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Improving Quality by Optimizing the Controllable Parameters of Industrial Processes Using the Design of Experiments Method

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Abstract

In the last few decades, quality improvement has evolved a lot. It has gone from temporary and limited measures concerning specific aspects of production to a general approach aimed at continuously mobilizing employees around objectives that affect the whole company. The improvement in quality results in innovative modifications in various fields such as the reduction or elimination of the number of faults in the good or service delivered, the reduction of waste (idle time, unnecessary travel, materials, etc..) and increasing the efficiency of work processes. The present research aims to present a study in order to improve quality by optimizing the controllable parameters of industrial processes using the design of experiments method (DoE). Our case study concerns the optimization of the parameters affecting the strength of drawn steel wires using response surface design. We proceed by the screening study after presenting the parameters. Screening study is implemented to eliminate negligible factors so that efforts may be concentrated upon just the important ones. By using response surface design on NEMRODW software, we developed a model that is validated statistically and experimentally through experience and ANOVA analysis. The correlation coefficient of this model (developed at 95% confidence interval) was calculated as 98.8%. This higher correlation coefficient explains the good agreement between estimated and experimental strength of drawn steel wires and then proved the strength of DoE methodology.

Keywords: *Design of Experiments, Response Surface Design, Optimization, Quality, Six Sigma, ANOVA Analysis, Strength of drawn steel.*

1. Introduction

Companies in the manufacturing industry today are faced with increasing challenges with respect to cost effectiveness, lead time and quality of the production system. Nowadays, it is essential for companies to engage in foreign markets, looking for much more efficient and creative business process management. Companies are achieving these goals of efficiency always more by using the offshoring strategy and new innovative approach.

In our present work, we are interested in quality control, as being part of the quality circle, and its “dynamic” relationship to the optimization of the operating parameters of industrial processes, by exploiting the production history and feedback from responsible departments. In a Six sigma approach, experience plans are generally implemented in the "Improve" phase of the DMAIC method. The Six Sigma approach is used in order to achieve production excellence at the quality level. In the industrial field, process improvement aims to determine the influencing factors in the design of a new product or process, optimize the settings of a manufacturing process, or even to predict the behavior of a process once the system modeling obtained. Experience planning is a discipline still little known in the production sector, but which is above all a methodology applied in the industrial field. It’s a Six Sigma approach that efficiently organizes industrial or scientific data.

Thanks to the deployment of quality in companies and easier access to computing resources, experience plans are taking on a more important place. The applications of Designs of Experiments (DoE) are becoming more and more numerous. This methodology will help the experimenter to structure his experimental approach in a different way, to compare and validate his own hypotheses, to better understand the phenomena studied and to solve the problems.

The manufacture of frames especially the drawn steel wires is a sector characterized by competitiveness increasingly fierce. Nowadays, more than ever, companies operating in this field are obliged to improve their industrial performance.

Wire drawing uses two concepts: traction and wire. It is a cold working process of passing the metal through an

orifice called "pipeline" under the action of a continuous traction. This technique uses the ability to plastically deform the metal.

The mechanical properties are retained on the drawn wire, more generally, those of traction and, in special cases, hardness, reversed bending and torsion [1].

Given the importance of the strength as a sign of good quality of drawn steel wires, in fact, strength should be over and above 550 N/mm², and as part of a continuous improvement process, we will introduce in this article, a uniform set of tools and algebraic statistical methods to establish and analyze the relationship between the studied variable (strength) and sources of expected changes (factors).

To achieve this objective, we conducted a research background on response surface design and experiments done, then we realised the screening study to select the most influential factors that will be concerned on the optimization plan. In this study, the second section presents the optimization plan using response surface design.

The aim of the present study is to optimize the six parameters affecting the strength of drawn steel wires using response surface design. The paper is structured as follows: firstly there is a brief research background on response surface design and experiments done, followed by the screening study to select the most influential factors that will be concerned on the optimization plan; secondly, the optimization plan has been done using response surface design. The third section shows the ANOVA analysis and results. Finally, the paper concludes with a summary and perspectives.

