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Factorial design and response surface optimization for modeling photovoltaic module parameters

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Abstract

In this paper, based on factorial design of experiments method (DoE), predictive model and surface response analysis methodology was used for studying, modeling, characterizing and optimizing the parameters of a mono-crystalline photovoltaic (PV) panel behavior considering the interactive effects of two variables surface PV cell temperature and solar irradiation levels. The DoE concept allows finding the predictive model of each parameter behavior that uses the experimental data. It enables accurate predictions of the responses according to input factors variations. This contribution evaluates the output parameters by predicting these mathematical models of the three responses of a mono-crystalline PV panel: the maximum power P_m , the short-circuit current I_{sc} and the open circuit voltage V_{oc} as function of the influences of both input parameter factors: illumination and temperature. In addition, to validate the results of the DoE predictive models, the surface response and the contour curves analysis were used to bring out the optimum of each response in each operating point covering the domain of the study by the use of a script developed under Minitab is deduced. The obtain results are compared with experimental data.

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Keywords: Factorial design of experiments method; Experimental design method; Predictive model; Surface response analysis; Photovoltaic modules; ANOVA

1. Introduction

Generally, the determination of the optimal production conditions consists in varying, step by step, only one parameter keeping all other parameters constant until identified an approximated model. This mode of practice

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requires a large number of trials, time-consuming and more generally a large increase of the related experimental costs [1]. By else, the interaction effects between different variables influencing the system behavior are not considered within this procedure. By this way, the results obtained are neither precise nor fully reproducible. Currently, the factorial design of experiments, DoE, method is an actual experimental and statistical design tool that is widely used in similar process optimization experiments allowing to correct the problems as presented above associated to the traditional methods [2–5]. Indeed, in order to overcome the drawbacks of classical methods, the experimental design method has become a fast and efficient alternative tool to understand and identify significant variables and their interactions that allow saving time and key information of each factor. The DoE method includes the factorial design of the domain study with a regressive analysis that evaluates the significant factors and represents the influence of the factors in main and combined actions on the considered response of the system [6,7]. The DoE method, used for modeling a large panel of physical and technological systems and processes can be advantageously adapted for a specific application in renewable energy to offer a practical way for studying, modeling, and characterizing the influence of the pertinent parameters involved in the response of PV panels. Indeed, the DoE method has been successfully introduced in industrial systems and research and has built its principles from statistical and mathematical methods [8]. Several domains use the DoE method as those mentioned in Refs [9,10]. Substantially, the DoE method is used to design new industrial products based on both a set of experimental trials and a statistical analysis process [11–13] in order to optimize the settings of a manufacturing process [14], to improve its performances [15], or to predict and characterize its behavioral model [16–19]. Based on a few experiments in a strict closed study domain of input parameters variation, DoE appears as an alternative method for evaluating the significant factors, correlation between several factors and their influences on the response of the studied system.

The DoE method does not require the knowledge of the physical model of the studied process that can be considered as a black-box, as mentioned in Fig. 1, thus offering a huge advantage on other physical methods [20–22], which can vary only one parameter at a time and are not able to measure the correlation between different input parameters influencing the system response. To overcome the shortcoming of these physical techniques, the DoE method allows the prediction of self-effects as well as the interactions between different variables involved in the experiment [13,23,24]. Otherwise, to characterize and model any system, the DoE method optimizes, then strongly minimizes the number of experiment trials without influencing the accuracy of the response [23]. To model any system, the DoE is concerned with a set of input variables that can modify a specific output variable named as the response of the system.

The DoE leads to deduce a mathematical model of factorial design of the response as a function of input factors that can vary in a bonded study domain limiting the input parameters variations [25–27].

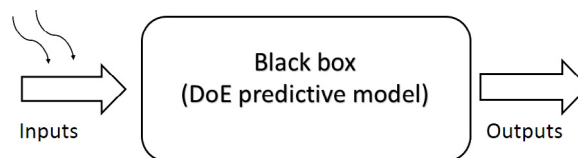


Fig. 1. Main schematic of the study system.

