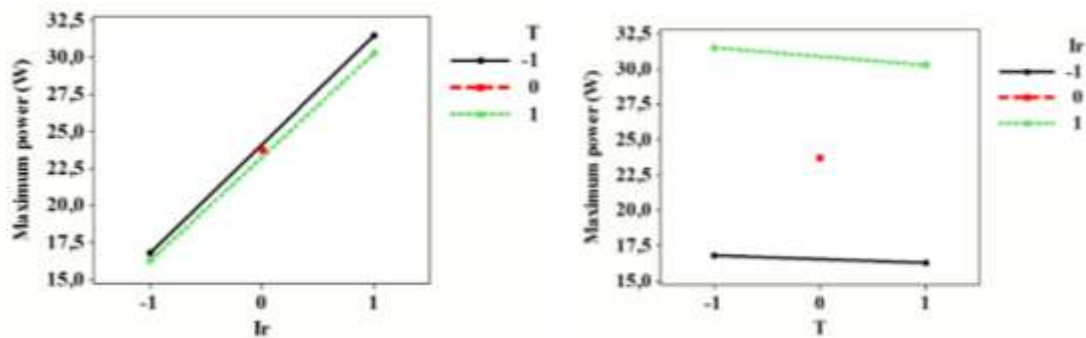


Figure 4. Illustration of interaction effect between solar irradiation and surface temperature for the maximum power response

In order to highlight the results obtained by the DoE approach on the influence of both factors on the photovoltaic electrical response, we analyze at first the maximum power behavior with the interaction effect between both factors, as represented in Figure 4. We observed, in the left part of Figure 4, the temperature/irradiation interaction effect named  $a_{12}$  which is the half difference between the solar irradiation effect when the surface temperature factor is at low level (black straight line), and the solar irradiation effect when the surface temperature factor is at high level (green dashed line). We also observed that this difference corresponds in the right part of Figure 4, to the irradiation/temperature interaction effect named  $a_{21}$ , which defined by the half difference between the surface temperature effect when solar irradiation factor is at low level (black straight line), and the surface temperature effect when the solar irradiation factor is at high level (green dashed line). The interaction effect  $a_{12}$  and  $a_{21}$  are the same value, which present a small contribution in the regression model noted by (2).

Figure 5 shows the response surface and the outline of the contours for the electrical response. As shown in these figures, we see that the evolution of the maximum power,  $P_m$  response for multi-crystalline module depends strongly with solar irradiation less than the surface temperature. From the surface response graph, we can deduce how the electrical response can varying under variations of solar irradiation and surface temperature, the maximum power increase in the same direction of solar irradiation and in opposite direction of surface temperature, which is confirmed by the outlines of the contours. We observe the strong dependence with solar irradiation comparatively with the surface temperature.

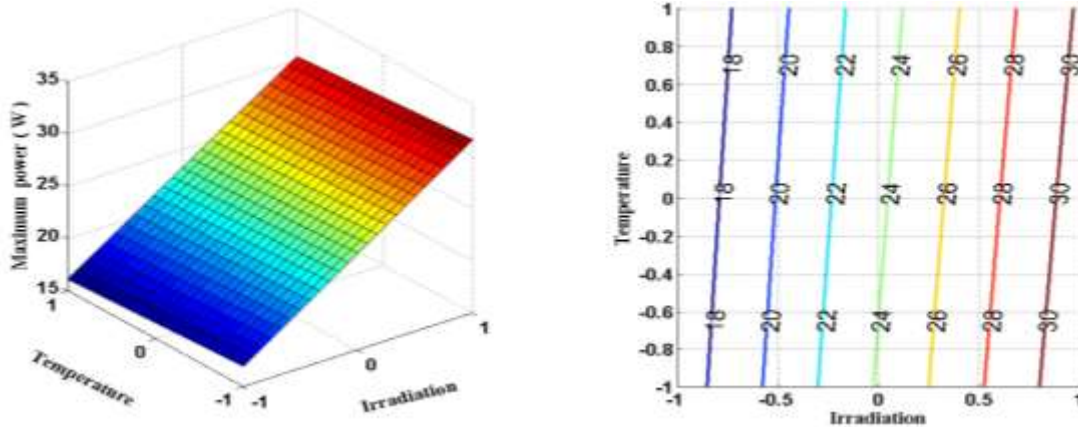


Figure 5. Surface response and outline contours of the maximum power response

Statistical analysis of the regression mathematical model were performed in the form of analysis of variance (ANOVA), which divided in three Tables. Table 2 gives the effect test of parameters and their contributions on the regression model. Table 3 shows the ANOVA for the fitted model of the response and Table 4 defines the parameters estimates for the regression model.

The regression model was been used for predicting the response variable at different operating conditions. For the purposes of measuring the accuracy of model fitting, we consider three measurements that commonly used coefficient of determination  $R^2$ , root mean squares error RMSE and t-student that can estimate which variable is more influence on output variable.