2. Research Background

The design of experiments method is both new and old [2]. New to mechanical and electronic engineering, which traditionally is carried by exact sciences. We realize today that far from denying technical knowledge, the method of experimental plans values it. Initially developed and put into practice by the British Mathematician Sir Ronald Fisher [3], in the early 1930s, the experimental designs were used to quantify the effect of the factors controlled by the experimenter in a context subject to numerous sources of heterogeneity. After 1945, the experimental plans gave rise to numerous publications and researches in the Anglo-Saxon world. Statisticians like Yates, Cochran, Plackett and Burmann, enrich and disclose the method [4-6]. Box and Hunter [7], building on the work of Yates [5], develop specific methods for constructing fractional experiment plans at two levels (screening). They were interested in the study of quantitative factors and introduced, in the 1960s, response surface models associated with planes such as centered composite planes.

However, at the time, only specialist statisticians could implement these methods. Starting in the 1950s, Japan began to breathe new life into its efforts to improve quality. Taguchi and Masuyama are developing tables for constructing experimental plans adapted to the majority of industrial problems [8, 9]. Taguchi's credit is for contributing to an easy-to-apply methodology. Initially difficult to access, these methods can be adapted, popularized to conquer an increasingly large circle of users.

The applications of experimental designs are currently tending to diversify; so we see the emergence of new plans. Their wide dissemination in companies, their teaching and their applications in universities are still in their infancy. The effort brought by Taguchi continues and more and more user-friendly software intended for the construction and analysis of experimental designs is being developed.

2.1 Variables and domain of study

For the mathematical transcription of the initial physical problem, mathematical variables are made to correspond to physical quantities (electrical, mechanical, thermal, etc.) supposed to intervene in the problem. We define the following terms:

Factors: An input parameter of a system (input variable) is called factor X. This factor is a possible cause of variation of the response Y.
The factors are fully characterized by the two values:
Lower bound (L_b): low limit (or low level) of the values that the factor can take;
Upper bound (U_b): upper limit (or high level) of the values that the factor can take;

Response: The response Y (output variable) corresponds to an output parameter of the system studied. An answer must be representative, quantifiable and as sparse as possible for controlled and constant input variables. To apply the methodology of the experimental plans, it is advisable to have a response expressed in quantitative form. Indeed, the methods of analysis of test results such as analysis of variance or regression analysis in the sense of least squares, are based on exclusively quantitative data. In addition, qualitative responses such as, for example, the morphology of a deposit (smooth, porous, etc.) which is not a quantitative criterion, can be interpreted using specific coding of the response methods.

Factors and responses are the only variables to intervene in the writing of experiment plans. DoE is indeed a tool for

establishing mathematical relationships between responses and factors (only).

The set of all the values that the factor can take between the low level and the high level, is called the domain of variation of the factor or more simply the domain of the factor. We usually write the low level by –1 and the high level by +1.
If there is a second factor, it is also represented by a graduated and oriented axis. We define, as for the first factor, its high level, its low level and its range of variation. This second axis is arranged orthogonally to the first. We thus obtain a Cartesian coordinate system which defines a two-dimensional Euclidean space. This space is called the experimental space.

The level X_1 of factor 1 and the level X_2 of factor 2 can be considered as the coordinates of a point in the experimental space. A given experience is then represented by a point in this system of axes. An experimental plan is represented by a set of experimental points.

The grouping of the domains of the factors defines the "domain of study or the experimental domain". This area of study is the area of the experimental space chosen by the experimenter to carry out his tests. A study, that is to say several well defined experiences, is represented by points distributed in the field of study.

2.2 Methodological approach to a DoE

Any experiment must be the object of a precise planning which is concretized in the form of a plan of experiments or experimental protocol. The methodological approach of a PE includes the following six steps [10, 11]:

1. Definition of objectives and responses

Taking into account the objectives to be achieved, it is first necessary to list the experimental responses that can be studied. This stage also makes it possible to set up the means and the budget necessary for the study.

2. Choice of factors and experimental area

This is the most important step in carrying out an experiment plan. It is necessary:
• Select the parameters, choose the methods and interactions to study;
• Identify the parameters that can influence the response and fix their methods;
• Identify the interactions likely to be sought;
• Dissociate the controlled factors from the noise factors;
• Set the area of study and the levels for each of the factors controlled.

3. Choice and construction of the experiment plan

The plan best suited to the situation will be chosen. It must have the following properties:
• Represent the experimental response studied in the experimental field well;
• To arrive at an acceptable quality estimate for the value of the response studied.

4. Estimation of effects

The value of the experimental response should be able to be estimated with acceptable quality at any point in the experimental area of interest.