In the way chosen in the current work, we tested a characterizing method, the design of experiments (DoE), originally applied here for modeling a photovoltaic module. Solar energy is the most abundant and inexhaustible source of energy, which ensures and responds on the important growth and the continuous need for energy all over the world. Photovoltaic solar energy (PV) is a part of non-polluting, clean and environment friendly energy, and will take a growing place in the future in the world energetic mix. Solar energy and among it, the solar photovoltaic energy is the subject of numerous researches and we can find in the literature a lot of interesting efficiency improvement tracks and results supporting by modeling [28,29], analysis [30], characterization [31–33], comparison [34–36] and optimization [37,38].

2. Theoretical background and general methodology

The main principle of the design of experiments method is that taking into account only input parameters and outputs of the studied system, and in absence of any specific information about the links between these inputs and

outputs, one can model all systems by a general polynomial relation $y = f(x)$. The development of this universal relation gives the following polynomial equation:

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

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

We report the different steps of the experimental design method in the flowchart of Fig. 2.

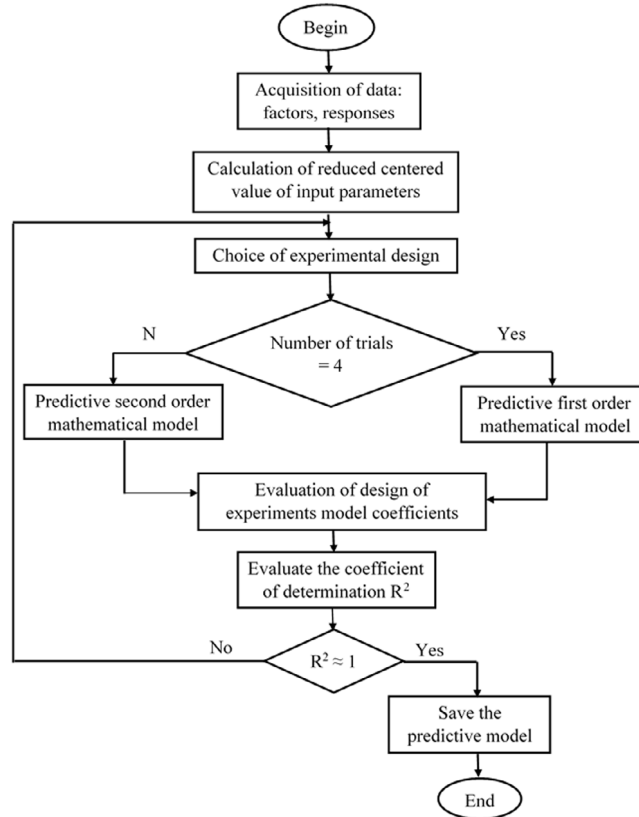


Fig. 2. Flowchart of DoE method.

The various step presented in Fig. 2 can be explained as follow:

- Acquisition of data from the test bench give the input (factors) and output (responses) parameters of the system;
- Calculating the Reduced Centered Values (RCV) of each factor in order to obtain the same unit of axis, *i.e* coded units. This is done using Eq. (2).

$$x = \frac{A - A_0}{Step} \quad (2)$$

where A_0 is the central value in the coded units and $Step$ is the half of the difference between the upper and the lower levels, both expressed in the original unit A of the factor. Each factor should be limited by both ends: the upper limit $+1$ and lower limit -1 respectively [24,26,29]. As indicated in Fig. 3, the intersection of this axis represents by else the study domain.

