الجمهورية الجزائرية الديمقراطية الشعبية

People's Democratic Republic of Algeria

وزارة التعليم العالي والبحث العلمي

Ministry of Higher Education and Scientific Research

جامعة غرداية

University of Ghardaïa

كلية العلوم والتكنولوجيا

Faculty of Sciences and Technology

قسم الآلية والكهروميكانيك

Department of automatics and electromechanics

Registration No.

…. /……./…….

Dissertation end of study, for graduation

Master

Domain: Sciences and Technology

Field: Renewable Energies

Specialty: Renewable Energies in Electrical Engineering

Theme:

Modeling of PV panel using design of experiments methods

Presented by :

BAHAZ Chaima

Publicly defended on: 03/06/2024

In front of the jury:

CHENINI Keltoum	Professor	Univ. Ghardaïa	President
ZEGAOUI Abdallah	Professor	Univ. Ghardaïa	Supervisor
TOUAFEK Khaled	MRA	URAER	Examiner
KHATTARA Abdelouahab	MCA	Univ. Ghardaïa	Examiner

Academic year 2023/2024

Abstract

The aim of this dissertation is to model the parameters of a monocrystalline photovoltaic (PV) panel in indoor conditions based on the effects of input parameters such as irradiance and surface temperature, using the factorial design. This research evaluates the main responses (maximum power, short circuit current, open circuit voltage) by creating accurate predictive models of the responses, to determine. Furthermore, this approach facilitates the graphical representation, using Minitab software, of response surfaces and contour curves for different responses so that these visualizations provide valuable insights into response behavior.

Keywords: Design of experiments, factorial design, Mathematical predictive model, surface response.

Résumé

L'objectif de cette thèse est de modéliser les paramètres d'un panneau photovoltaïque monocristallin (PV) dans des conditions intérieures sur la base des effets de paramètres d'entrée tels que l'irradiance et la température de surface, en utilisant le plan factoriel. Cette recherche évalue les principales réponses (puissance maximale, courant de court-circuit, tension en circuit ouvert) en créant des modèles prédictifs précis des réponses, à déterminer. De plus, cette approche facilite la représentation graphique, à l'aide du logiciel Minitab, des surfaces de réponse et des courbes de contour pour différentes réponses, de sorte que ces visualisations fournissent des informations précieuses sur le comportement des réponses.

Mots clé : Plan d'expériences, plan factoriel, Modèle mathématique prédictif, réponse de surface.

ملخص

الهدف من هذه الأطروحة هو نمذجة معلمات الألواح الكهروضوئية أحادية البلورية (PV) في الظروف الداخلية بناءً على تأثيرات معلمات المدخلات مثل الإشعاع ودرجة حرارة السطح، باستخدام التصميم العاملي. يقوم هذا البحث بتقييم الاستجابات الرئيسية (الطاقة القصوى، تيار الدائرة القصيرة، جهد الدائرة المفتوحة) من خلال إنشاء نماذج تنبئية دقيقة للاستجابات، لتحديدها. علاوة على ذلك، يسهل هذا النهج التمثيل الرسومي، باستخدام برنامج Minitab، لأسطح الاستجابة والمنحنيات الكنتورية للاستجابات المختلفة بحيث توفر هذه التصورات رؤى قيمة حول سلوك الاستجابة.

كلمات مفتاحية: تصميم التجارب، التصميم العاملي، النموذج التنبؤي الرياضي، الاستجابة السطحية، المنحنيات الكنتورية.

Acknowledgments

The present work carried out as part of the academic Master's thesis in Renewable Energy in electrical engineering at the Department of Automatics and Electromechanics of the University of Ghardaïa.

I thank Allah for granting me the courage, determination and patience to succeed in this work in the best conditions.

Above all, I would like to express my sincere gratitude to my supervisor, **Pr. ZEGAOUI Abdallah**, for his advice and support in supervising this work. I greatly appreciate his availability throughout my progress as well as their numerous help and valuable advice. I express to him my deep gratitude and my sincere appreciation.

I would also like to express my sincere gratitude to the members of the jury for the honor they gave me by participating in the evaluation of this work.

Finally, I extend my sincere thanks to all the people who participated or contributed, directly or indirectly, to the completion of this work.

Dedication

Praise be to Allah until praise reaches its utmost limit.

I dedicate this modest work:

To my dear father,

My dear mother,

For all their sacrifices, their love, their tenderness, their support and their prayers throughout my studies.

To my dear brothers,

My dear sisters,

For their moral support and valuable advice throughout my studies.

My beloved grandmother,

Whom I will always love, may Allah grant her the highest ranks of Jannah. I miss you; your memory will never fade.

To all my family (BAHAZ & RECIOUI)

To my besties Rania and Nesrine for the moral support they gave me and for their incessant encouragement,

To all my other friends,

As well as to all my colleagues at the Faculty of Technology.

To everyone who taught me a letter from elementary to middle school, high school, and university.

To all those I love and those who loves me.

Chaima

Table of Content

List of Figures

Chapter 1: Design of Experiments. Generalities

Chapter 2: Design of Experiments: cases studies

Chapter 3: Application of DoE technique to model photovoltaic panels

List of Tables

Chapter 1: Design of Experiments. Generalities

Chapter 2: Design of Experiments: cases studies

Chapter 3: Application of DoE technique to model photovoltaic panels

Abbreviation

PV: Photovoltaic.

DOE: Design of experiments.

RSM: Response surface method.

ANOVA: Analyze of variance.

SST: Total Sum of Squares.

SSE: Error Sum of Squares.

SSTr: Treatment Sum of Squares.

D*f*: Degrees of Freedom.

MS: Mean square.

F-value: Fisher-Snedecor Test.

P-value: Taguchi Test.

RCV: Reduces centered variables.

Symbols

A: Real variable.

X: Codded variable

n: The total number of sample

k: The number of factors

m: The number of levels

y: $the\ response$

a_0: The intercept

a_i: The coefficients.

xi: Level of factors i

xj : Levels of factor j

ni : number of treatments in factor i

nj : number of treatments in factor j

nij : total number of treatments

H_0: null hypothesis

H_a: alternative hypothesis

μ: the mean of samples

R^2: coefficinets of determination

Km: Kilometer

H: hour

Kg: Kilogram

C_G: Gas cosumption

y_0: center response value

X: experiment matrix

X^{-1}: Inverse matrix

$\bar{y}$: mean of response

CG: Gas consumption

I_{SC}: short circuit cuurent

V_{OC}: Open circuit volatage

P_m: Maximum power

General Introduction

General Introduction

Today's world is experiencing economic growth and spectacular technological development, which requires an ever-increasing energy requirement. Following the increase in energy demand, the countries of the world now need a large use of energy resources, which is why the modern trend seeks to know how to achieve this objective through diversification of resources. Fissile and fossil resources (nuclear, oil and natural gas) provide a large part of global energy production. Consumption from these resources leads to the emission of greenhouse gases and thus increases pollution. Therefore, the solution to maintain the pace of economic and technological growth while preserving the environment is to resort to other sources, in particular renewable energy resources, which do not negatively affect the environment. By renewable energy, we mean energy derived from the sun, wind, geothermal heat, water or biomass.

The use of renewable energies, especially photovoltaic solar energy, has become a major concern for all the policies of countries around the world, because it is a clean energy (no gas tax), inexhaustible (sun available for free use) and which does not cause any pollution to the environment. There are even international conventions between several countries around the world for delocalized production to supply countries far from the origin of the photovoltaic solar power plant. One way to harness this solar energy is the use of large-scale photovoltaic panels that convert solar radiation into electricity. Electrical energy produced from the sun by the photoelectric effect. The main factor in solar power generation is the efficiency of the solar cell, which is mainly manufactured on a large scale based on crystalline silicon technology. The efficiency of the solar cell is still not cost-effective enough, but the solar power generation capacity of the cell is excellent. Many factors affect the efficiency of a photovoltaic system during installation, maintenance and after, such as extreme conditions (irradiation, temperature, wind, dust, tilt angle).

Experimental designs are one of the most important tools in modern scientific research, as they play a major role in various fields of applied science. The DoE method has become a very effective tool for the design and even feasibility study of several technological systems. it is based on a few experimental trials and an operator expert with knowledge of the system to be studied and makes it possible to make well-defined scientific conclusions on the behavior of an output variables with the influence of the proper and especially interactive effects of the input variables.

For any system studied considered as a black box, the DoE method consists of modeling, characterization, optimization and even statistical calculation to minimize the errors induced in the considered response variable. It, the DoE technique, also includes different designs, the method of their implementation and the analysis of their data in order to obtain practical decisions in the simplest, most economical, and easiest to analyze and interpret and with a sufficient degree of precision.

This master thesis work aims to model several outputs of a monocrystalline photovoltaic panel using a full factorial design and to discover its performance and the state that affects it the most. To accomplish this, experimental trials are to be carried out on a monocrystalline PV module, and measurements satisfying the objectives will be collected.

This Master dissertation, describing our work, will be organized into three chapters:

In the first chapter, mainly interested in giving an overview of experimental design, its definition, a brief history of it, its most important terms, and types. The second chapter was devoted to an applied example of experimental design, named Goupy's Car, in how the technique of DoE is attempted to be understood, and manual calculations are performed, confronting them to simulations under Minitab software. The practical aspect, which will be displayed in the third chapter, is implementing the modeling of a single-crystalline photovoltaic panel using the MINITAB program and identifying the various interactions between these factors that affect the response. Starting from fifteen experimental trials carried out on the chosen PV module, measurements for the considered outputs: maximum power available on the PV panel, the short-circuit panel, and its open circuit voltage recorded.

Finally, the dissertation completed with a general conclusion

Chapter 1: Design of Experiments. Generalities

1.1. Introduction

Design of Experiments (DoE) technique is widely used in several scientific fields such as chemical process, pharmaceutic process, agriculture studies and so on… it really concerns scientists who run experiments and without deeply having knowledge on the system.

In order to study the influence of several input parameters on the output parameter, the classical experimental approach is to study the influence of each experimental variable separately. This one-variable-at-a-time strategy is easy to handle and widely employed. However, is it the most efficient way to approach an experimental problem? Since in the case that there are a large number of variables and each experiment lasts a long time. As the experimenter could not run large numbers of trials, he is obliged to choose another best research strategy.

For us, we have thinking about using DoE in electrical engineering studies. So it, DoE, can be used in modeling and optimizing process based on few experiments performed on the targeted output response of the studied system.

This first chapter outlines the areas in which experimental designs can be applied, defines objectives and raises the general problem of how to study a phenomenon.

However, this chapter provides a bibliographic summary of the necessary knowledge about DoE method. First, it is clearly necessary to recall concepts such as the definition of experimental plans, the principle, as well as the basic vocabulary (factor, response, experimental domain, etc.) related to the targeted theory.

1.2. Historical perspective

In the 1920s and 1930s, Ronald A. Fisher conducted research in agriculture in the UK with the goal of increasing crop yields. He pioneered the design of experiments (DoE) by advocating for simultaneous testing of multiple variables. Fisher's work marked the official beginning of DoE. In 1935, he authored a book on DoE. [1]

The credit for developing the Response Surface Method (RSM) goes to George Box, also from the UK. He focused on experimental design procedures for process optimization. Additionally, in the 1950s, W. Edwards Deming, along with his contributions to statistical methods, was also concerned with the design of experiments. Another notable figure, Genichi Taguchi, a Japanese statistician, particularly focused on methods for improving quality. [2]

1.3. Definition

Design **o**f **E**xperiments (***DoE***) is a structured approach employed to plan, execute, and analyze experiments systematically. It serves as a cornerstone in applied statistics, facilitating the scientific investigation of systems, processes, or products by systematically manipulating input variables to observe their impact on measured response variables. [2]

1.4. Principle

As depicted in (figure 1.1), this method views a physical system or process as a black box, (meaning there is no need to understand neither the internal structure of the studied object nor the mathematical model). Inputs and outputs of the considered system are termed factors and responses, respectively, and are modeled using statistical tools. Experimental design techniques allow us effectively address our needs. Essentially, the principle involves simultaneously varying the levels of one or more factors (which may be discrete or continuous variables) in each trial on the performed experimental process. This approach serves two main purposes: significantly reducing the number of required experiments while expanding the range of factors studied, and identifying interactions between factors while determining the optimal setting for these factors relative to a given response. The key aspect in utilizing experimental designs is to minimize the number of experiments conducted without compromising result precision. Currently, there exists a diverse range of designs, each tailored to solve specific problems based on their properties. [3, 4]

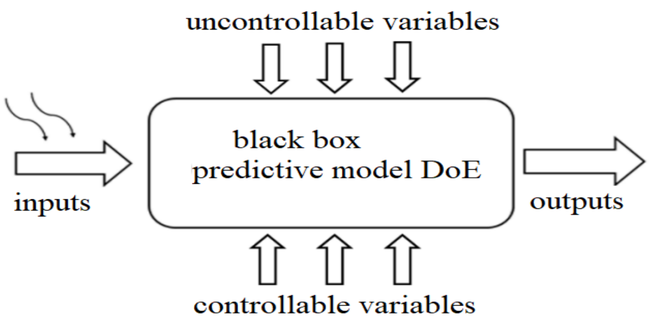

Figure1. 1: Representative diagram of the DoE method. [5]

1.5. The process of knowledge acquisition

The DoE method imposes to the investigator to ask a number of questions according to (Figure 1.2).

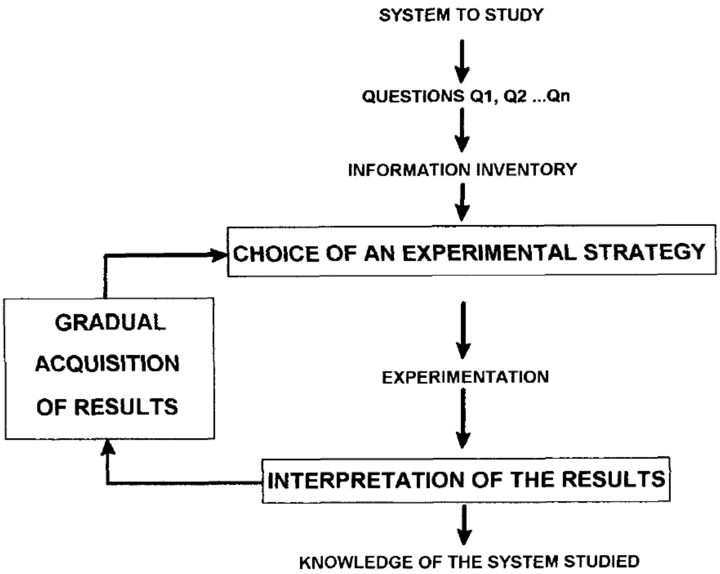

Figure1. 2: Steps for areas of experimentation definition. [1]

These questions, which should be the right one, define the problem and determine the work to be carried out to solve it. This is the more difficult task in the questioning process since questions are not already known in advance. The experimenter should first prepare an inventory of the available information, by compiling a bibliography, consulting experts, theoretical calculations, or any other method, which provides him with answers to the questions, asked without actually carrying out any experiments. It will then be necessary to carry out experiments to obtain all the answers required.

The best strategy should cover the steps in which the experimenter thinks about what experiments to perform, and our problem is how to select which experiments should be done and which should not be done. Such an ideal strategy should: [1]

- Deliver the desired results as quickly as possible.
- Avoid carrying out unnecessary experiments.
- Ensure that the results are as accurate as possible.
- Allow experiments to progress without failure.
- Provide modeling and optimization of the phenomena studied.

There is such an ideal strategy, and it is effective because it simultaneously takes into account three essential aspects of knowledge acquisition:

- Gradual acquisition of results.
- Selection of the best experimental strategy
- Interpretation of results.

1.6. Progressive acquisition of results

The results at the beginning of the study are unknown by the experimenter. He must work gradually in order to be able to reorient the study in the right side of the first results of the trials. A preliminary trial can be carried out to decide on any change in research orientation and thus better identify the most important experimental points of the study and rule out non-fruitful avenues for the study wasting time.

Therefore, it is recommended to work gradually. A first series of experimental trials can provide provisional conclusions. These first provisional conclusions initiate the carrying out of a new series of experimental tests. The results from these two series should then be used to get a better image of the results. Then, a third series of tests can be carried out if necessary. With this approach, the experimenter accumulates only the results he needs and the study stops when the initial questions have been answered. [1]

1.7. Selection of the best experimental strategy

The study strategy to be adopted should facilitate the organization of a progressive acquisition of results. It should also minimize the number of tests without degrading the quality of the experiment. In fact, the experimenter must ensure that the results are as precise as possible. Experimental designs, response surface methodology, fit our needs perfectly: [1]

- Gradual acquisition of knowledge.
- Only the required number of experiments
- The most accurate results.

1.8. Results interpretation

The initial choice of experiments should facilitate the interpretation of the results. The results must be easily interpreted and understood by everyone specialists or not. The above-recommended methods can help us achieve both goals.