5. Validation of the model

• A model is validated means that it represents the phenomenon studied in the experimental domain well enough and in this case, the objectives are achieved: we can use this model to make predictions at any point in the experimental domain;
• Once the model is validated, the optimal conditions for the studied problem can be sought, that is to say the values of the factors which minimize, maximize, or ensure a target value for the studied answer.

6. Implementation and monitoring

• The calculation of the response is possible at any point in the experimental field;
• From the calculated model, we can predict the results corresponding to the optimal configuration of the product or process.

2.3 Construction of the DoE

The DoE approach is often of major interest in the development of complex technology. The goal is to model the behavior of processes and / or products in order to better predict and increase their performance. The experimental modeling must make it possible to define the conditions of optimal use and to determine the factors to control or to pilot in order to control the process. Like the development of a manufacturing process and / or products, optimization requires the construction of an experimental model.

The method of experimental plans is essentially based on the creation and use of models of the objective function (response). It is therefore natural to analyze in detail this essential component.

The objective is the formatting of a model, most often polynomial, describing the variations of the response function taking the values, relative to the values of factors.

$$y = f(x_1,...,x_k) \quad (1)$$

With:

• N: the number of experiences;
• p: the number of coefficients of the postulated model;
• y: the column vector of the experimental responses.

2.4 Response Surface Design and ANOVA analysis

The experiences plans method can be used in two types of investigations :

- Screening,
- Response surface design.

The screening technique enables us to determine, among the factors identified by the experimenter, who have a statistically significant influence on changes in response. This is done implicitly to simplify the problem.

In one application of the response surface methodology (RSM), variations in the response are calculated based on the factors and interactions previously considered influential.

Response surface methodology is a collection of statistical and numerical optimization techniques used to optimize processes and product designs. The original work area dates from the 1950s and has been widely used, especially in the chemical and process industries [12].

Once we obtain a model, we should ensure its validity using Anova analysis.

The analysis of variance 1 , is to compare using a Fischer test the sum of squared deviations due solely to the regression (ie the model), with the sum of squared residuals . Ie comparing the residual variance (V res) or not explained to the variance due to regression (V reg). The statistical test is as follows :

- **H_0 : Vreg ≈ Vres** (Which proves that the regression is not significant)
- **H_1 : Vreg>Vres (**Regression is global significant).

Fisher test **F** then compares to a risk fixed in advance **Fobs** (**Vreg** / **Vres**) which is calculated with **F** (critical) read on Fisher's table with (p -1) and (n - p) degrees of freedom (p: number of samples , n: number of observations)[13]. The test rule is then selected for a risk α:

- If **Fobs** is lower than **F** (critical), the hypothesis **H_0** is accepted.
- If **Fobs** is over than **F** (critical), the hypothesis **H_1** is accepted.

The analysis of variance 2 is to compare the possible existence of a lack of fit. That is to say comparing the variance or model error (**Vlof**) to the variance due to pure error (**Vpe**) . In order to perform this test, it is necessary that at least one experiment was duplicated. The statistical test is as follows:

- **H_0 : V_{LOF} ≈ V_{PE}** (The model does not present an adjustment default, it is predictive)
- **H_1 : V_{LOF}> V_{PE}** (The model has a defect of adjustment, it is not predictive).

The test rule is then selected for a risk α:

- If **Fobs** is lower than **F** (critical), the hypothesis **H_0** is accepted.
- If **Fobs** is over than **F** (critical), the hypothesis **H_1** is accepted.

2.5 Parameters affecting the strengh of drawn steel wires

Various parameters can influence the strength of drawn steel wires.

The steel wire starts with a reel where there are two factors controlling this passage: the slit S and the pressure of the detector loop, then the wire goes to the lubrication step, later, this wire is treated in the cold rolling block according to many parameters such as: oscillating drum pressure and speed control, and finally the wire is wound in coil form and at this level will have one factor which regulates it: traction force of the winder.

3. Case study and Results

Optimal quality, reduced costs and faster time to market are major challenges for the armature industry.

To this end, companies are constantly improving their technologies. In particular, they take care to eliminate the causes of their customers' dissatisfaction. They seek to become the market leader and to do this, it is necessary to increase the production and especially the quality of their products by reducing the rate of hazards, hence the need to optimize the settings of parameters that can influence the

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quality of the product and implement different quality control tools, because a high defect rate can only negatively influence the credibility of the company and cause it considerable losses.

In order to ensure a better quality of the drawn steel wires, and in the framework of an improvement and an optimization of the process, we decided to exploit our knowledge namely the method of the experimental plans, to reach quality as good as possible.