- We can choice the adopted experimental design from the several relevant measures that allows predicting the corresponding model;

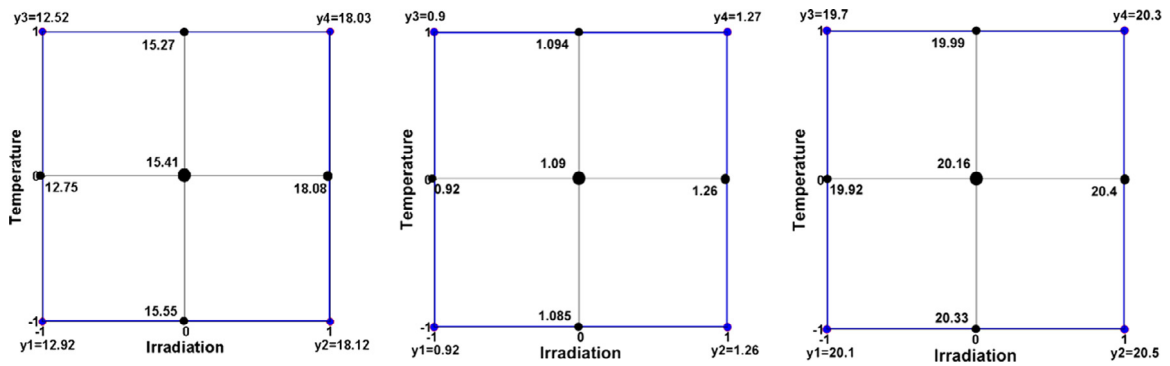


Fig. 3. Full factorial design for (a) maximum power, (b) short-circuit and (c) open-circuit voltage responses respectively.

- With only four trials for the experimental design, the method will produce the first order development of the mathematical predictive model for the considered response. Up to four trials and when the number of trials equals to the number of equations, the second order predictive mathematical model is imposed. However, these systems of equations can be simplified by a matrix system with unknown coefficients that need a resolution with numerical methods;
- Numerical methods allow to obtain the DoE model coefficients. By else, the substitution of these coefficients in the predictive models gives the calculated values of the responses. Whereas, an evaluation of difference between the measured and calculated value taken into account the coefficients of determination R^2 that are to be equal to one in case of using the four trials bonding the domain limits.
- If the coefficient of determination R^2 is close to 1, the predictive model reproduce the actual measures thus corresponding to an accurate model and if not, the choice of another experimental design from the relevant measures in the first steps of the method needs to be imposed.

In this work, and in order to apply the DoE method in PV module modeling, especially applied for predicting the responses of a mono-crystalline PV panel, we choose the first order mathematical model.

3. Practical implementation of the method and experimental results

Minitab statistical software design analysis is used for design of experiments, regression and graphical analyses of data obtained, surface response and contour curves analysis of the obtained models to evaluate the predictive model accuracy. By performing a set of 4 experimental trials on the desired response to model, a full factorial design is applied. Temperature and irradiation are the two independent variable inputs of the factorial design (see below for the actual application) that are investigated at two levels, as illustrated in Tables 1 and 2. Response surface and contour curves methodologies are used to predict and optimize different responses. The influence on the response efficiencies is, finally investigated and the relationships between the two selected independent variables are assessed on the growth and efficiency of the responses (El-Gendy et al. 2014; 1).

The experienced mono-crystalline module is the PS040PR with a maximum power of $P_m = 40$ W realized at voltage of $V_{mp} = 17$ V and a current $I_{mp} = 2.34$ A. Its open circuit voltage is $V_{oc} = 21$ V and its short circuit current is $I_{sc} = 2.56$ A. These values are extracted of the datasheet of the panels. This PV module is built within 76 cells in 4 rows of 19 cells, connected in 2 parallel strings of 38 in series, each row being bypassed by a diode.

Table 1, gives the experimental trials measurements and the observed responses: factors (Irradiation Ir and Temperature T) and responses (maximum Power P_m , short circuit current I_{sc} and open circuit voltage V_{oc}) and the chosen factorial design (corresponding to the four trials A06 to A09). The deduced upper and lower limits of each factor and those Reduced Centered Values are indicated in Table 2. We can notice that irradiation levels and temperatures were recorded during the same indoor experiments. Due to the artificial irradiation source (Hg lamps of Deltalab source), an important increase of PV cell temperature is link 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°C at the surface of the cell. This experimental choice allows us to compare in the responses the relative effect of both irradiation and temperature.

Table 1. The experimental trials measurements and the observed responses.