The availability of microcomputers and specialized software has made everything that used to be a long process of painful calculations to obtain results quite easy. Currently we realize that not only are the calculations carried out quickly and accurately, but also having the results graphically constitutes a spectacular way of conducting studies. [1]

1.9. Study of a phenomenon

The study of a phenomenon can be summarized as follows: the scientist may want to know a response variable depending on numerous input variables. These latter variables influence the response either with their own effects or with combined effects.

The ***response*** can be evaluated as, $\boldsymbol{y}$, which is a function of several independent variables, $\boldsymbol{x_i}$, called ***factors***. The mathematical function, which makes it, possible to link the response $\boldsymbol{y}$ to the factors, $\boldsymbol{x_i}$, is:

$$y = f(x_1, x_2, x_3, \dots, x_i, \dots, x_n, \dots) \qquad (1.1)$$

The study of a phenomenon requires carrying out experiments that measure the response for different sets of factor values. However, how this mathematical function is established by the “classical” method. [1]

1.10. Establishment of the response function by the classical method

The classic method of experimentation adopts to maintain all the factors at constant levels except one unfixed variable, which is used to carry out the trials. The response $\boldsymbol{y}$ is then measured as a function of several values of this non-fixed variable x_1. At the end of the experiment on this first variable, we draw a curve of $y = f(x_1)$ as mentioned in (figure 1.3).

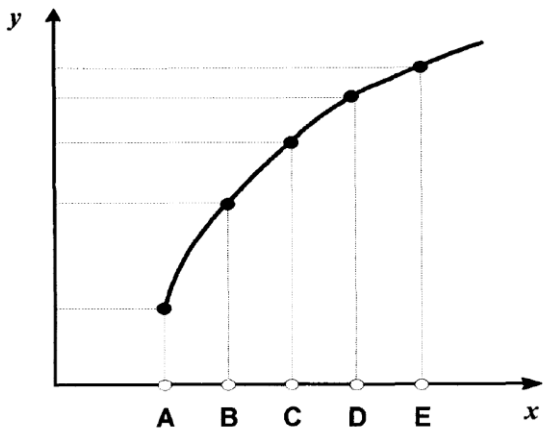

Figure1. 3: $y = f(x_1)$, function of several values of this non-fixed variable x_1. [1]

If the experimenter wishes to study the influence of all the variables on the same response $\boldsymbol{y}$, all the trials of the experiment must be repeated for each unfixed variable and in the same way, that is to say fix all the other variables at constant levels.

Using this method, if we want to study only seven factors, with only five trials per factor, we would have to carry out $5^7 = 78\,125$ experiments or trials.

This is enormous experimental work and is unlikely to be feasible. The experimenter must overcome this obstacle in two possible ways: either reduce the number of experimental trials per variable or reduce the number of variables. [1]

1.10.1. Reduce the number of experimental points

If the experimenter chooses to examine only three points per variable instead of five, he will have to perform $3^7 = 2\ 178$ trials.

Two measurement points per variable would require$2^7 = 128$. It is always an enormous work and it often requires too much budget or available time. As there must be at least two experimental points per variable, the experimenter has no choice but to: [1]

1.10.2.Reduce the number of variables

However, even if a system with four variables, testing each of them at three values requires $3^4 = 81$ trials. This way of operating is both tedious and un satisfactory. If certain variables are ignored, people may doubt the results and the investigator will be forced to apologize for presenting incomplete conclusions. The downside of this approach is particularly obvious when it comes to security or large sums of money. This is precisely why we will now look at the experimental design method. [1]

1.10.3.Experimental design methodology

The main difference between the classic method of variation of one variable at a time and the experimental design is that the DoE allows the variation of the values of all the factors in each experiment and this is performed in a programmed and rational manner. The DoE approach of simultaneously varying several variable settings, far from posing difficulties, offers several advantages: [1]

- Fewer experimental trials.
- A large number of factors studied.
- Detection of interaction between factors
- Detection of optimal values.
- Better accuracy of results.
- Optimization of results.
- Construction of a model from the results.

The major interest in the application of the DoE is the search for influencing factors from the moment that the number of the studied factors (continuous and discrete variables) is no longer limited, the experimenter initially reduces the number of experimental points per factor. The search for influencing factors consists of:

- Choosing only two values (high and low) for each factor, these values are called levels.
- Studying as many factors as possible, even those that may seem at first sight to have little influence.

Many of the factors considered will likely have no influence on the selected response. The results can be reused to choose new experimental points to define one or more specific aspects of the study. In this way, all the influencing factors on the response will have been detected and studied, while minimizing the number of experimental trials. The study can therefore be carried out without waste of either time or money. [1]

1.11. Terminology related to the DoE method

1.11.1.Response

The quantities measured in each trial, which are of interest to the experimenter, called responses. These are the studied quantities or the produced quantities. Selecting appropriate responses is a challenging task and lies outside the realm of experimental design theory. It is only after thorough analysis of the phenomena, considerations of objectives, limitations, and study issues that the correct response(s) can be determined. [6-7]

1.11.2.Factors

A factor is any variable, necessarily controllable, likely to influence the observed response. The fundamental difference between the classic notion of variable and that of factor therefore lies in the fact that any factor must be able to modify without difficulty. This hypothesis is mandatory for experimental designs. [8]

Design of Experiments (DOE) serves as a tool for establishing mathematical relationships solely between responses and factors.

1.11.3.Factor types

a) **Continuous Factors (quantitative):** therefore represents values taken by continuous factors (Wavelength, concentration, temperature), any value in the interval can be chosen [n_{low} n_{up}].

b) **Discrete Factors (qualitative):** These factors can take on values like names, letters, or numerical labels, but these numbers do not represent quantities; they are simply identifiers.[8]

c) **Boolean Factors:** These factors can only have two levels, like high/low, open/closed, or black/white, -1 and 1 and so on. [9]

1.11.4.Factor domain

The factor can represented by a graduated and oriented axis. The value given to a factor to carry out a test called "level". When we study the influence of a factor, in general, we limit its variations between two limits. The lower limit is the low level. The upper limit is the high level. The set of all values that the factor can take between the low level and the high level called the domain of variation of the factor or more simply the **domain of the factor**. We usually note the low level by –1 and the high level by +1. [10]

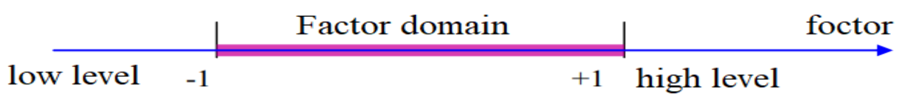

Figure1. 4: Domain of a factor. [11]

1.11.5.Experimental Space

When there is a second factor, it also represented by a graduated and oriented axis. We define, like the first factor, its high level, its low level and its range of variation. This second axis arranged orthogonally to the first. We thus obtain a Cartesian reference frame, which defines a two-dimensional Euclidean space. This space called the experimental space. [10]

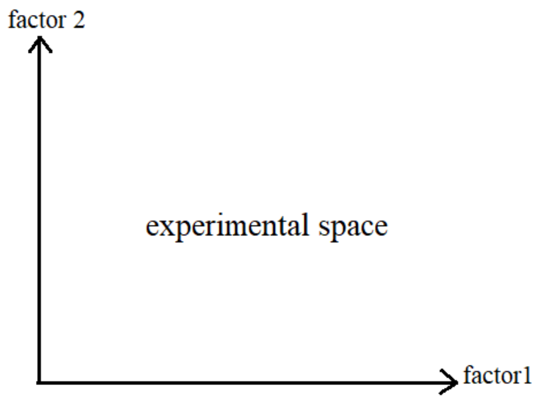

Figure1. 5: Experimental space.

1.11.6.Study Domain

The study domain defined as the collective union of the domains from various factors.

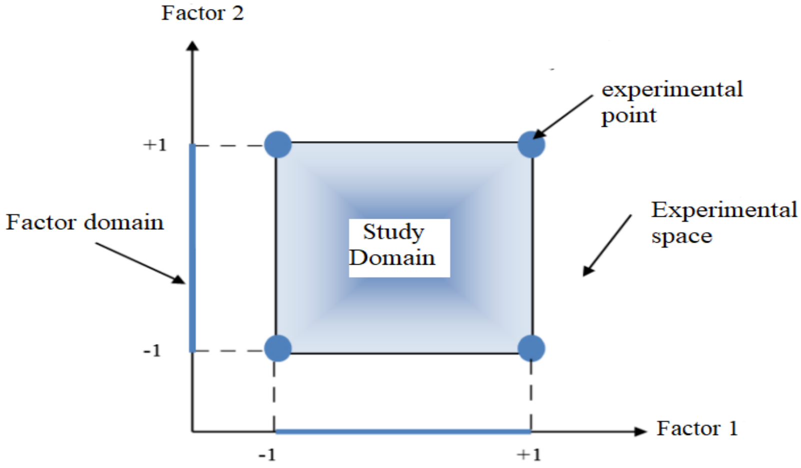

Figure1. 6: Representation of a two-factor experimental design. [5]

1.11.7. Nuisance variables: randomization and blocking

Nuisance variables are factors that affect experiment outcomes but are not directly controllable or of primary interest. If the influence of a nuisance variable is known, it is treated as a regular design factor, known as blocking. However, if the influence is unclear or unpredictable, experiment conditions assigned randomly to different values of the nuisance variable, a method called **randomization**. [12]

1.11.8. Response Surface

We assign an axis to the response. This axis is perpendicular to the experimental space. The geometric representation of an experimental plan and its associated response requires a space with one more dimension than the experimental space. For example, representing the results of a two-factor plan requires a three-dimensional space: one dimension for the response, and two for the factors.

Each point in the study domain corresponds to a response. The set of all points in the study domain corresponds to a set of responses that define a surface called the response surface. [7]

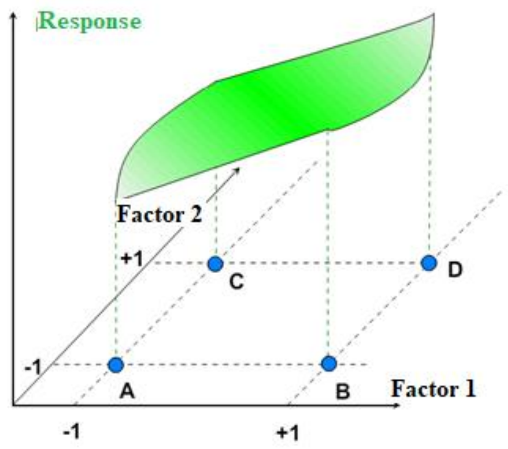

Figure1. 7: The collection of responses that correspond to all the points in the study domain forms the response surface. [10]

1.12. Advantages of experimental designs

The main advantages of this method are:

- Reduction in the number of attempts.
- Possibility of studying a large number of factors.
- Detection of interactions between factors.
- Modeling of the responses studied.
- Optimum precision of results.

The design of experiments method allows rapid and unequivocal interpretation by providing a precise experimental model of the system studied. [13]

1.13. Steps in DOE

- Define the purpose of the experiment.
- Identify the response.
- Consider potential models and select design factors.
- Choose an appropriate experimental design.
- Validate the chosen design.
- Data analysis (ANOVA, Regression, Graphical analysis).
- Result and conclusion.

The effectiveness of the design hinges on the experiment's objectives. These must clearly defined initially.

Next, it is important to identify and classify variables as independent, dependent, nuisance, or intermediate. Independent variables are further categorized into those to be varied (design factors) and those to be kept constant. Tentative models of system response considered to determine which variables should be included as design factors in step 3. The suitability of designs in step 4 relies on the assumed response model. [12]

1.14. Centered and Scaled Variables

Most often, reduced centered variables are used rather than variables measured in original units. The interest of this transformation lies in the fact that the geometric and matrix representations are more general and that the modeling is simpler.

Let A be the natural or real variable, where the low level of A corresponds to the standardized variable -1 and the high level A+ corresponds to +1.

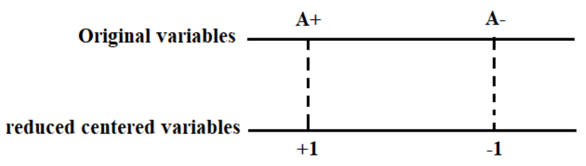

Figure1. 8: Original and reduced variables.

The central or middle value of the domain is:

$$A_0 = \frac{A^+ + A^-}{2} \tag{1.2}$$

The notion of step:

$$Step = \frac{A^+ - A^-}{2} \tag{1.3}$$

The transition from the original variables A to the coded variables denoted X given by: [14-15]

$$X = \frac{A - A_0}{Step} \tag{1.4}$$

1.15. The difference between the classic method and the DOE

The method of experimental designs can briefly compared to the traditional methodology known as "factor by factor variation". To study the influence of two factors on a response, two experimental strategies can adopted for the design of the tests.

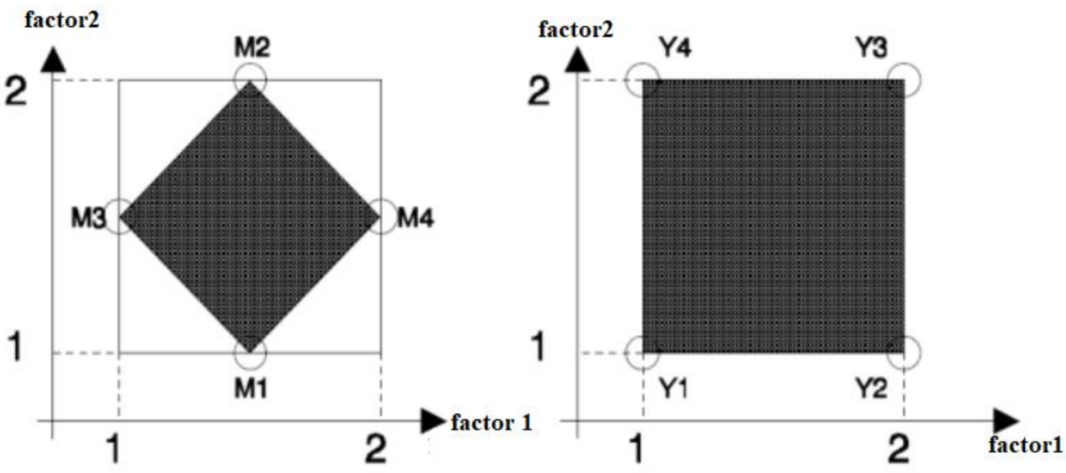

Figure1. 9: On the right, the DOE method, on the left the classic method.

According to the traditional method, we block factor 1 at the center of the variation domain and we vary factor 2 at the two ends of its domain: we obtain the measurements M1 and M2. With factor 1 we carry out the same operation to obtain points M3 and M4. In this method, the effect of 2 will measured from measurements M1, M2, and that of A from measurements M3 and M4. So for each factor only half of the measurements used to account for an effect. The experimental design method will consist of carrying out 4 tests at the ends of the experimental domain. The effect of 1 appears as the difference between the mean $\frac{(Y2+Y4)}{2}$ and the mean$\frac{(Y1+Y3)}{2}$. The same reasoning applies for the effect of 2. In this second strategy, all measurements used to calculate an effect. We therefore understand that the precision obtained will be higher with the design of experiments method. Another advantage of the design method lies in a much lower number of experiments to carried out than in the traditional method when the number of factors increases. [16]

1.16. Mathematical Model of the Response

Most often, the study of a phenomenon can formalized in the following way. The answer which depends on a large number of variables "factors", $x_1, x_2, \dots.. x_k$. Mathematical modeling consists of finding a function f such that$y = f(x_1, x_2, \dots.. x_k)$.

The classic study method consists of measuring y for several values of x while leaving the $(k-1)$ other variables fixed, and then iterating this method for the other variables. As we have already said above, this method quickly leads to a prohibitive number of experiments.

The design of experiments method proposes a factorial experiment that is to say that all the factors vary simultaneously. The results processed using multiple linear regression and analysis of variance. [17-18]

In the design of experiments method, the key approach involves developing and employing models of the objective function (response). Consequently, it is logical thoroughly analyze this essential aspect. Where there is experimental data linking the response y to the factors xi. [6, 9, 19]

$$\boldsymbol{y} = a_0 + \sum_{i=1}^{k} a_i x_i + \sum_{\substack{i,j=1 \\ i<j}}^{k} a_{ij} x_i x_j + \sum_{i=1}^{k} a_{ii} x_i^2 + \cdots \tag{1.5}$$

Where:

y: It is the response or measurement of interest to the experimenter.

x_i: Represents a level of factor i.

$x_{j:}$ Represents a level of factor j.

a_0, a_i, a_{ij}, a_{ii}: The coefficients of the polynomial.

1.17. Design of Experiments software

DoE software plays a crucial role in the experimental design process, offering features for planning, executing, and analyzing experiments. It simplifies the complex task of organizing experimental data. With the help of DoE software, researchers can quickly uncover valuable insights, aiding them in improving products and methodologies. Here are five popular DoE software used by professionals in both industry and academia: **Quantum Boost**, **JMP**, **Design Expert**, **Minitab** and **Modde**. [20]

1.18. Experimental Design Types

The two main possible uses of the Design of Experiments Method are:

1.18.1.Screening Technique

Among the factors identified by the experimenter, this tool allows determining those that have a statistically significant influence on variations in the response. This implicitly simplifies the problem. The aim is to understand why the response varies (in terms of which factors).

a) Factorial Designs: This experimental method involves creating runs that are combinations of factor levels.