This study is based on a single case-study research: an optimization study of the strength of drawn steel wires using response surface design. The study aims to determine mathematical models approached the response expressed by the factors.

The six parameters generated and affecting drawn steel wires, and their fields of variation are presented in the table 1.

After setting the influential parameters, we ought to measure strength of drawn steel wires in the society quality laboratory performing tensile tests on the finished product. The test consists in subjecting a test piece to a deformation due to a tensile force ; using an extensometer ; generally up to rupture, for determining one or more mechanical properties (See Figure 1). Results are obtained by using a software attached to the machine, according to the following chart presented in Figure 2.

This analysis will be qualitative: screening study (determination of influential factors) followed by a quantitative study: methodology of response surface. The third part presents the model developed, ANOVA analysis and results.

Table 1: Factors set and their areas of change

Factors	Number of levels	Levels
X1 : Pressure of the detector loop (Bar)	2	0,5
		0,8
X2 : The slit S (Mm)	2	7,2
		9,4
X3 : Layer of lubricant (cm)	2	8,0
		9,0
X4 : Oscillating drum pressure (Bar)	2	1,2
		1,4
X5: Speed control (m/s)	2	6,0
		8,0
X6: Traction force of the winder (N/mm2)	2	1500
		1850

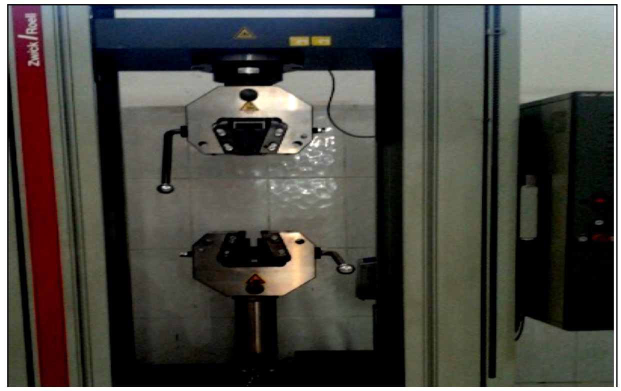

Fig. 1. Machine tensile testing

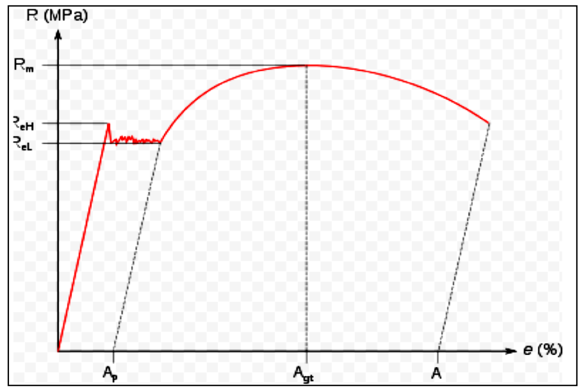

Fig. 2. Graph of mechanical properties

3.1 Screening study

Preliminary studies carried out by H. Hidalgo [14] in collaboration with F. Louvet, have made it possible to study the weight of the factors thanks to an experimental plan called a screening plan.

In the case of six parameters at two levels, it is necessary to make a screening study using the best known screening experiments matrices for factors at 2 level : Hadamard or Plackett and Burman (1946) matrices, this plan requires eight tests in case of six factors. The characteristics of the problem are presented in Table 2.

The postulated model is a model of first degree without interaction as shown on (2):

$$Y = b_0 + b_1 * X_1 + b_2 * X_2 + b_3 * X_3 + b_4 * X_4 + b_5 * X_5 + b_6 * X_6 \quad (2)$$

The results of experiments are summarized in Table 3.

Nemrodw Software gives us the weights effects graph presented on Figure 3. It clearly shows that the speed factor and the pressure of the loop detector had a significant influence on the strength. Pareto diagram presented on Figure 4 confirm this conclusion.