N	Factor		Response		
	I_r (W/m ²)	T (°C)	V_{oc} (V)	I_{sc} (A)	P_m (W)
A06	823	34.6	20.1	0.918	12,92
A07	823	37.0	19.7	0.908	12,52
A08	1317	34.2	20.5	1.263	18,12
A09	1317	37.1	20.3	1.269	18,03

Table 2. Ranges and levels of independent variables.

Original variable irradiation I_r (W/m ²)	823	1070	1317
Reduced Centered Value (RCV)	−1	0	1
Original variable temperature T (°C)	34,2	35.65	37,1

We applied the DoE method only on the maximum available power response as function of irradiation and temperature and the same steps can be generalized to obtain the predictive models of the other responses of a PV panel as the short-circuit current and the open circuit voltage.

Thanks to the DoE theory, the experimental matrix or effects matrix X is a square matrix, which represents the effects factors and interaction, the first column represents the constant coefficient, the second and the third column represent the RCV of factors and the last column for the interaction between factors. It is given by Eq. (3):

$$Xa = y \quad (3)$$

yielding to

$$a = X^{-1}y \quad (4)$$

where a is the coefficient vector and y the measured response of system. Those values are reported in Table 1. For the four trials model, Eq. (1) is simplified to a similar system as indicated in Eq. (3), and that we can write:

$$y = a_0 + a_1x_1 + a_2x_2 + a_{12}x_1x_2 \quad (5)$$

where, in our case, x_1 and x_2 are the irradiation and the temperature factors respectively, a_0 is the coefficient representing the central value and 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 .

In addition, according to Eqs. (4) and (5), and the RCV of the factors and from the results obtained in the trials performed with the 2² factorial designs, the following hierarchical first-order response equation was established to correlate the dependent and independent variables:

$$\begin{bmatrix} 1.0000 & -1.0000 & -0.7241 & 0.7241 \\ 1.0000 & 1.0000 & -1.0000 & -1.0000 \\ 1.0000 & -1.0000 & 0.9310 & -0.9310 \\ 1.0000 & 1.0000 & 1.0000 & 1.0000 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_4 \end{bmatrix} = \begin{bmatrix} 12.92 \\ 18.12 \\ 12.52 \\ 18.03 \end{bmatrix} \quad (6)$$

yielding to:

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_4 \end{bmatrix} = \begin{bmatrix} 15.4100 \\ 2.6776 \\ -0.1225 \\ 0.0776 \end{bmatrix} \quad (7)$$

4. Results and discussions

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

$$P_m = 15.41 + 2.6776 x_1 - 0.1225 x_2 + 0.0776 x_1 x_2 \quad (8)$$

Similarly, one can obtain the predictive models of the short-circuit current and the open circuit voltage respectively:

$$I_{sc} = 1.0896 + 0.1765 x_1 - 0.001 x_2 - 0.0041 x_1 x_2 \quad (9)$$

$$V_{oc} = 20.1525 + 0.2535 x_1 - 0.1508 x_2 + 0.0408 x_1 x_2 \quad (10)$$

It is to be noted that all parameters are calculated with four significant digits assuming an accurate model by allowing the consideration of all various contributions, including the interaction between the different factors as evidenced in the Eq. (9) of the short circuit current. Moreover, in Eq. (9), the two last coefficients, found very small by the model, are related to the direct and combined influence of the temperature on the short circuit current, confirming its well-known small dependence on temperature. Finally, in the experimental procedure we will neglect in Eq. (9) the two terms related to x_2 and interaction $x_1 x_2$. We maintain this independency for plotting the effects of both factors, illumination and temperature.

Fig. 3 illustrates the full factorial design of the maximum available power response of the considered PV panel. The coefficients as indicated in the predictive first order mathematical model of the maximum available power is simplified including all the responses. The signification and direction of the variation of response due to the direction of the factors is clear from the centered response value. However, it is to be noted that, the influence of the irradiation factor growth in the same direction and it is more significant than the temperature factor. By cons, and as expected, the temperature factor influence inversely on the direction of the power response. The response at center of the study domain corresponds to the central value $a_0 = 15.41$ at the calculating operating point ($I_r = 1070 \text{ W/m}^2$ and $T = 35.65 \text{ }^\circ\text{C}$).