-Full factorial designs: It cover all possible combinations of factors at designated levels. Given by the equation:

$$n = m^k \tag{1.6}$$

Where:

n : represents the total number of samples,

k : is the number of factors,

m : is the number of levels for each factor.

Two-level full factorial designs are highly effective screening tools as they enable the estimation of main effects and interactions of input factors on output responses. it commonly used as a screening stage, However, their main drawback lies in the significant number of experiments needed compared to fractional factorial and Placket-Burman designs.

Figure1. 10: in the right Two-level full factorial design for two factors, in the left Two-level full factorial design for three factors. [11]

- Fractional factorial designs: extensively employed for screening purposes due to their ability to assess a large number of input factors while requiring fewer experiments. They are specific subsets of full designs, denoted by the equation:

$$n = m^{k-p} \tag{1.7}$$

Where:

p : represents the number of times the design reduced.

b) Placket–Burman designs: are unique variants of two-level fractional factorial designs (specifically, resolution III). They facilitate the examination of up to N-1 input factors using N experiments (where N must be a multiple of 4).

c) Response Surface Methodology (RSM): Variations in the response calculated based on the previously identified influential factors. This study is quantitative, aiming to determine how the response varies. Logically it applied following the screening study, by using only the factors previously identified as influential.

1.18.2. Optimization Designs

The Box-Behnken, **D-optimal** and **central composite designs (CCDs)** are examples of designs with three or more levels frequently used in response surface methodology (RSM) for function optimization.

There are other experimental designs include **Taghuchi**, **Doehlert, G-optimal**, and **mixture designs**. [6, 21-24]

Table 1. 1: Summary of screening and optimization designs characteristics, number of experiments, levels, and factors. [19]

Applications	Experimental design	Experiments	Levels	Factors
Screening	Placket–Burman	N	2	<N-1
	Fractional factorial	2^{K-P}	2	K>4
	Two-level full factorial	2^{K}	2	2<k<5
Optimization	Box-Behnken	2k(k-1)+C	3	3 < k < 5
	Central composite	2^{k} +2k+C	5	2 k< 5
	3-level factorial	3^{k}	3	2 < k < 3

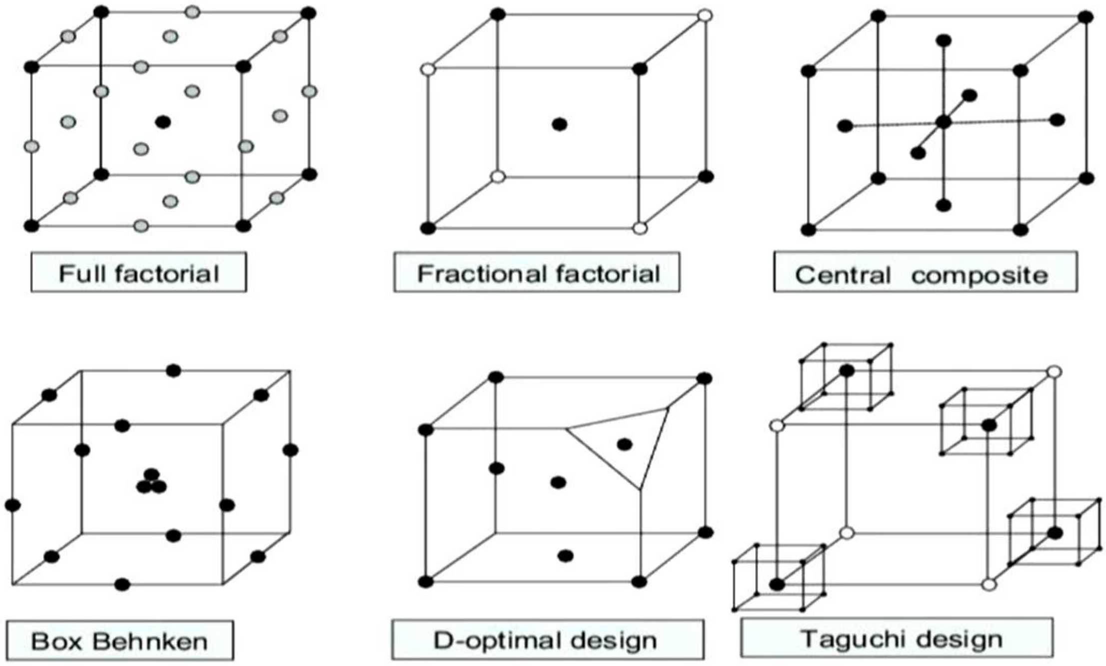

Figure1. 11: Some Types of DOE (3levels, 3 factors). [25]

1.19. Statistical Analysis

1.19.1.ANalyse Of VAriance (ANOVA)

Since the researchers wants to get as much information as possible from the experimental data, using the appropriate statistical techniques is important. ANOVA, or Analysis of Variance, is a statistical method used to analyze the differences among group means in a sample. It is particularly useful when comparing means of three or more groups to determine if there are statistically significant differences between them. ANOVA works by partitioning the total variance observed in a data set into different sources, such as variation between groups and variation within groups, and then assessing whether the variation between groups is significantly greater than the variation within groups. [26]

It goes with Hypothesis assumption:

$$H_0: \mu_1 = \mu_2 = \ldots = 0$$
$$Ha: at\ least\ one\ \mu 2 \neq 0$$

Where:

μ : The mean of sample.

The null hypothesis typically states that there is no effect or no difference, while the alternative hypothesis suggests otherwise.

Table 1. 2: ANOVA table.

Source of variation	Degrees of Freedom (df)	Sum of Squares (SS)	Mean Squares (MS)	F-ratio
A-Treatment	n_i-1	SSA	MSA	MSA/MSE
B-Treatment	n_j-1	SSB	MSB	MSB/MSE
Interaction	(n_i-1)(n_j-1)	SSAB	MSAB	MSAB/MSE
Error	n_{ij} -[$\mathrm{df_a} - \mathrm{df_b} - \mathrm{df_{int}}$]	SSE	MSE	
Total	n_{ij}-1	SST		

1.19.2.ANOVA Table Terms

- **SST:** The *total sum of squares* represents the total variability observed in the dependent variable Y. It calculated as the actual total squares of the dependent Y variable minus a correction factor (CF).

$$SST = \sum Y^2 - \frac{(\sum y)^2}{n} = \sum Y^2 - CF \quad (1.8)$$

- **SSE:** The *error sum of squares*, which is a total sum of unexplained variation.

$$SSE = \sum (Residuals)^2 \quad (1.9)$$

- **SSTr:** The *treatment sum of squares,* the sum of each treatment.

$$SSTr = \sum \frac{(\sum y_i)^2}{n_i} - CF \quad (1.10)$$

- $\boldsymbol{df}$ **:** The *number of degrees of freedom*. In a treatment df_t , (n_i) is the number of levels it takes in a design of experiment.

$$df = n - 1 \quad (1.11)$$

- **MS:** The **Mean square** it is equal to:

$$MS = \frac{SS}{df} \quad (1.12)$$

- **F-value:** Computed F-value calculated by dividing the mean square MS by the error MSE. The F-value compared to a critical value (derived from the F-distribution to determine statistical significance). If the F-value is greater than the critical value, it suggests that there are significant differences between the group means.

- **P-value:** The last term is were introduced to ANOVA analysis by Genichi Taguchi, a pioneer of DoE Taguchi method, and are intended as an alternative to the F-test. P % (considered as evidence of the hypothesis), it is the contribution percentage of each source of variation and is derived as a percentage of total SST. It is easier and more quantitative for engineers to appreciate a quantitative % contribution of a source of variation as opposed to a binary F-test that determines only whether the factor is significant or not. Taguchi recommends that if the modified source of variation is p % > 5%, then it should be considered not significant and pooled into the error by this we fail to reject the null hypothesis and vice versa.
- **Test of R^2**

  The coefficient of determination (R^2) is an indicator, which makes it possible to judge the quality of a linear, simple or multiple regression. With a value between 0 and 1, it measures the adequacy between the model and the observed data. Sure, the R^2 has its imperfections, but its usefulness matched only by its simplicity. [27-30]

1.20. Graphical analysis

One of the main advantages of experimental designs is the presentation of results in graphical form. Various graphs are available for interpreting the equation of the empirical model (**Pareto chart** using in the screening step, **Normal plot**, **Histogram of the residuals**, **Response optimizer plot**, **Surface plot**, **Contour plot**). [31]

1.21. Conclusion

The design of experiment (DoE) is therefore a very powerful tool to phenomenon study and a set of complementary techniques helping its user in determining the experiments to be carried out as well as in understanding and exploiting the obtained results. This tool is essentially based on statistical and algebraic bases. This particularity induces the almost permanent possibility of knowing the errors conceded on the experimental data and on those, which are deduced from them. In the next chapter, we will present the application of the DoE method in the modeling of photovoltaic panels.

Chapter 2: Design of Experiments: case studies

2.1. Introduction

Initially and with the aim of mastering the application of the DoE method and highlighting it, this chapter presents a comprehensive review of case study focusing on the application of Design of Experiments (DOE) in various fields. The case study discussed in this chapter offers valuable insights into the practical implementation of DOE methodology to address real-world challenges.

First, the calculations relating to the DoE technique were performed manually while rigorously respecting the steps of the method. Afterwards, and in the second step, the calculations were carried out by the Minitab software in order to learn how to implement data, to get results and their discussion. The famous example studied case is that of Goupy's car.

2.2. The Goupy's car case Study

In this study, **Jacques Goupy, Lee Creighton**, wanted to answer questions like, "What is the consumption of gas when we drive at 88,5 Km/h with a weight of 125 Kg?", so they defined the objective of the study which is "to know the gas consumption of a car when you drive with or without extra weight, while driving fast or slow". [9]

The experimental trials of the study were performed using one of the author's cars. At this point "The Response", it has been determined and it's the **consumption of gas** in *liter per kilometer* (*l/km*), after that they researching the factors that may influence the response, there are two main factors "Speed" and "Additional weight", for the factors levels they choose 72.4 as low speed, 113 as high speed and 0 Kg(the car and the driver) for low additional weight, 250 kg high additional weight.

The information summarized in the following table (Table 2.1).

Table 2. 1: Factors and study domain.

Factors	Low Level	High Level
1- Speed	72.4	113
2- Additional weight	0	250

There is no way to predict results out of this study domain.

Examining the Constraints is about control the nuisance factors and ensure that the experiment gives as accurate results.

- Decreasing of tank while the driving.
- Temperature, wind, rain so the tests should be all in the same day.
- Checking of the tire pressure.

After choosing the design, it is important to conduct the experiments, there are two factors to study, and each of them will take two levels: high and low. The best design to choose is a 2^2 full factorial design.

Experimental trials can be presented in table form. When using technical measurements (Km/h, Kg), the table is called an experimental table spreadsheet. In contrast, when using measurements coded (-1, 1), the table is called an experimental design or experimental matrix. [9]

2.3. Running the experiments

The distance covered by the car was 112.6 km taking into account the time needed to add fuel, measure fuel consumption and load the car by extra weight. A full factorial design of 2^2 means that there will be 4 experiments to be carried out. After running all the experiments, they are drawn up in a table (Table 2.2).

Table 2. 2: Experimental matrix with results [9].

Trial	**Speed**	**Additional Weight**	**Gas Consumption (C_G)**
	Factor 1	Factor 2	l/Km
1 (A)	-1	-1	12.7543
2 (B)	+1	-1	10.6268
3 (C)	-1	+1	11.4789
4 (D)	+1	+1	8.9280
-1 Level	72.4 Km/h	0	
+1 Level	113 Km/h	250 Kg	

2.4. Study domain

The study domain as shown in (figure 2.1), is defined by low and high level of each factor.

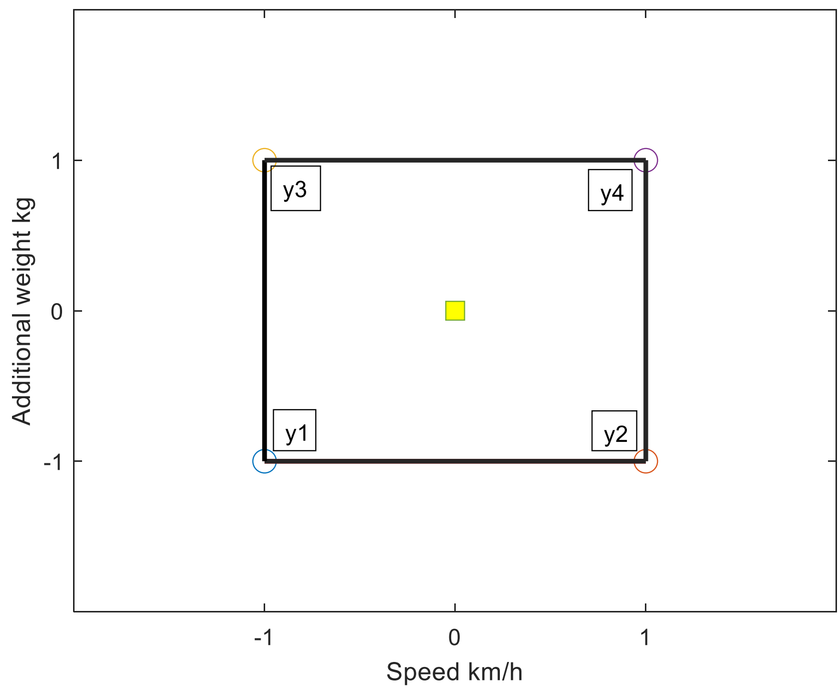

Figure 2. 1: Study domain of the experiment.

2.5. Interpreting the Coefficients

Predictive Mathematical Model of the Response (from chapter1):

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

For 2^2 full factorial design, the response model equation be like:

$$y = a_0 + a_1 x_1 + a_2 x_2 + a_{12} x_1 x_2 \qquad (2.1)$$

Where:

y: Is the Gas consumption.

x_1: Represents the level of the speed factor (factor 1).

$x_{1:}$ Represents the level of the additional weight factor (factor 2).

a_0, a_1, a_2, a_{12}: The coefficients of the Factor's effects.

2.5.1. The intercept a_0:

It is represent the center of the study domain and the response value in this point is y_0 with the couple (0, 0) as coordinates.

$$y_0 = a_0 + a_1 \times 0 + a_2 \times 0 + a_{12} \times 0 \times 0 \tag{2.2}$$

$$y_0 = a_0$$

To solve the mathematical model there is two ways.

2.5.2. Matrix way

The matrix form of equation 2.1 is:

$$y = X.a \tag{2.3}$$

With **y** representing the individual response recorded for the four trials in the study domain, and x being the design matrix, which must be a square matrix, the coefficients of the model can be estimated from Equation (2.1).

$$a = X^{-1}.y \tag{2.4}$$

The coefficients is the half of the factor's effect (see chapter 1).

The four experiments, as indicated in the domain study, give the following linear system with four equations:

$$\begin{cases} y_1 = a_0 - a_1 - a_2 + a_{12} \\ y_2 = a_0 + a_1 - a_2 - a_{12} \\ y_3 = a_0 - a_1 + a_2 - a_{12} \\ y_4 = a_0 + a_1 + a_2 + a_{12} \end{cases} \tag{2.5}$$

This system in its matrix form is:

$$\begin{bmatrix} 1 & -1 & -1 & 1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \times \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_{12} \end{bmatrix} = \begin{bmatrix} 12.7543 \\ 10.6268 \\ 11.4789 \\ 8.9280 \end{bmatrix} \tag{2.6}$$

Solving the linear system in Equation 2.6 allows obtaining the calculated coefficients (resolution of this system of equations is easy to perform):

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_{12} \end{bmatrix} = \begin{bmatrix} 10.9470 \\ -1.1696 \\ -0.7435 \\ -0.1058 \end{bmatrix} \tag{2.7}$$

2.5.3. Compare transactions way

a) For factor 1

The mean of the Response at the high level of the speed factor (factor 1):

We take the values of response at the high level (1) of the factor. [7]

$$\bar{y}_{+} = {(y_2 + y_4)}/{2} = {(8.9280 + 10.6268)}/{2} = 9.7774\ \mathrm{l/km} \quad (2.8)$$

The mean of the Response at the low level of the speed factor (factor 1):

We take the values of response at the low level (-1) of the factor. [7]

$$\bar{y}_{-} = {(y_1 + y_3)}/{2} = {(12.7543 + 11.4789)}/{2} = 12.1166\ \mathrm{l/km} \quad (2.9)$$

The mean of the coefficient of speed effect is the half of the difference means: [7]

$$a_1 = \frac{1}{2}[\bar{y}_{+} - \bar{y}_{-}] = -1.1696\ \mathrm{l/km} \quad (2.10)$$

The graphical evaluation of speed effect with the consumption of gas presented in (figure 2.2).