Table 2. Effect test of parameters

| Source    | Degree of freedom <i>df</i> | Sum of squares SS | Mean of squares MS | F Ratio  | Probability | Contribute (%) |
|-----------|-----------------------------|-------------------|--------------------|----------|-------------|----------------|
| A: Ir     | 1                           | 206,92823         | 206,92823          | 342030,1 | <0,05       | 99,565         |
| B : T     | 1                           | 0,78322           | 0,78322            | 1294,587 | <0,05       | 0,376          |
| AB : Ir*T | 1                           | 0,11902           | 0,11902            | 196,7355 | <0,05       | 0,057          |

From Table 2, we can deduce that the factor A is the most significant factor, it determines the solar irradiation. Factor A contributes with 99,565 % of overall process, followed by factor B (surface temperature) with 0,376 % and factor AB (interaction between factors A and B) with 0,057%.

Table 3. ANOVA Table of the response model

| Source | Degree of freedom <i>df</i> | Sum of squares SS | Mean of squares MS | F Ratio  | Probability |
|--------|-----------------------------|-------------------|--------------------|----------|-------------|
| Model  | 3                           | 207,83048         | 69,2768            | 114507,1 | 0,0022      |
| Error  | 1                           | 0,00060           | 0,000605           |          |             |
| Total  | 4                           | 0,11902           |                    |          |             |

ANOVA Table mentioned by Table 3, gives information on total system and especially on regression predictive model. All variable presenting a probability small than the  $\alpha$  value of 0.05, the variable is significant. The regression model present a probability of 0.0022 which is inferior of the critical value of  $\alpha$  that defined the quality of the regression predictive model and that is an efficient model.

Table 4. Parameters estimates of regression model

| Term      | Coefficients | Standard error | T_Student | Probability |
|-----------|--------------|----------------|-----------|-------------|
| Intercept | 23,718       | 0,011          | 2156,2    | 0,0003*     |
| A : Ir    | 7,1925       | 0,012298       | 584,83    | 0,0011*     |
| B : T     | -0,4425      | 0,012298       | -35,98    | 0,0177*     |
| AB : Ir*T | -0,1725      | 0,012298       | -14,03    | 0,0453*     |

From Table 4, we observe that each coefficient differ to others values and all coefficients contain a T\_Student, which means a statistical test for neglecting or not the coefficient. The T\_Student is an important parameter to check the significance of each regression coefficient in the multiple regression model. In addition, neglect a no significant variable gives an accuracy regression model. The probability (P-value) is accepted when the estimated parameters are less than the critical value = 5% . In Table 4, the graphical test (\*) means that the parameter, when the probability less or equal than 0.05, is accepted and it is a pertinent parameter introduced in the regression model as given by (2).

The reconstitution of the coefficients in the predictive model give the maximum available power response:

$$P_m = 23.717 + 7.1925x_1 - 0.4425x_2 - 0.1725x_1x_2 \quad (3)$$

From equation 3, we can deduce the positive relationship between the  $P_m$  and  $I_r$ , the coefficient  $I_r$  takes the highest value, which means the great influence on the maximum power. By cons, there is a negative relationship between the  $P_m$  and  $T$  also with interaction  $I_r$  and  $T$ , the correspondant coefficients values are lowest than the  $I_r$  value, it records to the small influence on the response.

The regression model shows the determination coefficient ( $R^2$ ) values for 0.999997, which means that the variance of the response  $P_m$  has been exactly express by the regression model. However, the RMSE is 0,024597 for the considered response. As shown in Table 3, for the maximum power response model predicted by Eq.3, the probability (P-values) for the regression model was less than 0.05, indicating that the regression model is a good describing of the maximum power response and explain the accuracy of the predictive model.

## 5. CONCLUSION

Design of experiments approach is a practical tool used for establishing the predictive model and for estimating the effect of several independents factors on the shosen response, based on statistical and algebraic calculation. Otherwise, using multiple linear regression is to justify the relationship between the input variables and output variables, also to determine which variables are more influence for output variable. In the current contribution, the DoE approach was developed for modelling the behavior of the electrical response of a multi-crystalline photovoltaic module under indoor solar irradiation and surface temperature changes. In the regression predictive model, we have considered as input factors the solar irradiation and surface temperature levels and as response factor the electrical parameters of the module such as the maximum power in our case. We have highlighted the main and interaction effects of both factors on the variation of the responses. Additionally, with the knowledge of the actual responses of a PV modules obtained by experiments, we have analyzed, explained and validated the predictive model behavior obtained by simulation with the DoE approach.

Finally, we have shown that, the design of experiments approach enables reducing experimental time and number of runs for modelling a system. Moreover, it is possible to obtain a large set of functioning informations with only few experimental runs. Especially in the current contribution, we have shown that design of experiments approach is a reliable tool that can be easily applied for the determination of the behavior of photovoltaic system applications.

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