However, by adding the a_1 coefficient to the central value, the maximum power increases from of 15.41 to $15.41 + 2.665 = 18.075$ (to be compared to the experimental value = 18.08) when the irradiation varies from RCV 0 (corresponding actual value is 1070 W/m^2) to RCV +1 (corresponding actual value is 1317 W/m^2). Whereas, the maximum power response decreases from the central value by the coefficient a_1 , i.e. from 15.41 to $15.41 - 2.665 = 12.745$ (to be compared to the experimental value = 12.7) when the irradiation passes from the RCV 0 (1070 W/m^2) to the RCV -1 (833 W/m^2). By cons, with the second factor, i.e. the temperature, the maximum power decreases from the central value by the coefficient a_2 from 15.41 to $15.41 - 0.143 = 15.267$ (to be compared to the experimental value = 15.27) when the temperature varies from the RCV 0 ($35.65 \text{ }^\circ\text{C}$) to the RCV +1 ($37.1 \text{ }^\circ\text{C}$). Whereas, the same response passes from 15.41 to $15.41 + 0.143 = 15.553$ (to be compared to the experimental value = 15.55) when the temperature vary in the opposite direction from the RCV 0 ($37.1 \text{ }^\circ\text{C}$) to the RCV -1 ($35.4 \text{ }^\circ\text{C}$).

Statistical of the developed mathematical models were performed in the form of analysis of variance (ANOVA). The ANOVA for the fitted quadratic polynomial models of the three responses of the process is shown in Table 3.

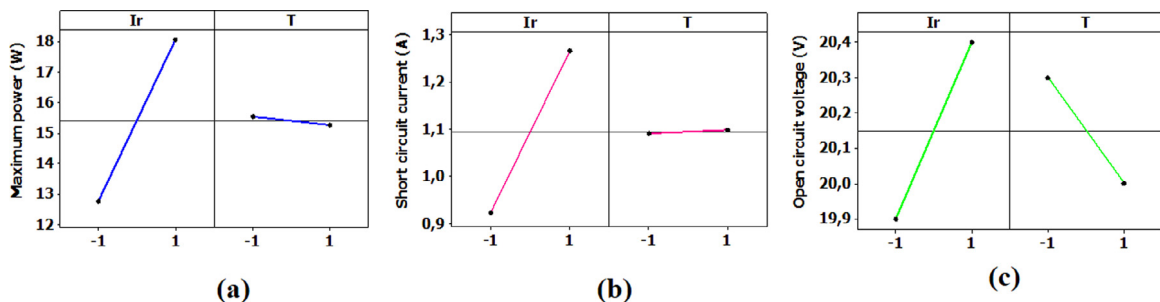
The quadratic regression models showed the determination coefficient (R^2) values for >0.99 for all the considered responses. As shown in Table 3, for the maximum power response model predicted by Eq. (7), P -values for different factor effects was less than 0.04, indicating that it was significant for describing the maximum power. We remember that in the method, a positive effect of a factor means that the response is improved when the factor level increases and a negative effect of the factor means that the response is not improved when the factor level increases. For the short-circuit response, only the P -value related to the effect of the temperature factor is greater than 0.05 allowing the possibility to neglect this effect. The model is thus adjusted and the relative $adj - R^2$ was greater than 0.99. This leads to conclude that within neglecting the temperature effect on the short-circuit response, the adjusted mathematical predictive model remain reliable. It is also to be noted that, as indicated by ANOVA results, that in the case of the open-circuit voltage response, the P -value for the interactive effect of both factors is greater than 0.05 and can be neglected as, its removal will give an adjusted model greatly acceptable with a $adj - R^2$ of 0.99.

Table 3. ANOVA for the quadratic models of various response of the process.