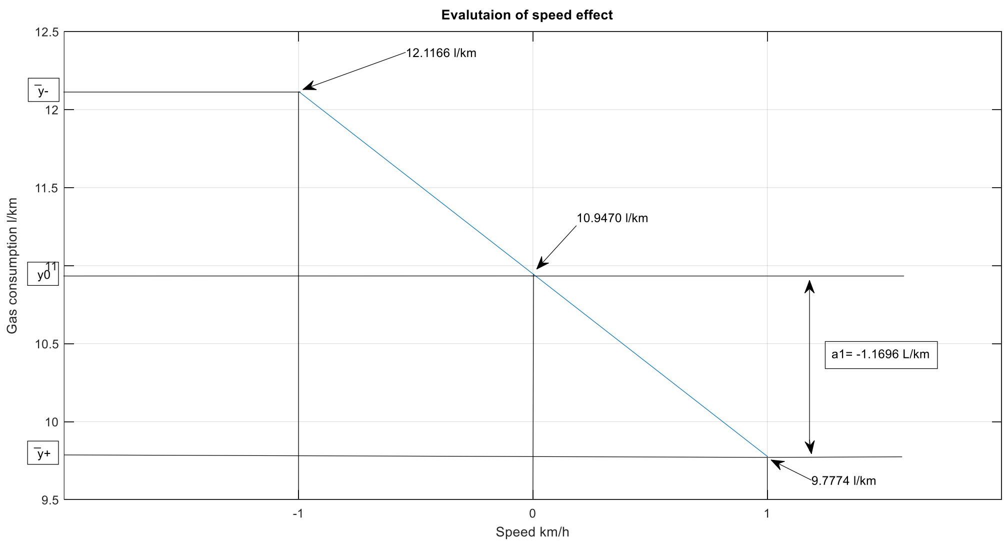

Figure 2. 2: Evaluation of the speed effect.

b) For factor 2

The same method employed to calculate factor 2 and the interaction coefficients.

The mean of the Response at the high level of the additional weight factor (factor 2):

$$\bar{y}_{+} = {}^{(y_3 + y_4)}\!/_{2} = {}^{(11.4789 + 8.9280)}\!/_{2} = 10.2034 \ \text{l/Km} \quad (2.11)$$

The mean of the Response at the low level of the additional weight factor (factor 2) calculated as follow:

$$\bar{y}_{-} = {}^{(y_1 + y_2)}\!/_{2} = {}^{(12.7543 + 10.6268)}\!/_{2} = 11.6905 \ \text{l/km} \quad (2.12)$$

The mean of the coefficient of additional weight effect is the half of the difference of means:

$$a_2 = \frac{1}{2}[\bar{y}_{+} - \bar{y}_{-}] = -0.7435 \ \text{l/km} \qquad (2.13)$$

The graphical evaluation of additional weight with consumption of gas is depicted in figure 2.3.

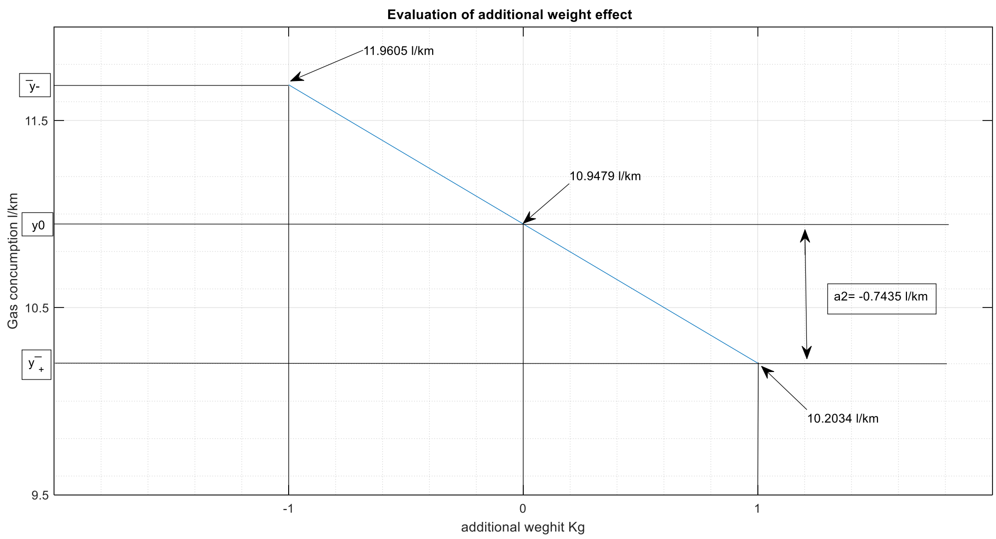

Figure 2. 3: Evaluation of the additional weight effect.

c) **For interaction (speed/additional weight), a_{12}**

$$\bar{y}_{+} = {}^{(y_4 - y_3)}\!/_{2} = {}^{(8.9280 - 11.4789)}\!/_{2} = -1.2754 \ \text{l/km} \quad (2.14)$$

This is the effect of factor 1(speed) when the factor 2 (additional weight) at its high level.

The mean of the Response at the low level of the additional weight factor (factor 2):

$$\bar{y}_- = {(y_2 - y_1)}/_2 = {(10.6268 - 12.7543)}/_2 = -1.0637 \text{ l/km} \quad (2.15)$$

This is the effect of factor 1(speed) when the factor 2 (additional weight) at its low level.

The mean of the coefficient of interaction (factor 1in factor 2):

$$a_{12} = \frac{1}{2}[\bar{y}_+ - \bar{y}_-] = -0.1058 \text{ l/km} \quad (2.16)$$

The graphical illustration of the interaction of factor 1 when factor 2 changed is:

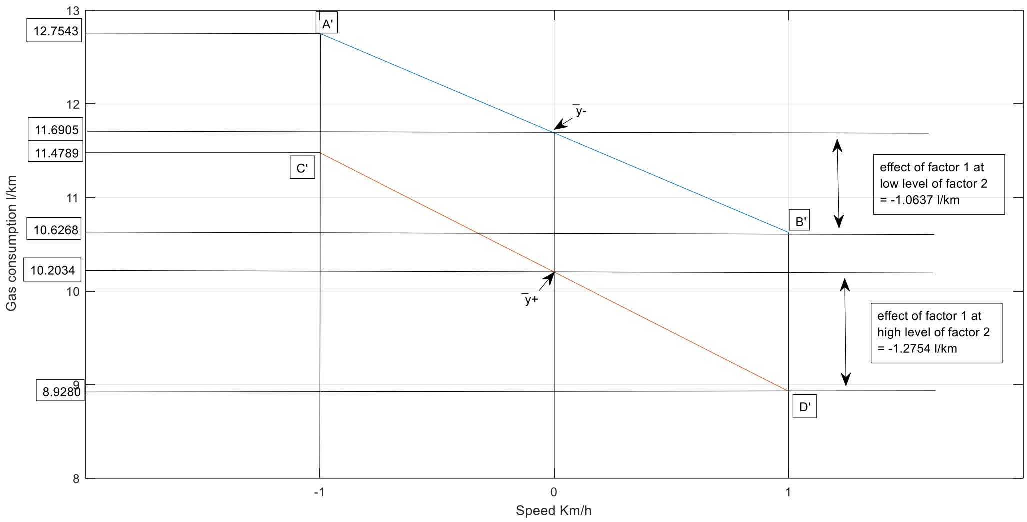

Figure 2. 4: Illustration of the interaction effect (a_{12}).

As we can see, the slopes are different so there is an interaction between the two factors. If the slopes are in parallel we say, there is no interaction between the factors.

d) For interaction (additional weight/ speed), a_{21}

$$\bar{y}_+ = {(y_4 - y_2)}/_2 = {(8.9280 - 10.6268)}/_2 = -0.8494 \text{ l/km} \quad (2.17)$$

This is the effect of factor 2(additional weight) when the factor 1 (speed) at its high level.

$$\bar{y}_- = {(y_3 - y_1)}/_2 = {(11.4789 - 12.7543)}/_2 = -0.6377 \text{ l/km} \quad (2.18)$$

This is the effect of factor 2(additional weight) when the factor 1 (speed) at its low level.

The mean of the coefficient of interaction (factor 2 in factor 1):

$$a_{21} = \frac{1}{2}[\bar{y}_{+} - \bar{y}_{-}] = -0.1058 \text{ l/km} \tag{2.19}$$

$$|a_{21}| = |a_{12}| \quad \text{Always the same/}$$

The graphical illustration of the interaction of factor 2 when factor 1 changed is:

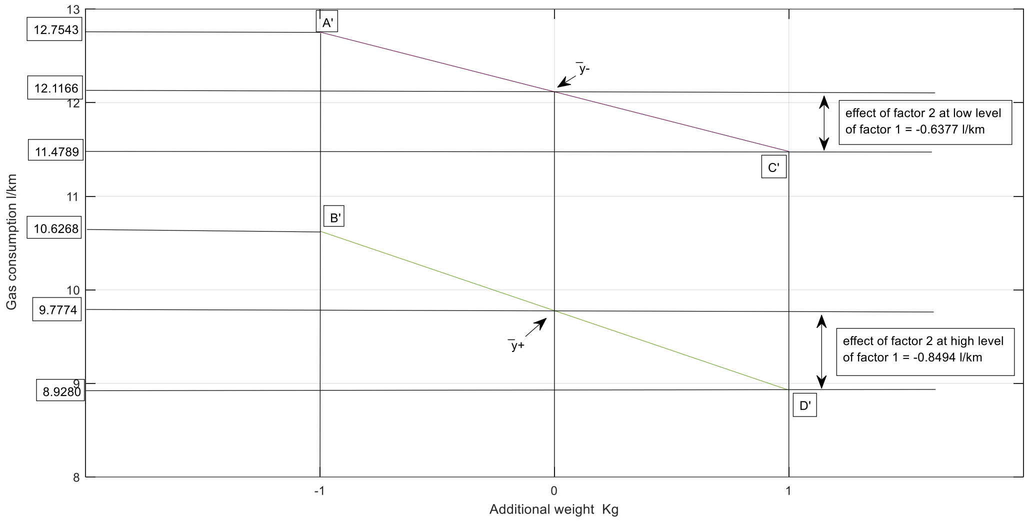

Figure 2. 5: Illustration of the interaction effect (a_{21}).

2.6. Interpreting the Results

After all this calculations and by setting the calculated coefficients in Eq. 2.1, we can calculate all the responses within the study domain with this model:

$$C_G = 10.9470 - 1.1696\, x_1 - 0.7435 x_2 - 0.1058\, x_1 x_2 \tag{2.20}$$

Now it is the moment to answer the question, "What is the consumption of gas when we drive at 88.5 Km/h with a weight of 125 Kg?"

To respond to such question we must, first determine the coded units:

$$x = \frac{A - A_0}{Step} \tag{2.21}$$

For factor 1:

$$x_1 = \frac{A_1 - A_{0,1}}{Step_1} \tag{2.22}$$

For factor 2:

$$x_2 = \frac{A_2 - A_{0,2}}{Step_2} \qquad (2.23)$$

The central or middle value of the domain of factor 1 is:

$$A_{0,1} = {(A^+ + A^-)}/{2} \qquad (2.24)$$

$$A_{0,1} = {(113 + 72.4)}/{2} = 92.7 \text{ Km/h} \qquad (2.25)$$

Also the step:

$$Step_1 = {(A^+ - A^-)}/{2} \qquad (2.26)$$

$$Step_1 = {(113 - 72.4)}/{2} = 20.3 \text{ Km/h} \qquad (2.27)$$

Then the coded unit of 88.5 Km/h is:

$$x_1 = {(A_1 - A_{0,1})}/{Step_1} = {(88.5 - 92.7)}/{20.3} = -0.2 \qquad (2.28)$$

So:

- 88.5 Km/h = -0.2 in coded units
- 125 kg = 0 in coded units

By compensation of the coefficients in Eq. (2.20), we can write:

$$C_G = 10.9470 - 1.1696 \times (-0.2) - 0.7435 \times (0) - 0.1058 \times (-0.2) \times (0)$$

$$C_G = 11.1809\ Km/L \qquad (2.29)$$

Therefore, in this way, it is possible to answer questions like these and many others involving speed and load.

2.7. Calculation using Minitab software

After implementing the experiment in the Minitab program, we obtained the following results

2.7.1 The study domain

We can see the value of the response for various points in the study domain as indicated in figure 2.6.

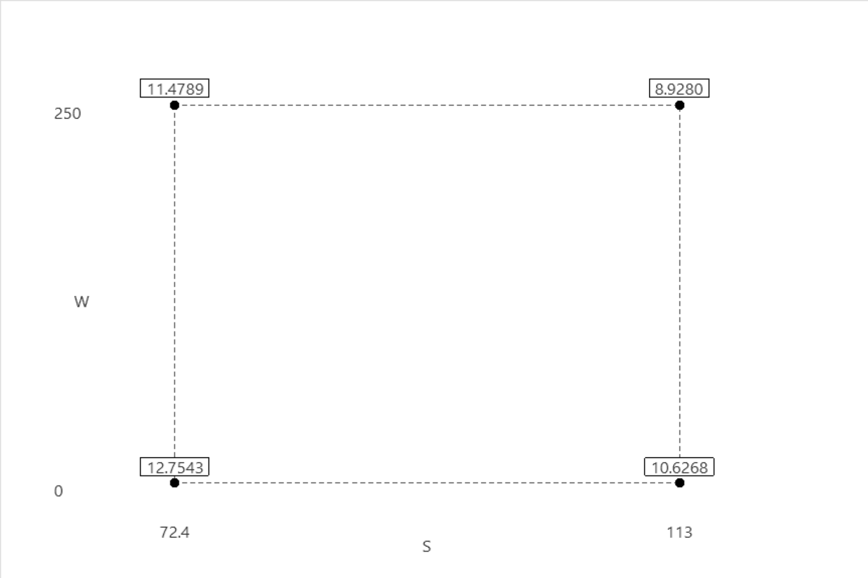

Figure 2. 6: Study domain of the experiment.

2.7.2. The coefficients

Term	Effect	Coef
Constant		10.95
S	-2.339	-1.170
W	-1.4871	-0.7436
S*W	-0.2117	-0.1058

Figure 2. 7: The intercept, the coefficients and the effects.

Where: S represents the speed factor and W is the Weight factor.

As we have already seen in the DoE theory, the coefficient of factors is the half of the effects, and that is what exactly represented by Minitab in (figure 2.7).

2.7.3. Factors effects

Figure 2.8 represents the main effect (called also the proper effect) of the two considered factors as given by Minitab software.

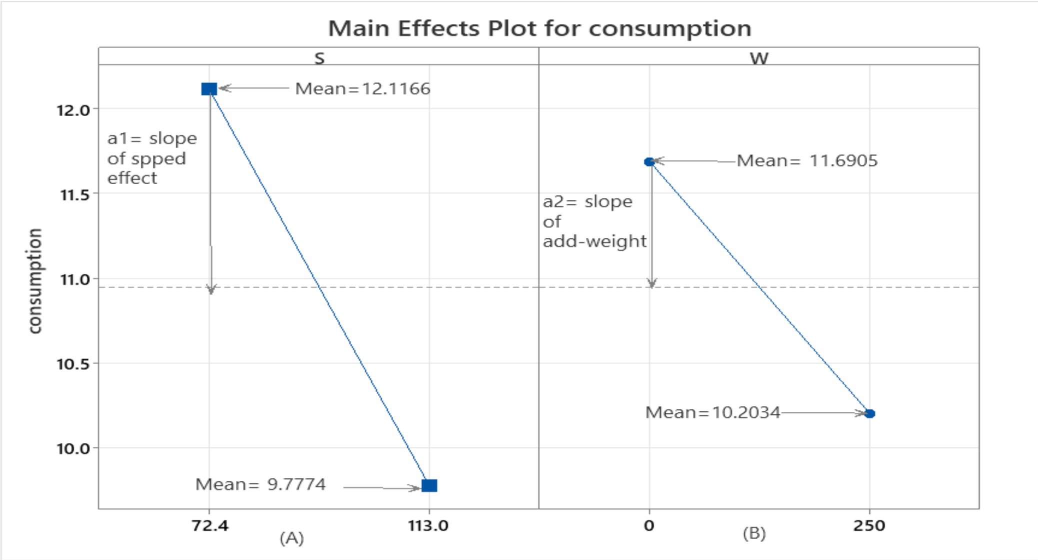

Figure 2. 8: (A) the evaluation of speed effect with the consumption. (B) Evaluation of additional weight effect with consumption.

2.7.4. The interaction between Factors

Figure 2.9 and 2.10 present the interactive effects (called also the mutual effect) of the two considered factors as given by Minitab software.