	Factor	Model coefficients	Std error	<i>T</i> _student	<i>P</i> – Value (* accepted)
<i>P_m</i> <i>R</i> ² = 0.999996 <i>RMSE</i> = 0.01118	Intercepts	15.4	0.005	30 800	0.0002*
	T	−0.1225	0.00559	−21.91	0.0290*
	Ir	2.6775	0.00559	478.87	0.0013*
	T*Ir	0.0775	0.00559	13.86	0.0458*
<i>I_{sc}</i> <i>R</i> ² = 0.999996 <i>RMSE</i> = 0.000447	Intercepts	1.0896	0.0002	5448	0.001*
	T	−0.001	0.000224	−4.47	0.14
	Ir	0.1765	0.000224	789.33	0.008*
	T*Ir	0.004	0.000224	17.89	0.0356*
Since <i>P</i> -value = 0.14 > 0.05, the temperature factor is insignificant. The model should be adjusted as follow: adj- <i>R</i> ² = 0.999994. then the adjusted model became <i>I_{sc}</i> = 1.0896 + 0.1765 <i>Ir</i> + 0.004 <i>T</i> * <i>Ir</i>					
<i>V_{oc}</i> <i>R</i> ² = 0.999771 <i>RMSE</i> = 0.008944	Intercepts	20.152	0.004	5038	0.001*
	T	−0.15	0.004472	−33.54	0.0190*
	Ir	0.25	0.004472	55.90	0.0114*
	T*Ir	0.05	0.004472	11.18	0.0568
Since <i>P</i> -value = 0.0568 > 0.05, the interactive influence of both factors is insignificant. The model should be adjusted as follow: <i>R</i> ² adj = 0.999086. then the adjusted predictive model became <i>V_{oc}</i> = 20.152 − 0.015 <i>T</i> + 0.25 <i>Ir</i>					

Deduced from Minitab software analysis, the results reported in Fig. 4 present the responses, i.e. the maximum power, the short circuit current and the open circuit voltage as function of the various factors respectively. The plot of these effects helps us to have the desired precision and the concordance between results of both simulation and experimentation. However, we have achieved the same results with the code developed under Minitab software environments and, these modeling results are identical with those obtained experimentally.

In Fig. 4, we report the simulation results obtained with both software of the Maximum Power, short-circuit current and the open circuit voltage, respectively.

**Fig. 4.** Illustration of effect factors of the (a) maximum power response, (b) short-circuit current and (c) open circuit voltage using Minitab software.

As it is the usage with the DoE method [20], we will analyze the simulation results considering the central point as the reference. In Fig. 4.a., one can observe and validate that the effect of the irradiation factor is more significant than the effect of the temperature factor. In the RCV coordinates, on the right of the centered value, the power follows the irradiation increase and on its left side, the power follows the factor decrease. The effect of the temperature factor acts on the opposite direction of those of the irradiation resulting in a negative slope showing that the variation of the power increases with the irradiation and decreases with the temperature. The maximum power behavior is the first qualitative phenomenological validation of the DoE method and the associated model for PV modules.

One we consider the response as the short circuit current, Fig. 4.b., the effects associated to both factors on the response are in the same direction within different weights and the irradiation factor affect strongly the short circuit response which is very poorly affected by a temperature change.

Finally, considering Fig. 4.c., the directions of variations of the open circuit voltage with irradiation and temperature factors are similar to that obtained for the maximum power. Nevertheless, according to a higher slope, we can notice that the open-circuit voltage is stronger dependent with temperature than the maximum power.

This analysis points that both the maximum power and the short circuit current responses are strongly dependent on the irradiation factor variations and slightly affected by the temperature variations. By cons, the open circuit voltage slightly depends on the irradiation factor and depends on the opposite direction of the temperature factor.

Additionally, thanks to the DoE method, we analyze the interaction effects between irradiation and temperature of the three considered responses: maximum power, short-circuit current and open circuit voltage. 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 with Minitab software and represented in Fig. 5. In the three responses, the left part of the figures corresponds to the interaction effects between irradiation and temperature at a low (black straight line) and upper temperature levels (red dashed line). The right part of the figures corresponds to the complementary interaction effects between temperature and irradiation at a low (black straight line) and upper (red dashed line) irradiation levels.