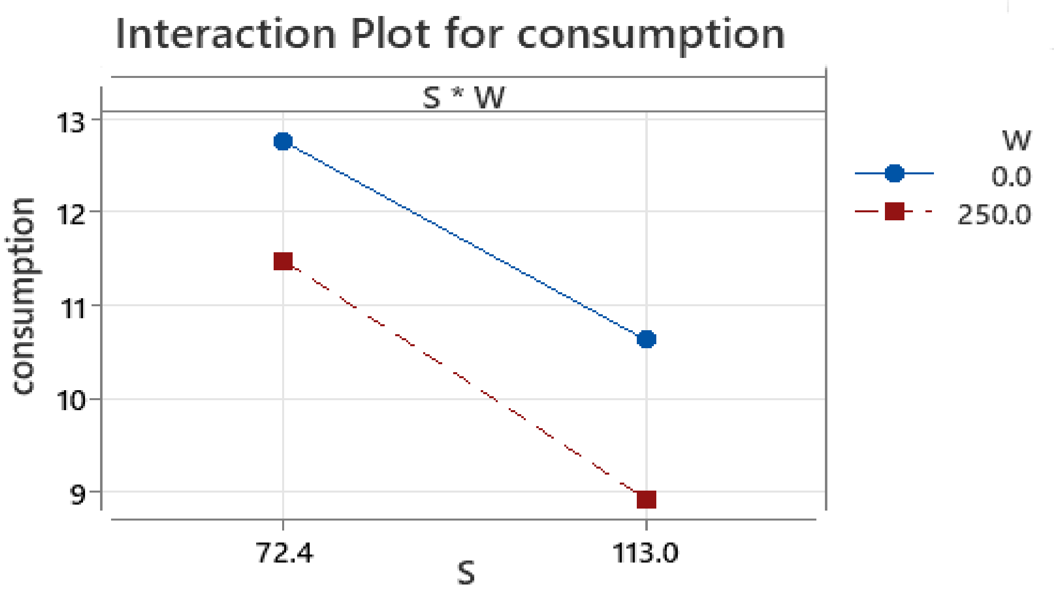

Figure 2. 9: The effect of factor 1 when factor 2 changed.

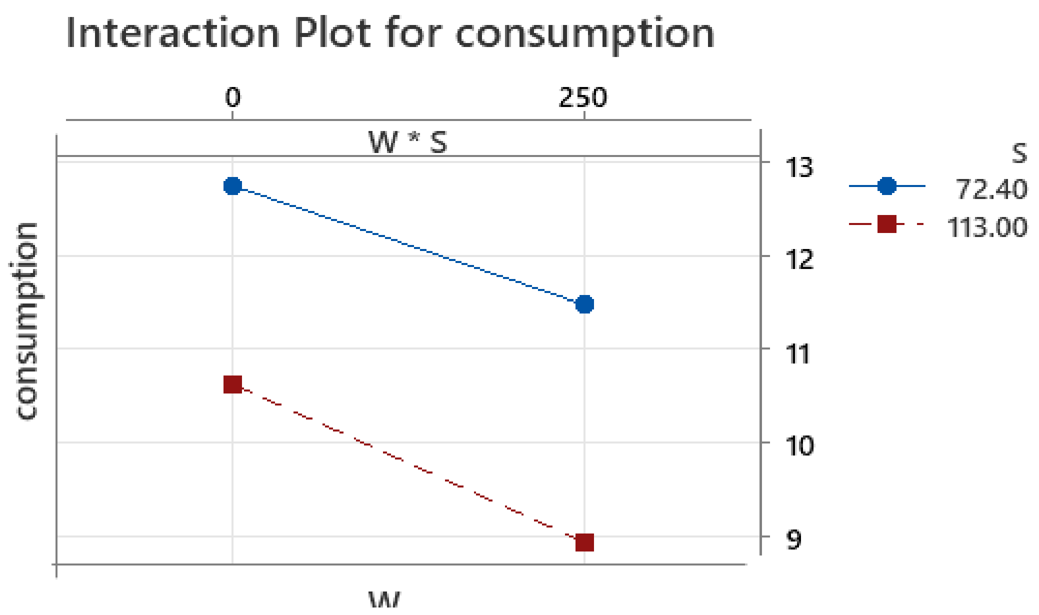

Figure 2. 10: The effect of factor 2 when factor 1 changed.

2.7.5. Prediction for consumption

The predicted mathematical model of the consumption given by Minitab as indicated by the following screenshot depicted in figure 2.11.

Regression Equation in Uncoded Units

Consumption = 10.95 - 1.170 s - 0.7435 w - 0.1058 s*w

Figure 2. 11: Regression equation.

Finally, the answer the question: "What is the consumption of gas when we drive at 88.5 Km/h with a weight of 125 Kg?" Presented in the following figure 2.12.

Settings

Variable	Setting
S	88.5
W	125

Prediction

Fit	SE Fit	95% CI	95% PI
11.1890	*	(*, *)	(*, *)

Figure 2. 12: Prediction of consumption.

2.7.6. Contour plot of consumption for speed and additional weight

Contour curves are two-dimensional views where contour lines created by connecting locations with the same response value [32]. The graph indicates the necessary changes in speed owing to the added weight if I wish to reach 11.5 km/l for example. This contour curves indicate the behavior of the response due to the variation of both factors. In figure 2.13, G-C is the response, which represents the Gas Consumption, W is the Weight factor and S is the speed factor. Colors of the curves in the contours.

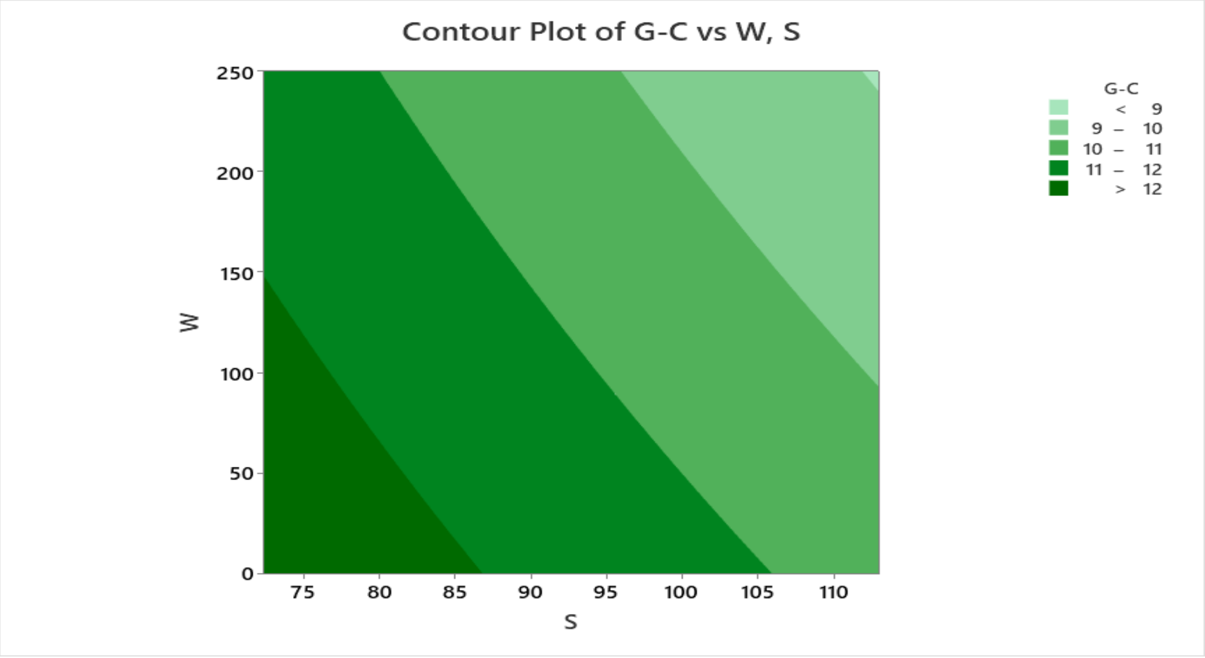

Figure 2. 13: Contour Plot of the experiment.

2.7.7. Surface response plot

The results of the study can be recorded in what the DoE method calls response surfaces. The results of our studied example are presented in figure 2.14.

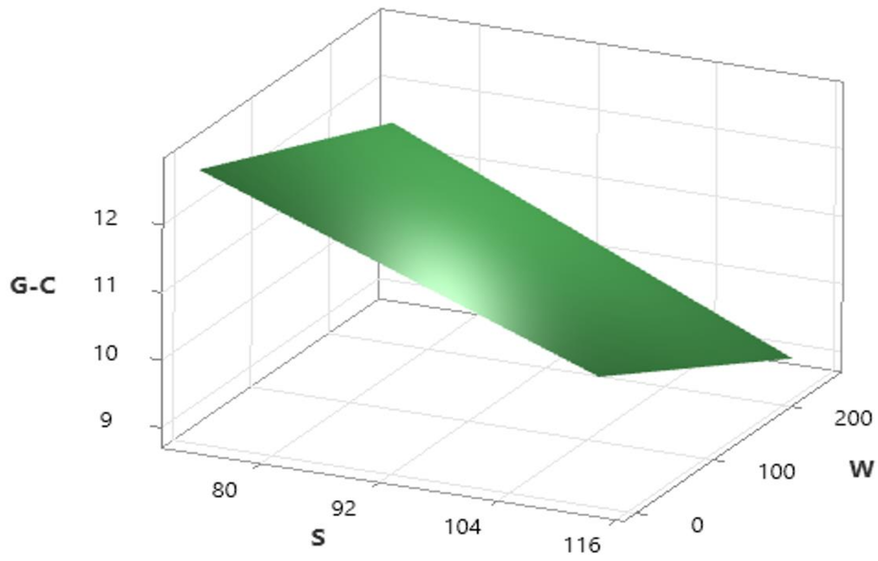

Figure 2. 14: Surface response Plot of the experiment.

2.8. Conclusion

Through a comprehensive review of the case study, we observed how the DoE technique was successfully used to address a range of challenges especially when it comes to study a complex processes with a host of factors.

Thanks to the discussions made on the experiment carried out in our example, we can rely on everything that was carried out in this study to apply it to examples of more complex size. we were also able to know how to have the mathematical predictive model of response behavior when the input variables vary within the limits set by the domain of study based on few experiment trials. we also knew how to calculate and present graphically the effects of the different factors as well as the presentation of the response in the form of contour curves or in the form of response surface curves using the Minitab software. By applying DOE principles and techniques, we aim to design robust experiments that produce actionable insights.

Chapter 3: Application of DoE technique to model photovoltaic panels

3.1. Introduction

Understanding the performance of photovoltaic (PV) panels are crucial steps towards enhancing their efficiency and usability. Design of Experiment (DOE) methodology, coupled with Minitab, provides a systematic approach to analyze and model the complex relationships between factors affecting PV panel performances and its key parameters.

This chapter delves into the application of Design of Experiment techniques using Minitab software to model the performance of PV panels. The primary focus lies on three critical responses: maximum power output, short circuit current and open circuit voltage. These responses are fundamental indicators of a PV panel's efficiency and functionality.

3.2. The experiments

In this study, the objective is to modeling the electrical response of a monocrystalline photovoltaic module in using Design of experiments approach. The main purpose is to evaluate the maximum power and the short-circuit current and open circuit voltage " The responses" dependence within the indoor conditions of variations of solar irradiation and surface temperature " The Factors ", The Design of Experiments method is employed to estimate both the individual and combined effects of the two independent variables, Experiments were conducted in the laboratory, and the experimental errors associated with temperature and electrical measurements, including irradiation measurements, are estimated to be standard at 10% of the values.

The experiencers choose the mono-crystalline module, 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.

Experiments are performed within exposing the chosen PV panel to the irradiation emitted by the Halogen DELTALAB light source and due to the variation of the irradiation level (by acting on the bulbs) we record the irradiation, temperature, the open circuit voltage, the short circuit current and the maxim disponible power on the PV panel.

The solar irradiation levels and surface temperature measured concurrently during indoor experiments. By using (Hg lamps of Deltalab source) as irradiation source. We have realized fifteen (15) trials.

The parameters were experimentally determined:

- Solar irradiation measured by using a fluxmeter positioned at the center of the PV panel. Its sensitivity was recorded as S = 10.33 µV/ W/m^2.

- Surface temperature at the center of the PV panel measured by using an infrared thermometer, with recordings accurate within 1%. [5]

The experimental trials measurement given in (table 3.1):

Table 3. 1: Table of Experiment on the monocrystalline panel. [5]

Monocristallin					
	Factors		Responses		
N°	***I r*** (mV)	***T*** (°C)	***V co*** (V)	***I cc*** (A)	***P m*** (W)
01	5,9	28,9	20,1	0,706	9,93
02	5,9	32,6	19,9	0,712	9,92
03	5,9	34,7	19,7	0,716	9,87
04	5,9	37,4	19,6	0,719	9,86
05	8,5	30,5	20,5	0,894	12,83
06	8,5	34,6	20,1	0,918	12,92
07	8,5	37	19,9	0,915	12,75
08	8,5	42,3	19,6	0,899	12,33
09	13,6	34,2	20,5	1,263	18,12
10	13,6	37,1	20,3	1,269	18,03
11	13,6	41,1	19,8	1,282	17,77
12	13,6	43,9	19,4	1,281	17,40
13	18,4	36,3	20,5	1,633	23,43
14	18,4	38,1	20,3	1,638	23,28
15	18,4	45,1	19,8	1,653	22,91

3.3. Modeling and characterization of the PV panel response

Based on these experiments, and using of the 2^2 full factorial experimental design theory, i will choose a sample of experiments consisting of four experiments (trials numbers: 05, 08, 13, 15 as indicated in table 3.1) to analyze them with a full factorial design 2^2 and see the importance of the influence of change of factors on desired responses, the reason for choosing them is trying to find the best samples to study to get the best results.

First, as we can see in the table 3.2, the irradiation is in (mV unit expressed on the fluxmeter), so we are going to convert it to (W/m^2) based on the sensitivity of the commercial fluxmeter. The converting formula is then:

$$Irradiance\ (W/m^2) = Voltage\ (mV)\ /\ (S\ (\mu V/(W/m^2))\ \times\ 1000)\ .\ [33]$$

Where:

S: is the sensitivity of the fluxmeter S = 10.33 $\mu V/\ W/m^2$.

The experimental trials measurements summarized in the table. (Table 3.1)

Table 3. 2: Experimental trials measurements and observed response.

Trial	Irradiation (mV)	Irradiation (W/m²)	Surface Temperature (°C)	Maximum power (W)	Short-circuit current (A)	Open circuit voltage (V)
		Factor A	**Factor B**	**Response 1**	**Response 2**	**Response 3**
1	8.5	829	30.5	12.83	0.894	20.5
2	8.5	829	42.4	12.33	0.899	19.6
3	18.4	1781	36.3	23.43	1.633	20.5
4	18.4	1781	45.1	22.91	1.653	19.8

Now, from the dressed table 3.2, we can affect the levels +1, 0 and -1 to the considered factors that what we called reduced centered values as depicted in table 3.3.

Table 3. 3: Original and Reduced Centered Values.

	Factor A	Factor B
-1 Level	829 W/m²	30.5 °C
0	1305 W/m²	37.8 °C
+1 Level	1781 W /m²	45.1 °C

The reduced centered coordinates for irradiation (W/m²), represented by x_A, and temperature (°C), represented by x_B, will be calculated.

a- Factor A

The step:

$$Step_A = {(A^+ - A^-)}/_2 = {(1781 - 1317)}/_2 = 476\ W/m^2 \qquad (3.1)$$

The central value of the domain:

$$A_{0,A} = {(A^{+} + A^{-})}/{2} = {(1781 + 1317)}/{2} = 1305\ W/m^2 \qquad (3.2)$$

The coded units:

$$x_A = \frac{A - A_{0,A}}{Step} \qquad (3.3)$$

b- Factor B

The step:

$$Step_B = {(A^{+} - A^{-})}/{2} = {(38.1 - 34.2)}/{2} = 7.8\ °C \qquad (3.4)$$

The central value of the domain:

$$A_{0,B} = {(A^{+} + A^{-})}/{2} = {(38.1 + 34.2)}/{2} = 37.8\ °C \qquad (3.5)$$

The coded units:

$$x_B = \frac{A - A_{0,2}}{Step} \qquad (3.6)$$

Then all the reduced central coordinates (RCV) of the other values of the factors involved were calculated, in order to standardize the units of the variables.

3.4. Modeling the PV panel for Maximum power (W)

Minitab v21 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 [19].

we applied the DoE method 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.

3.4.1. Mathematical analysis

a) Linear regression model

We consider only the linear variables influences and the interactive effects. Therefore, and according to the DoE theory, the predictive mathematical model related to such linear regression is:

$$y = a_0 + a_A x_A + a_B x_B + a_{AB} x_A x_B \qquad (3.7)$$

Where:

- y: It can be one of the three considered responses "Pm, I_{SC}, V_{OC}" from measurements.
- x_A: Represents the level of the Solar Irradiation factor (factor A).
- x_B : Represents the level of the Surface Temperature factor (factor B).
- a_0 : The intercept.
- a_A, a_B, a_{AB}: The coefficients associated with the effects of the factors x_A, x_B and the interaction effect.

The simple regression model is a predictive model of a full factorial design composed of two factors each one has two levels. The effects of the two factors and their interaction define this model. The experiments carried out with this model and the reduced center coordinates are shown in the following table (table 3.4). [34]

Table 3. 4: Experimental data of the simple regression model.

Trial	Ir (W/m²)	T (°C)	Ir (RCV)	T(RCV)	Pm (W)	I_{SC} (A)	V_{OC} (V)
1	829	30.5	-1	-1	12.83	0.894	20.5
2	829	42.3	-1	0.6250	12.33	0.899	19.6
3	1781	36.3	1	-0.2054	23.43	1.633	20.5
4	1781	45.1	1	1	22.91	1.653	19.8

RCV: means reduced centered variables.

By replacing in equation (3.7) the response y, which is the maximum power Pm, and the factors x_A and x_B by their centered values indicated in table 3.4 for each trial, we obtain the following linear system:

$$\begin{cases} y_1 = a_0 - a_A - a_B + a_{AB} \\ y_2 = a_0 - a_A + 0.6250\, a_B - 0.6250 a_{AB} \\ y_3 = a_0 + a_A - 0.2054 a_B - 0.2054 a_{AB} \\ y_4 = a_0 + a_A + a_B + a_{AB} \end{cases} \tag{3.8}$$

We can write the system represented in (3.8) in a matrix form as follow:

$$\begin{bmatrix} 1 & -1 & -1 & 1 \\ 1 & -1 & 0.6250 & -0.6250 \\ 1 & 1 & -0.2054 & -0.2054 \\ 1 & 1 & 1 & 1 \end{bmatrix} \times \begin{bmatrix} a_0 \\ a_A \\ a_B \\ a_{AB} \end{bmatrix} = \begin{bmatrix} 12.83 \\ 12.33 \\ 23.43 \\ 22.21 \end{bmatrix} \tag{3.9}$$

The resolution of this system of equations gives the following coefficients values:

$$\begin{bmatrix} a_0 \\ a_A \\ a_B \\ a_{AB} \end{bmatrix} = \begin{bmatrix} 17.93 \\ 5.41 \\ -0.3695 \\ -0.06185 \end{bmatrix} \tag{3.10}$$

The results of the means of the responses and interaction, summarized in this following table:

Table 3. 5: The means of the responses/interaction.

The mean of the response at different factors and levels (W)	$\bar{y}_{A+}$	$\bar{y}_{B-}$	$\bar{y}_{B+}$	$\bar{y}_{B-}$
	23.34	12.52	17.56	18.30

The mean of the interaction at different factors and levels(W)	$\bar{y}_{AB+}$	$\bar{y}_{AB-}$	$\bar{y}_{BA+}$	$\bar{y}_{BA-}$
	5.9	5.3	-0.26	0.25

Where:

- $\bar{y}_{A+}$: The mean of the response at high level of factor A.
- $\bar{y}_{A-}$: The mean of the response at low level of factor A.
- $\bar{y}_{B+}$: The mean of the response at high level of factor B.
- $\bar{y}_{B-}$: The mean of the response at low level of factor B.
- $\bar{y}_{AB+}$: The mean of interaction of factor A when factor B is in high level.
- $\bar{y}_{AB-}$: The mean of interaction of factor A when factor B is in low level.
- $\bar{y}_{BA+}$: The mean of interaction of factor B when factor A is in high level.
- $\bar{y}_{BA-}$: The mean of interaction of factor B when factor A is in low level.

By replacing coefficients of the equation (3.7) by their calculated values obtained in equation (3.10), the predictive first order linear mathematical model gives the maximum available power response Pm on the considered PV panel:

$$P_m = 17.93 + 5.41\, x_A - 0.3695\, x_B - 0.06185\, x_A x_B \qquad (3.11)$$

As it can be seen in equation (3.11) which represents the predictive first order mathematical model, the influence of the irradiation factor growth in the same direction and it is more significant than the temperature factor (power increases with increased light intensity) since its coefficient is positive and is the greatest. This result is very close to the reality. A negative coefficient for temperature (expected and coincides with PV panel behaviors) suggests power decreases with rising temperature. The response at the center of the study domain is the intercept a_0 = 17.93W at the calculating operating point (Ir = 1305 W/m² and T = 37.8 °C).

By looking in the model, when irradiation is varied from RCV 0 (1305 W/m²) to RCV +1 (1781 W/m²), adding the a_1 coefficient to the central value increases the maximum power. When the irradiation passes from the RCV 0 (1305 W/m²) to the RCV −1 (829 W/m²).

The maximum power response decreases from the central value by the coefficient a_1. The opposite is true for direct surface temperature effect and the interaction, when it goes from RCV 0 (37.8°C) to RCV +1 (45.1°C) the maximum power decreases from the central value, and when it passes from RCV 0 (37.8°C) to RCV -1 (30.5 °C) the maximum power increases.

3.4.2. Graphical analysis

Graphical analysis helps determine the significance and direction of variations in the response based on simultaneous variation in factors. It also makes it possible to confirm the results of the mathematical analysis. This graphical analysis can be presented in the form of slopes of regression lines showing the effects of factors and their interactions, or in the form of a response surface, or even corresponding contour curves [5]. Calculations were performed thanks to Minitab software.

In the cube plot, here in figure 3.1 we can see the study domain that i studied is not orthogonal. That is due to impossibility of mastering the operating points of the PV panel in experiment conditions.

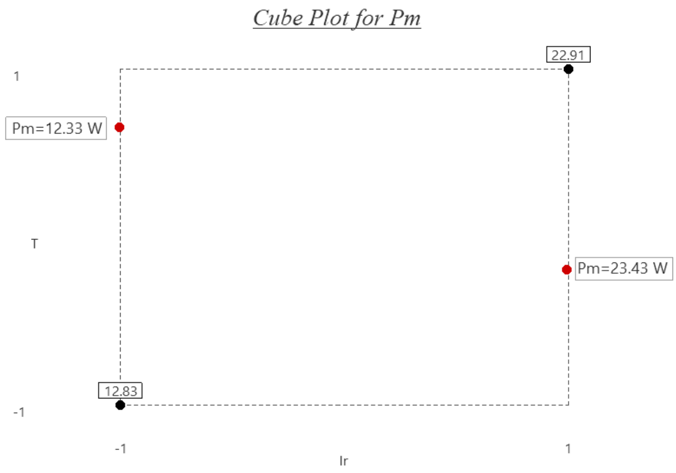

Figure 3.1: Study Domain.

a) Pareto chart

A Pareto chart, also known as the 80/20 rule chart, is a graphical tool that combines a bar graph and a line graph to depict the relationship between factors and their cumulative impact. It named after Vilfredo Pareto, an Italian economist who observed that, in many contexts, roughly 80% of consequences come from 20% of the causes. [36]

Figure 3.2 presents Pareto chart, as shows the factors and interaction effects, factor A, factor B and factor AB. as we can see the most influential Factor is factor A which represents solar irradiation level.

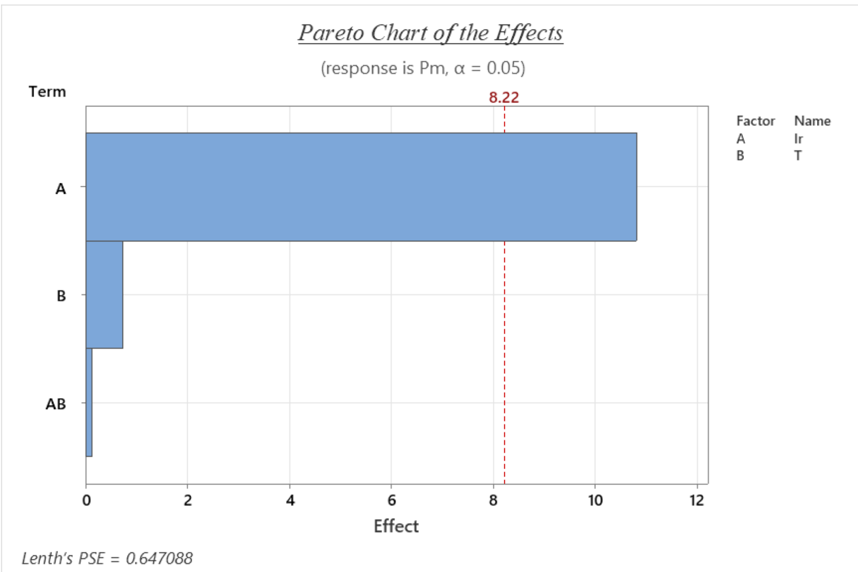

Figure 3. 2: Pareto chart of the effects.

b) Factorial Plots for P_M

The overall effect of a factor is the difference between the average of responses at the high level of the factor and the average of responses at the low level. However, the average effect or effect of one factor is half of the overall effect. [5]

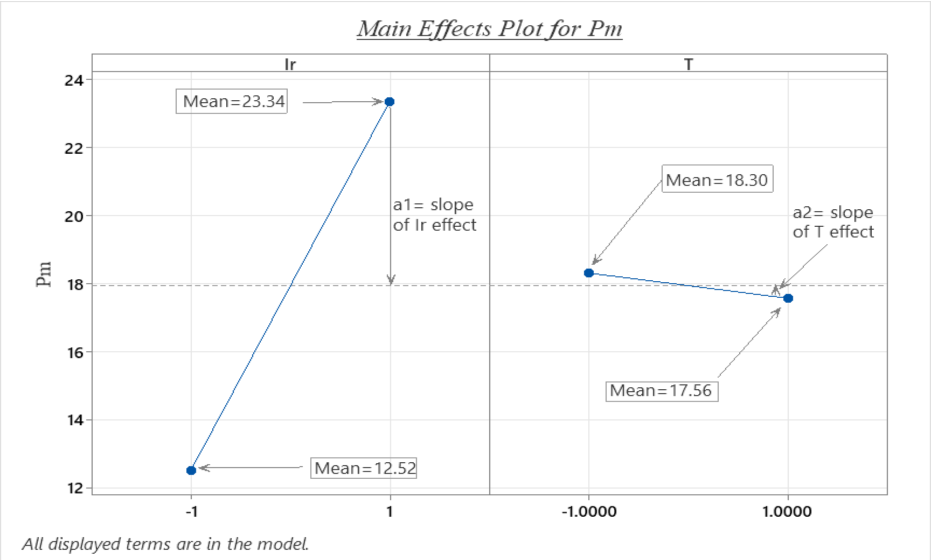

Figure 3. 3: Main effect plots for Pm.

Figure 3.3, on the left side, shows the irradiation varies from level -1 to level +1 the maximum power goes from 12.52 W to 23.34W, with a value of 10.8W, which represents the global effect of factor 1.

Also, figure 3.3, on its right side, there is the plot of PV cell surface temperature, which is influences inversely on the direction of the power response (negative slope). when it varies from level -1 to level +1, Pm decrease from 18.30W 17.56W that is global effect with value of 0.74 W.

These conclusions obtained by the simulations faithfully reflect the reality of the behavior of photovoltaic solar panels.

c) Interaction plots

Indeed, with the theory of experimental designs we can analyze the interaction (mutual) effect between solar irradiation and PV cell surface temperature on the variation of the maximum power response. The interaction effect plot is a set of plots of average effects, each corresponding to a different value of the second variable. If the lines are not parallel or the contour curves are not equidistant over the entire range of the independent variable, then there is an interaction between the two independent variables. [35]

Figure 3.4 presents the interaction effect between factor A and B equal to -0.06158 W. The interactive effect of PV cell surface temperature on solar irradiation, the slope of blue plot represents $\bar{y}_{AB-}$ the mean effect of irradiation when temperature is in the low level (30.5°C) it equal to 5.9W, the slope of red plot represents $\bar{y}_{AB+}$ the mean effect of irradiation when temperature is in high level (45.1°C) and it equal 5.3 W.

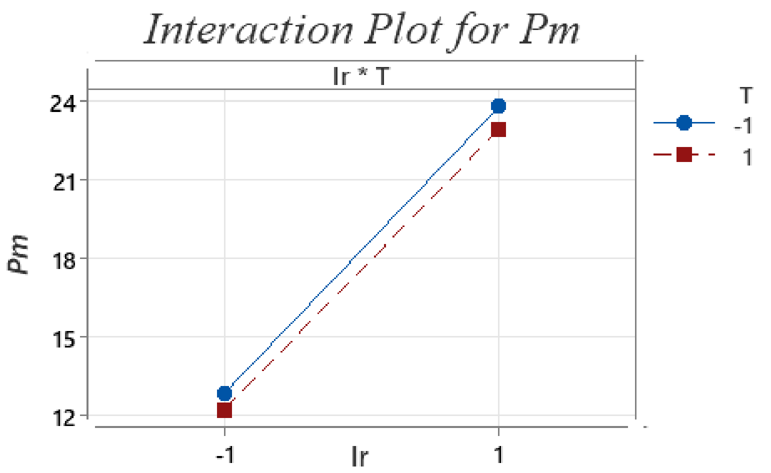

Figure 3. 4: The effect of factor 1 when factor 2 changed.

This figure presents the irradiation/temperature interaction, which means the combined effect of these two variables on the designed response. When the irradiation is 829 W/m^2, the effect of temperature is 0.25 W (blue plot). When the irradiation is 1781 W/m^2 (red plot), the effect of temperature on power is -0.62 W, this means that the effect of irradiation is a little higher when the temperature decreases.

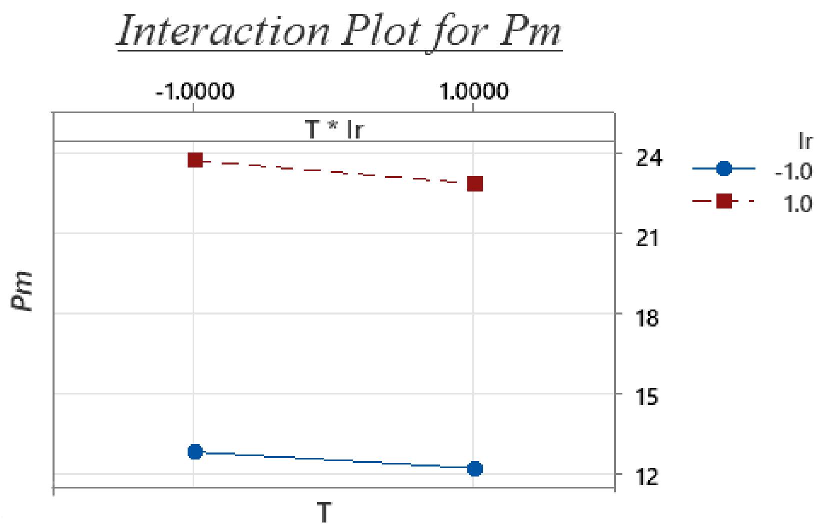

Figure 3. 5: The effect of factor 2when factor 1 changed.

d) Contour and surface plots

Figure 3.6 shows the surface response and the contour curves of the maximum power due to the variation of irradiation levels and surface temperature of PV cell of the considered PV module. From the surface response graph, we see that the variation of the maximum power acts in the same direction of variation of the effect of solar irradiation and in the opposite direction of the variation of the effect of the PV cell surface temperature of the PV module. Moreover, the same note in contour outlines. This highlights of higher dependency on solar irradiation levels compared to PV cell surface temperature where we see a lower dependency.

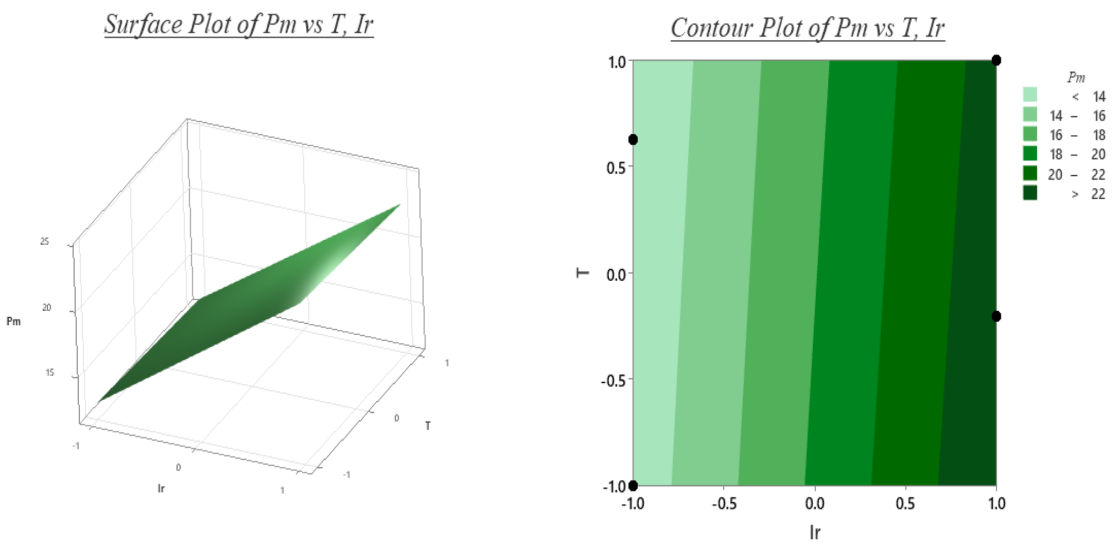

Figure 3.6: Surface response and contour plots of the experiment.