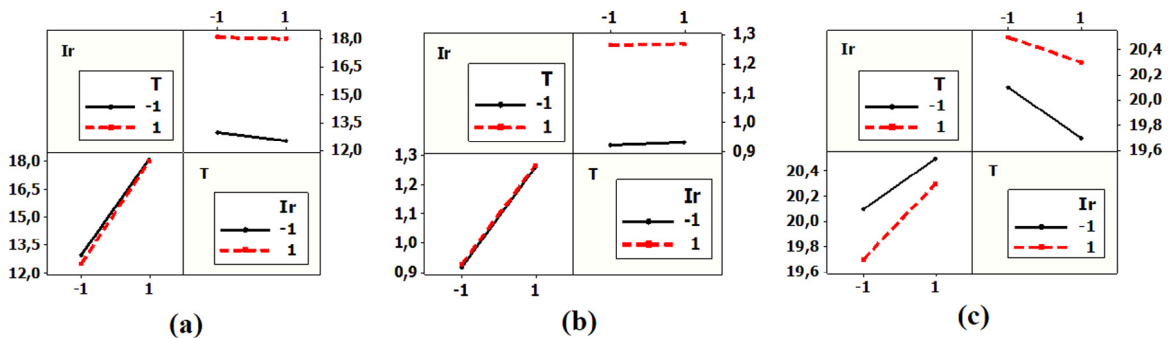


Fig. 5. Illustration of interaction effect between irradiation and temperature (see explanations in the text) for the three responses (a) maximum power, (b) short-circuit current and (c) open circuit voltage.

In order to highlight the results obtained by the DoE methods on the influence of both factors on the photovoltaic electrical parameters, we analyze at first the maximum power behavior with the interaction effect between both factors, as represented in Fig. 5.a. We observed, in the left part of Fig. 5.a., a slight difference between the slopes at low (black straight line) and high (red dashed line) temperatures. We also observed that this difference corresponds in the right part of Fig. 5.a., to a slight change of the slopes indicated the higher influence of the temperature at low (black straight line) than at high (red dashed line) irradiation levels. Following the same approach, we remark that, in Fig. 5.b. that the interaction between the temperature and the irradiation is insignificant, whatever the considered levels. Moreover, we notice in Fig. 5.c., in both left and right parts, the large interaction between irradiation and temperature on the open circuit voltage behavior with very different slopes when considered at the low (black straight lines) and upper (red dashed lines) levels of each factor. The change of the slopes also indicates the higher influence of the temperature at low than at high irradiation levels.

In Figs. 6 and 7, the surface responses and the contour curve responses analysis (SRA, CCRA) are displayed for all the three considered responses by the use of their respective predictive models.

Figs. 6 and 7 show the outline of the contours of the response surface performed under Minitab software. As shown in these figures, we see that the evolution of the maximum power, P_m response for the mono-crystalline module follows the same direction as the main effect of solar irradiation but varies in the opposite direction with the main effect of temperature. All the simulation results presented in these figures show that the interactive effect of the two factors influences P_m response in the same direction. This shows that the increase of the irradiation compensates by a dominant effect the decrease of the P_m response caused by the rise of the temperature. However, the short-circuit current, I_{sc} is strongly influenced by the main effect of the solar irradiation factor whereas the