3.5. Modeling the PV panel for Short-circuit current

The same procedures followed during the study of the behavior of the maximum available power response relating to the variation of the two factors sunshine and temperature will be reproduced for the study of short-circuit current and open-circuit voltage responses.

3.5.1. Mathematical analysis

The same theory and factors we apply it to execute the result, and see the effects on the short circuit current (response).

a) Linear regression model

Calculation of the intercept and coefficient is the same way.

$$y_0 = a_0 = 1.267\ \text{A} \tag{2.26}$$

The results of the means of the responses and interaction, summarized in this following table:

Table 3. 6: The means of the responses/interaction.

The Effect of both factors (A)	a_A	a_B	a_{AB}	a_{BA}
	0.3697	0.0098	0.0068	0.0068

The mean of the response at different factors and levels (A)	$\bar{y}_{A+}$	$\bar{y}_{A-}$	$\bar{y}_{B+}$	$\bar{y}_{B-}$
	1.636	0.8971	1.277	1.257

The mean of the interaction at different factors and levels (A)	$\bar{y}_{AB+}$	$\bar{y}_{AB-}$	$\bar{y}_{BA+}$	$\bar{y}_{BA-}$
	0.377	0.3695	0.01	0.0025

The predictive first order mathematical model give the maximum available power response:

$$I_{SC} = 1.267 + 0.3697\, x_A + 0.0098\, x_B + 0.0068\, x_A x_B \qquad (2.27)$$

Like the maximum power response, short circuit current influent by the irradiation more than the temperature, So much, so that we can neglect the effect of temperature and interaction.

3.5.2. Graphical analysis

a) Pareto Chart

The chart here can prove it, as it shows the huge difference between the effects.

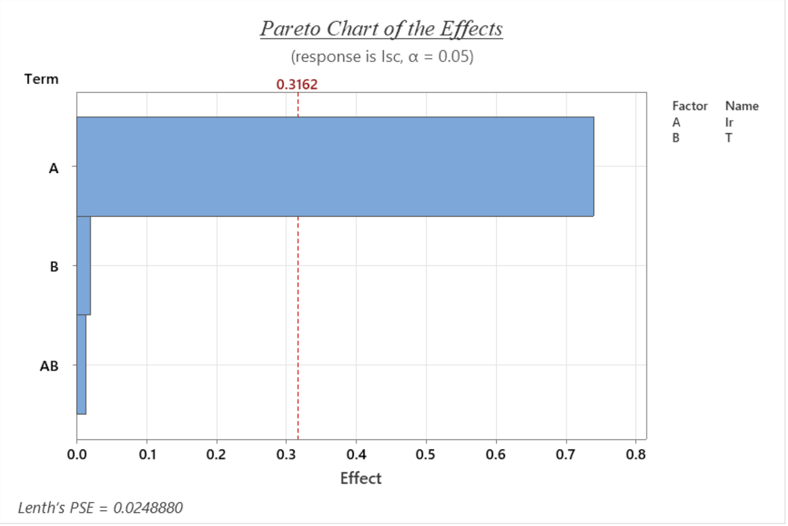

Figure 3. 7: Pareto chart of the effects.

b) Factorial Plots for I_{SC}

The following plots shows on the left, the irradiation varies from level 0 to level +1 the short-circuit goes from 1.267 Amps to 1.636 Amps, with a rising value of 0.369 Amps, which represents the mean effect of factor 1. On the right side of figure 3.8, there is the plot of PV cell surface temperature, when it varies from level 0 to level +1, but the deference between maximum power and short-circuit current that the I_{SC} increase from 1.267Amps to 1.277 Amps that is mean effect with value of 0.01 Amps.

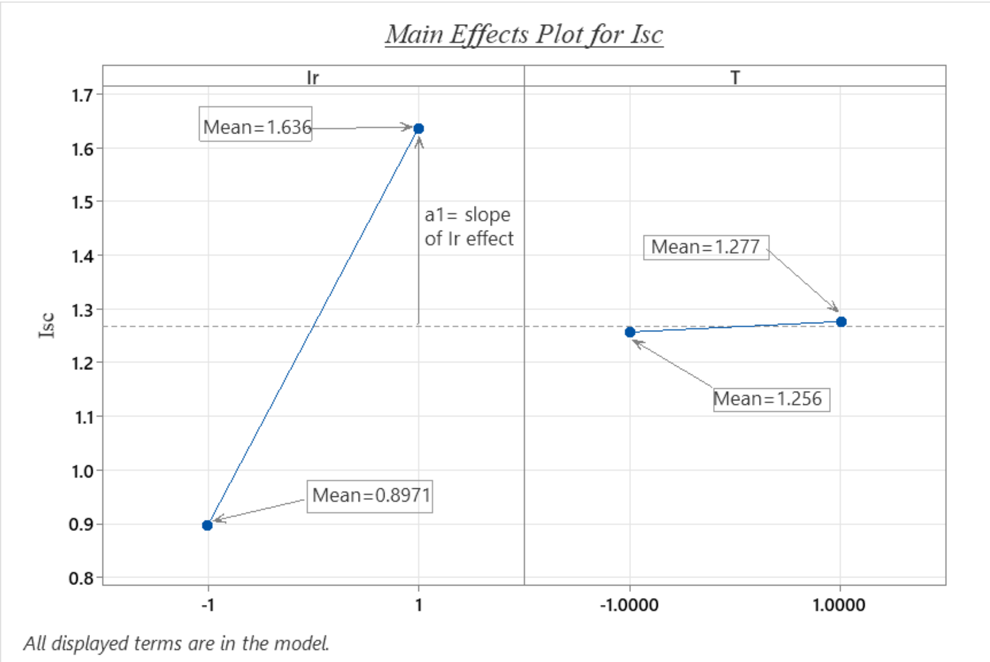

Figure 3. 8: Main effect plots for I_{SC}.

c) Interaction plots

The following figures 3.9 and 3.10 present, the interaction effect between the factors on the response. The difference between the two slopes of the factor responses indicates the presence of an interaction between these two factors but with a very low value dependency. So both temperature and irradiations variations with combined effect affect very low the short-circuit current of the studied PV module.

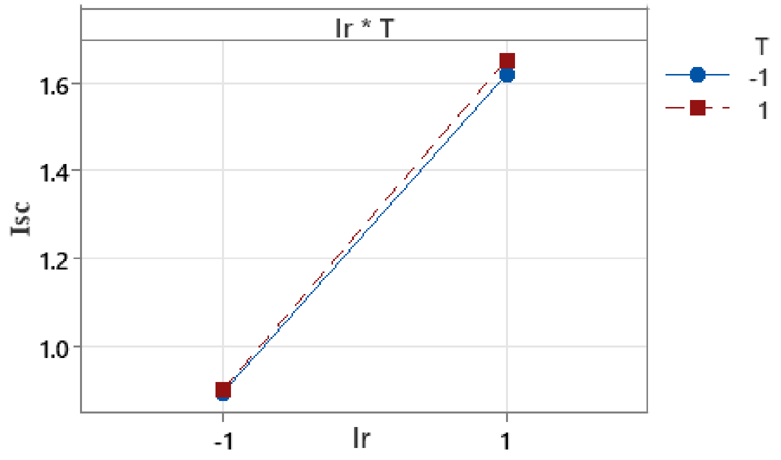

Figure 3. 9: The effect of factor 1 when factor 2 changed.

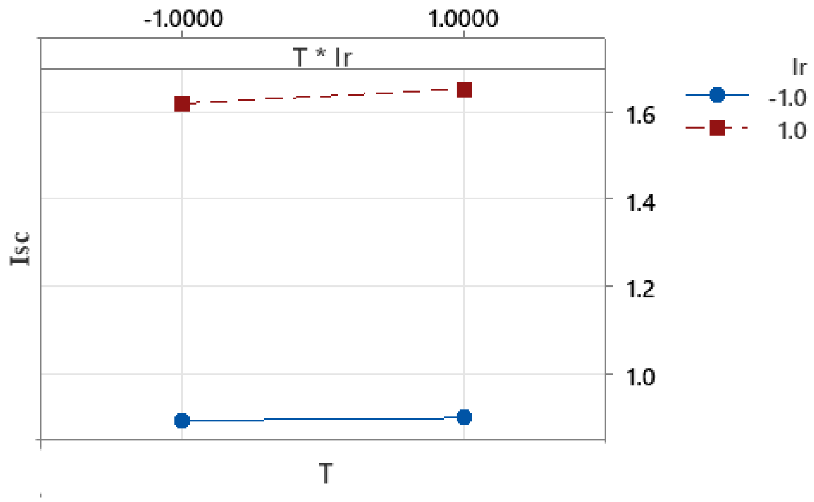

Figure 3.10: The effect of factor 2 when factor 1 changed.

d) Contour and surface plots

The Figure 3.11 present short-circuit current response surface and the corresponding contour plot. This graphic representation thus confirms the behavior of the short-current response as a function of solar irradiation and surface temperature.

The short circuit current is strongly not dependent on temperature variations and increases proportionally with irradiation level variations.

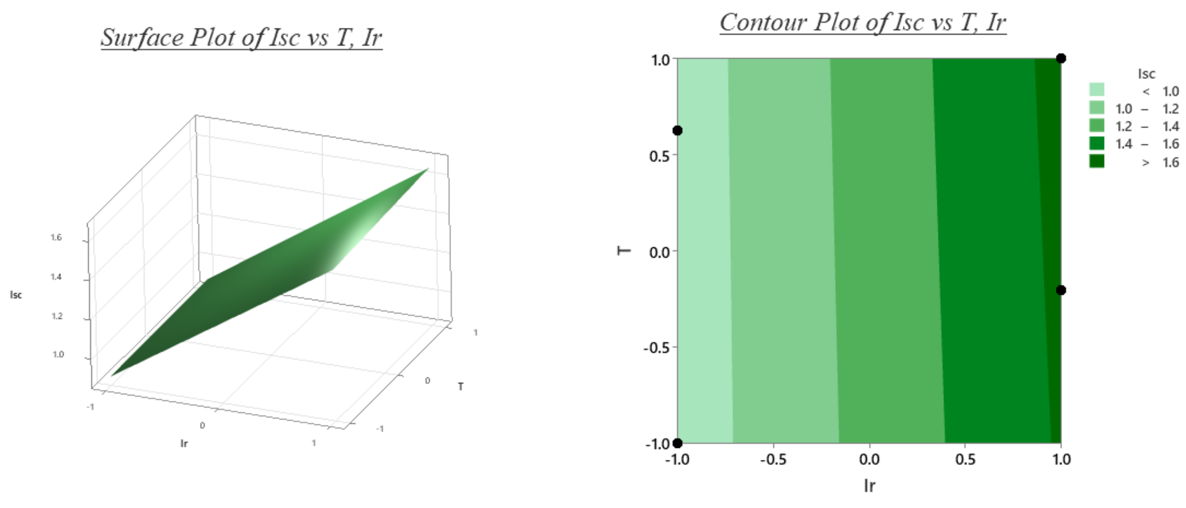

Figure 3.11: Surface response and contour plots of the experiment.

3.6. Modeling the PV panel for Open-circuit voltage response:

From the characteristic curves of the module, it is clear that the open circuit voltage of the photovoltaic module, the point of intersection of the curve with the horizontal axis.

Varies little with solar radiation changes. It is inversely proportional to temperature, i.e., a rise in temperature produces a decrease in voltage.

3.6.1. Mathematical analysis

a) Linear regression model

Calculation of the intercept and coefficient is the same way.

$$y_0 = a_0 = 20.16\,V \tag{2.28}$$

The results of the means of the responses and interaction, summarized in this following table:

Table 3. 7: The coefficients / The means of the responses/interaction.

The Effect of both factors (V)	a_A	a_B	a_{AB}	a_{BA}
	0.2173	-0.5673	0.01344	-0.01344

The mean of the response at different factors and levels (V)	$\bar{y}_{A+}$	$\bar{y}_{A-}$	$\bar{y}_{B+}$	$\bar{y}_{B-}$
	29.23	19.95	19.60	20.73

The mean of the interaction at different factors and levels (V)	$\bar{y}_{AB+}$	$\bar{y}_{AB-}$	$\bar{y}_{BA+}$	$\bar{y}_{BA-}$
	0.1	0	-0.35	-0.45

The predictive first order mathematical model give the maximum available power response:

$$V_{OC} = 20.16 + 0.2173\, x_A - 0.5673\, x_B - 0.01344\, x_A x_B \qquad (2.29)$$

We see from the linear regression model, that the open circuit voltage, unlike other responses it is more affected by temperature more than the irradiation.

3.6.2. Graphical analysis

a) Pareto Chart

The Pareto chart shows that there is no significant effect, but it shows us that the effect of temperature (effect B) is greater than the rest.

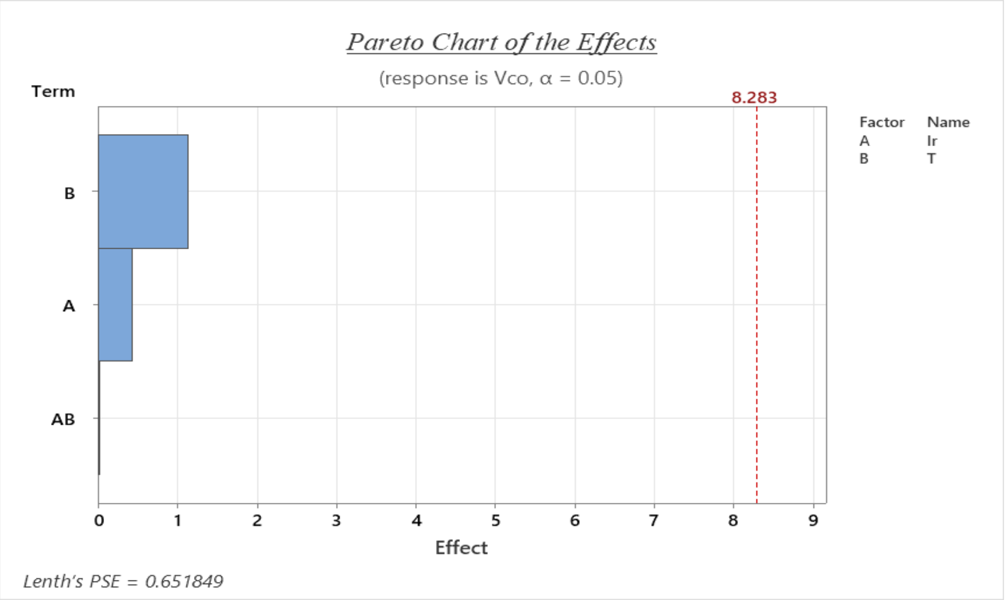

Figure 3.12: Pareto chart of the effects.

b) Factorial Plots for V_{OC}

As it seems very clear in figure 3.13, the effect of the temperature factor acts on the opposite direction to that of irradiation leading to a negative slope showing that the open circuit voltage response increases slowly with irradiation but decreases sharply with temperature.

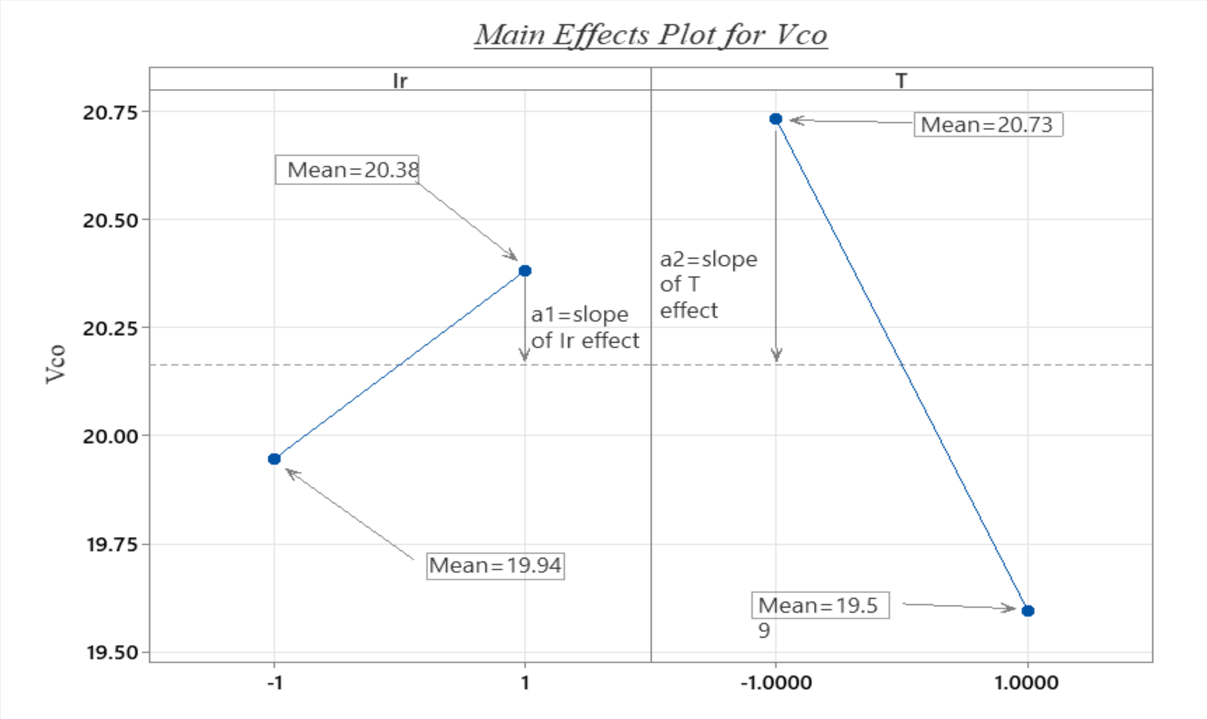

Figure 3.13: Main effect plots for Voc.

c) **Interacting effects plots**

The open circuit voltage presented in the following 3.14 and 3.15 figures, presents a different behavior to those of the other two responses, we notice the existence of a little difference between the slopes of the effects of the factors, hence the absence of a strong interaction between them. So the interactive effect of both input variables (irradiation levels and temperature) on the open circuit voltage response can be neglected.