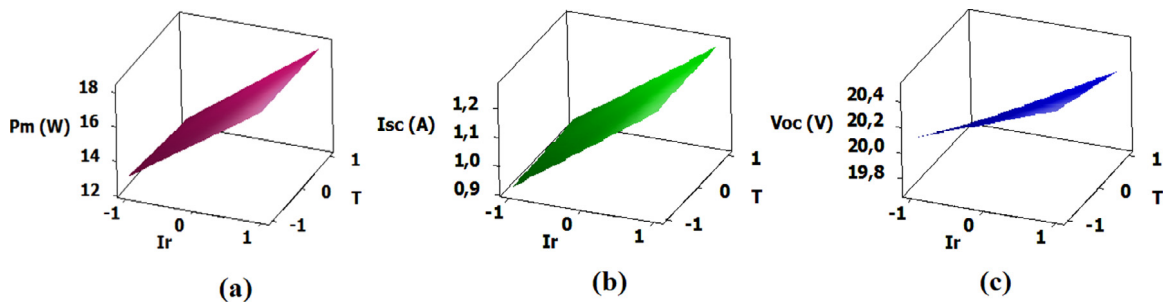


Fig. 6. The SRA surface plots for the evolution of (a) Power Max, (b) Short circuit current and (c) the Open circuit voltage in the considered design using Minitab software.

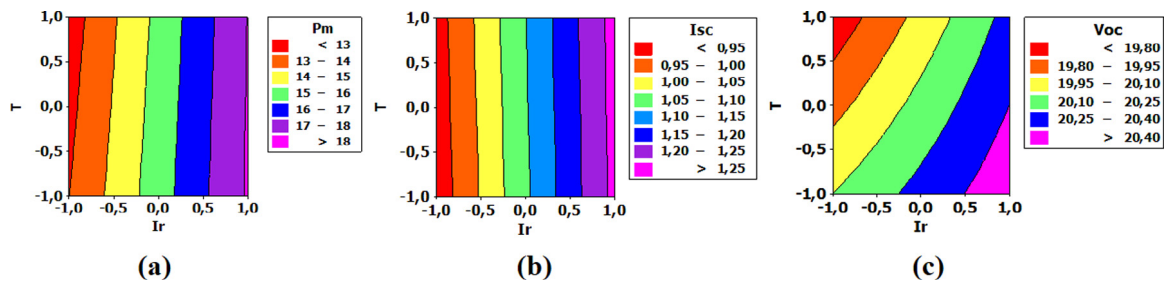


Fig. 7. The CCRA surface plots for the evolution of (a) Power Max, (b) Short circuit current and (c) the Open circuit voltage in the considered design using Minitab software.

influence of the main effect of the temperature factor is smaller as being illustrated more evidently by the CCRA method. The interactive effect of the two factors on I_{sc} response shows that it follows the same direction of the evolution of the variation of both factors. Finally, the main effect of each factor on the open circuit voltage, V_{oc} response is presented. The increase in the main effect of the irradiation factor leads to an increase in V_{oc} response, which acts opposite to the main effect of the temperature factor. Concerning the interactive effect of the two factors on V_{oc} response, the effect of temperature attenuates the positive effect of irradiation, but this effect of irradiation remains the dominant effect ensuring, whatever the temperature, an increase in V_{oc} response.

5. Conclusion

Factorial design of experiments method is a practical tool applied for establishing the predictive mathematical model, based on statistical and algebraic calculation. In the current contribution, the factorial design method was originally developed for characterizing and modeling the behavior of photovoltaic module under indoor illumination and temperature changes. The method was implemented under Minitab software environments and based on a set of experimental trials. In the model, we have considered as input factors the irradiation and temperatures levels and as responses the electrical parameters of the module such as the maximum power, the short circuit current and the open circuit voltage.

By using the factorial design method, we have highlighted the direct and combined effects of both temperature and irradiation factors on the various responses. Additionally, with the knowledge of the actual responses of a PV modules obtained by experiments, we have analyzed, explained and validated these behaviors obtained by simulation with the factorial design methods. We have shown that the response surface method analysis, RSMA proved to be reliable for the modeling, optimization and studying the main and interactive effects of both factors, being the temperature and solar irradiation, of a solar module behavior. This method can be easily extended for a usage in large scale of electrical power production to maximize energy efficiency adapted to the location of a given site.

Finally, we have shown that, the factorial design of experiments method enables reducing experimental time and number of trials for modeling a system, considered as a black box, i.e. without the knowledge of its specific physical properties. Moreover, it is possible to obtain a large set of functioning information with only few experimental trials.

Especially in the current contribution, we have shown that factorial design of experiments method is a reliable tool that can be easily applied for the determination of the behavior of photovoltaic system applications.

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