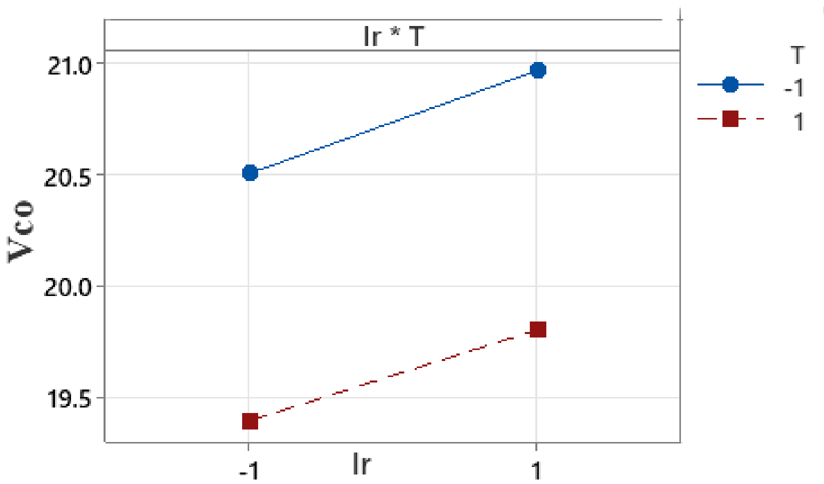

Figure 3. 14: the effect of factor 1 when factor 2 changed.

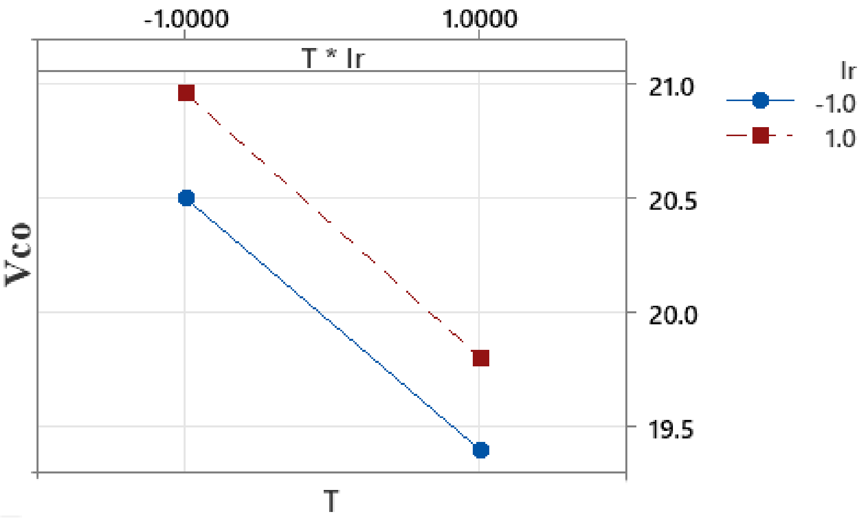

Figure 3. 15: the effect of factor 2 when factor 1 changed.

d) Contour and surface plots:

It is clear in the following 3.16 figure that temperature plays a major role in changing the open circuit voltage.

It greatly affects the studied response because the open circuit voltage decreases when the temperature rises and is directly proportional to the direction of radiation change.

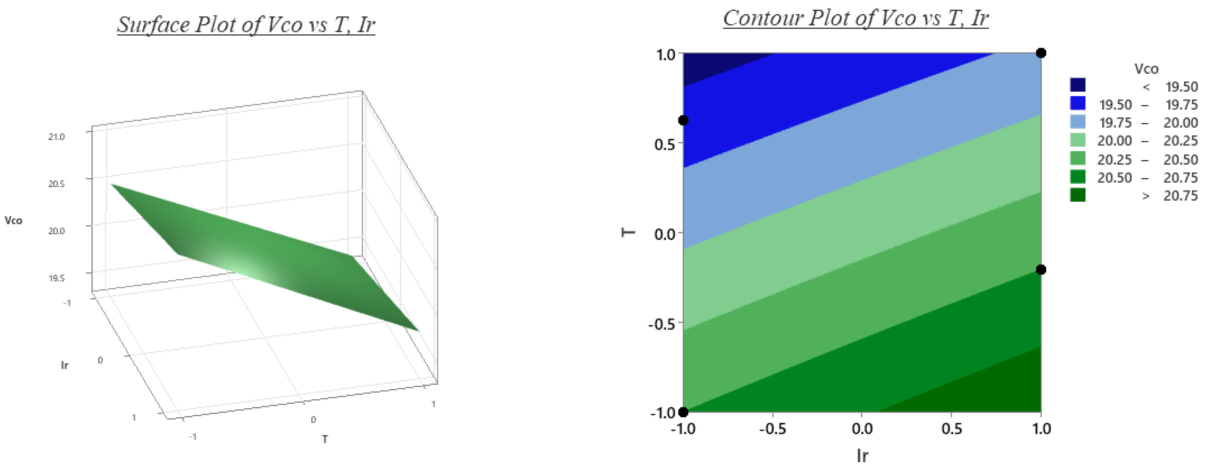

Figure 3.16: Surface response and contour plots of the experiment.

3.7. Conclusion

In conclusion, the utilization of Design of Experiment (DOE) techniques in conjunction with Minitab software offers a powerful framework for modeling the performance of photovoltaic (PV) panels.

By applying methodologies facilitated by Minitab, such as factorial designs, we can effectively identify significant factors and their interactions effects on the response closer to the domain of the study. After results and discussion, we notice that the three responses vary in the same direction of variation of solar irradiation, but differently with the direction of variation of surface temperature.

General Conclusion

General Conclusion

The DoE technique and its implementation in modeling technological processes were effectively utilized. The DoE approach was used for modeling and characterizing photovoltaic modules. By employing this method, the behavior of a monocrystalline PV panel was simulated, showcasing it as a practical modeling technique that necessitates only a few measurements for the input variables (factors) and outputs (response), while yielding satisfactory precision. Data from experiments conducted on a monocrystalline photovoltaic panel were analyzed.

The first chapter covered generalities about the design of experiments were presented, including its principle, the most important designs, and its usage principle. the second chapter, featured an applied example of design of experiments to control the gasoline consumption of Goupy's car was presented, showing how the design of experiments is carried out and how results are extracted both algebraically and graphically manually, without using software, and comparing these results with those calculated using Minitab software. The third chapter involved using DoE for modeling the PS040PR type monocrystalline photovoltaic panel within the Minitab environment.

In this study, radiation levels and temperatures were considered as input factors and compared to the unit's electrical parameters such as maximum power, short circuit current, and open circuit voltage, which were the response variables of the system studied. The DoE concept allowed for accurate predictions of responses based on input factors. Using the 2^2 factorial design method, the direct and combined effects of the temperature and irradiation factors on the three selected responses were highlighted. Furthermore, by comparing the real responses of a PV module obtained experimentally, these behaviors obtained by simulation with factorial design methods were analyzed, explained, and validated. The algebraic calculation using simple linear regression justified the relationship between input and output variables and determined which variables had the most influence on the output variable. Additionally, graphical representations were used to trace the effects of the factors on the studied responses and the interaction effects between the factors.

The study revealed that DoE enables acquiring meaningful information using response surfaces and contour curves within a well-defined study area, obviating the need to conduct experiments at every point within this domain. This signifies that initial limited experiments allow extrapolation of response behaviors across the study domain.

Finally, it was demonstrated that the experimental design approach makes possible to reduce the running time of experiments (reduced number of tests) and the number of executions for modeling a system. Additionally, a wide range of operational information can be obtained with only a few experimental trials. This contribution has shown that the design of experiments approach is a reliable and quality tool that can be easily applied to determine the behavior of photovoltaic system applications.

We recommended to use the mathematical predictive model of the photovoltaic panel during the stages of study, design, installation, and implementation of the systems to provide a future vision of its performance after installation.

References

References:

[1]: J. L. GOUPY, «Methods for experimental design: principles and applications for physicists and chemists», Elsevier Science Publishers B.V, 1993.

[2] : W. TINSSON, «plans d'expériences : constructions et analyses statistiques », Springer, 2010.

[3] : I. YAHIAOUI, «Les plans d'expériences Initiation à la construction et l'analyse des plans factoriels complets à deux niveaux et du plan composite centré», Doctoral thesis, A.MIRA University, Bejaia, 2015.

[4]: F. HANNANE *et al*, «Forecasting the PV panel operating conditions using the Design of Experiments method », Energy Procedia, Vol.36, pp 479 – 487, 2013.

[5] F.Z. KESSAISSIA, «caractérisation et modélisation des cellules, modules et bus continu HVDC photovoltaïque par les plans d'expériences (Design of Experiments method) », 2020, Doctoral thesis, Univ-Chlef, Alegria & Univ-Lorraine, France.

[6] : S. VIVER, «Stratégies d'optimisation par la méthode des plans d'expériences et Application aux dispositifs électrotechniques modélisés par éléments finis», Doctoral thesis, University of Sciences and Technologies of Lille, 2002.

[7] : J. GOUPY, «Plans d'expériences pour surface de réponse», DUNOD, 1999.

[8]: B. DURADKOVIC, «Design of Experiments Application, Concepts, Examples», Periodicals of Engineering and Natural Sciences, Vol. 5, pp. 421–439, 2017.

[9]: J. GOUPY, L. CREIGHTON, «Introduction to Design of Experiments with JMP Examples», SAS, 2007.

[10] : J. GOUPY, «Les plans d'expériences », Revue MODULAD, N° 34, 2006.

[11] : Y. ISMAILI, «Optimisation des conditions d'immobilisation de la lipase candida rugosa (CRL) par la Méthode des Surfaces de Réponse (RSM) », Master Thesis, ECHAHID HAMMA LAKHDAR University of Elouad, 2016.

[12]: R.R. BARTON, L.W. SCHRUBEN, «Graphical methods for the design and analysis of simulation experiments», Winter Simulation Conference, pp 51-61, 1989.

[13] : F. GILLON, « Modélisation et optimisation par les plans d'expériences d'un moteur a commutations électroniques», Doctoral thesis, University of Sciences and Technologies of Lille, 1997.

[14] : T. BELKADI, L.MAKKED, «Traitement des margines d'olives par Co précipitation en utilisant les plans d'expériences», Master thesis, Mouloud Mammeri University of Tizi-Ouzou, 2016.

[15] : J. GOUPY, « Etude comparative de divers plans d'expériences», Revu. Statistique Appliquée, Levallois-Perret (France), pp 5-44, 1990.

[16] : P. TRIBOULET, « Notions de basse sue les plans d'expériences », handout, Lycée Niepce – Chalon sur Saône, 2008.

[17] : J. ROUSSELLE, « Les contours actifs, une méthode de segmentation : application à l'imagerie médicale », Thèse doctorat, Université TOURS, 2003.

[18]: M.H. KUTNER, C. J.NACHTSHEIM, J.NETER, W.LI, « Applied Linear Statistical Models (5th edition) », McGraw-Hill, 2005.

[19]: F. Z. KESSAISSIA, *et al*, « Design of experiments approach for modeling the electrical response of a photovoltaic module », Indonesian Journal of Electrical Engineering and Computer Science, Vol. 20, N° 3, pp. 1140-1147, 2020.

[20]: Akaam, The 5 best design of experiment (DOE) software [online], 2024, [consulted in March 2024], https://medium.com/@akaam_43444/the-5-best-design-of-experiment-doe-software-77f845235f69

[21]: P. YU, M. YIN LOW, W. ZHOUA, «Design of experiments and regression modelling in food flavour and sensory analysis: A review», Trends in Food Science & Technology, Vol. 71, pp. 202–215, 2018.

[22]: D.B. HIBBERT, «Experimental design in chromatography: A tutorial review», Journal of Chromatography B, Vol. 910, pp. 2-13, 2012.

[23]: I.M. FUKUDA, *et al*, «Design of Experiments (DoE) applied to Pharmaceutical and Analytical Quality by Design (QbD) », Brazilian Journal of Pharmaceutical Sciences, 2018.

[24]: A.I. KHURI, S. MUKHOPADHYAY, «Response surface methodology », WIREs Computational Statistics, Vol. 2, pp. 128-149, 2010.

[25]: K. SHAKIR PAK, « Introduction to Design of Experiments », Al Nahrain University, 2019.

[26]: D. GRANTO, V. MARIA, A. CALADO, B. JARVIS, «Observations on the use of statistical methods in Food Science and Technology», Food Research International, Vol. 55, pp. 137-149, 2014.

[27]: F.Z. KESSAISSIA, « Caractérisation et modélisation des cellules, modules et bus continu HVDC photovoltaïque par les plans d'expériences (Design of Experiments method », thèse doctorat, université hassiba benouli, chlef, 2020.

[28]: S. SHINA, **«**Industrial Design of Experiments: A Case Study Approach for Design and Process Optimization**»**, 2022, Springer.

[29]: T.A. REDDY, G.P. HENZE, «Applied Data Analysis and Modeling for Energy Engineers and Scientists, Second Edition», Springer, 2023.

[30]: R.S. KENETT, *et al*, «Industrial Statistics: A Computer-Based Approach with Python», Birkauser, 2023.

[31]: L. KHOUFRANE, «Optimization and Modelling of Biodiesel production from waste cooking oil using design of Experiment», Master Thesis, KASDI-MERBAH University of Ouargla, 2020.

[32]: Minitab Support, [consulted in April 2024], https://support.minitab.com/

[33]: Campbell Scientific Forum, [consulted in May 2024], https://www.campbellsci.in/forum?forum=1&l=thread&tid=2863

[34]: F.Z. KESSAISSIA, *et al*, « Factorial design and response surface optimization for modeling photovoltaic module parameters», Tmrees, EURACA, Athens, Greece, 2019.

[35]: D. C. Montgomery, «Design and Analysis of Experiments (10th ed) », John Wiley & Sons, 2020.

[36]: Institute for Healthcare Improvement, «Pareto Diagram», Institute for Healthcare Improvement, Boston, Massachusetts, USA, 2004.

[37]: M. Abdulkadir, *et al*, «Modeling and Simulation of a Solar Photovoltaic System, Its Dynamics and Transient Characteristics in LABVIEW», International Journal of Power Electronics and Drive System (IJPEDS), Vol. 3, N° 2, pp. 2088-8694, June 2013.

الجمهورية الجزائرية الديموقراطية الشعبية
République Algérienne Démocratique et Populaire
وزارة التعليم العالي والبحث العلمي
Ministère de L'enseignement Supérieur et de La recherche Scientifique

Université de Ghardaïa
Faculté de sciences et technologie
Département automatique et électromécanique

جامعة غرداية
كلية العلوم و التكنولوجيا
قسم الآلية و الكهروميكانيك

إذن بالطباعة (مذكرة ماستر)

بعد الاطلاع على التصحيحات المطلوبة على محتوى المذكرة المنجزة من طرف الطلبة التالية أسمائهم:

1. **الطالب (ة):** بهاز شيماء

تخصص : طاقات متجددة في الكهرو تقني

نمنح نحن الأساتذة :

الاسم واللقب	الرتبة -الجامعة الأصلية	الصفة	الامضاء
شنيني كلثوم	أستاذ التعليم العالي	مصحح (1)	
توافق خالد	باحث رتبة أ	مصحح (2)	
خطارة عبد الوهاب	أستاذ محاضر رتبة أ	مصحح (3)	Khattara
زقاوي عبد الله	أستاذ التعليم العالي	مؤطر	

الإذن بالطباعة النسخة النهائية لمذكرة ماستر الموسومة بعنوان:

"Modeling of PV panel using design of experiments methods"

إمضاء رئيس القسم

العلمي عبد اللطيف
رئيس قسم الآلية
و الكهروميكانيك

جامعة غرداية
قسم الآلية والكهروميكانيك -1-
كلية العلوم و التكنولوجيا

CS CamScanner