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Table 2: Problem characteristics

Aim of study	Screening study
Number of variables	6
Number of experiments	8
Number of coefficients	7
Number of responses	1

Table 3 : Design of Experiments

N° Expérience	X_1	X_2	X_3	X_4	X_5	X_6	Y(Rm)
1	0,8	9,4	8	1,2	8	1850	535
2	0,5	9,4	9	1,4	8	1500	549
3	0,5	7,2	9	1,2	8	1850	560
4	0,8	7,2	9	1,4	6	1850	573
5	0,5	9,4	8	1,4	6	1850	599
6	0,8	7,2	8	1,4	8	1500	573
7	0,8	9,4	9	1,2	6	1500	564
8	0,5	7,2	8	1,2	6	1500	597

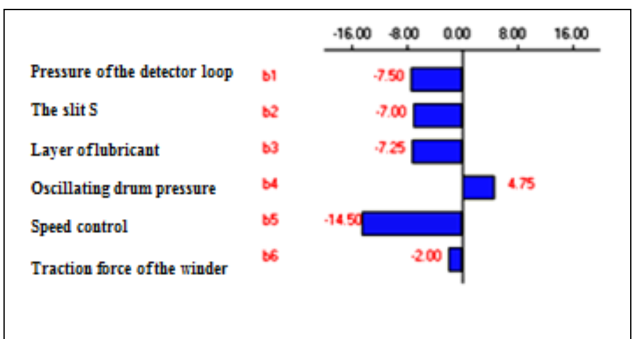

Fig. 3. Weights effects graph

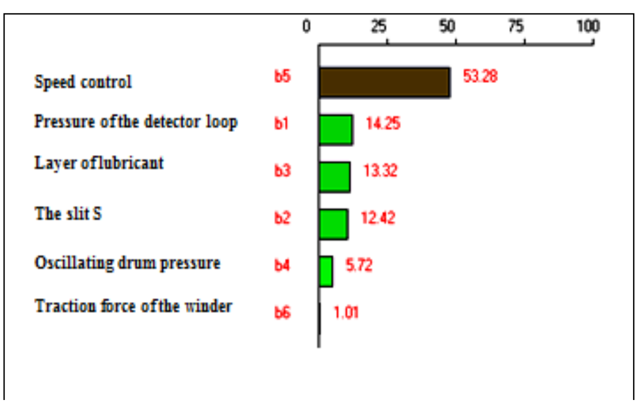

Fig. 4. Pareto diagram

After analyzing the results of this screening level, we find that:

- The speed factor has a significant influence on the resistance.
- The factor of the loop detector Pressure also has a significant influence on the response.

3.2 Optimization plan

We retained, compared to the screening study, some fixed parameters (deemed irrelevant to the reply), other variables with a slight change of setting.

The range of operability is grouped in the table 4.

We propose in this study a model of the second degree. Our choice fell on a central composite design. This plan requires 9 trials.

A composite design consists of three parts:

- A factorial design whose factors are two levels.
- At least one experimental point in the center of the study area (in our case we put 3 points in the center);
- Axial points these experimental points lie on the axes of each of the factors.

The characteristics of the problem are summarized in Table 5.

Table 4 : Factors set and their areas of change

Factors	Center	No variation
Speed control	7	1
Pressure of the detector loop	0,65	0,15
Slit S	7,2 Fixe	
Traction force of the winder	1500 Fixe	
Oscillanting drum pressure	1,2 Fixe	
Layer of lubrificant	8 Fixe	

Table 5 : Problem characteristics

Aim of study	Response surface design study
Number of variables	2
Number of experiments	9
Number of coefficients	6
Number of responses	1

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The applied mathematical model is a quadratic model with interaction as shown in (3):

$$Y = b_0 + b_1 * X_1 + b_2*X_2 + b_{11}*(X_1*X_1) + b_{22} * (X_2*X_2) + b_{12} * (X_1*X_2) \quad (3)$$

The table 6 gives the design of experiments.

3.3 Results and discussions: ANOVA analysis

The table 7 shows the results of the analysis of variance of the response.

The ANOVA 1 shows that the regression does not explain the phenomena studied since the significance of the risk is greater than 5 % , and since:

H_0 : Vreg ≈ Vres ➔ Which proves that the regression is not significant.

So the model postulated is not validated.

The table 8 represents the standard deviation of the response and the two correlation coefficients.

The model coefficients for the response are summarized in the table 9.

According to the Table IX, there is no significant coefficient except b_0 term.

This is explained by the presence of outliers. Both experiments 4 and 11 seem to be the problem.

The two points were eliminated by referring to the graphic residue analysis and the straight line of Henry (See Figure 5 and 6). This two points are red and circled.

Table 6: Design of Experiments

N° Expérience	**Speed (m/s)**	**Pressure of the detector loop (Bar)**	**Strength (N/mm²)**
1	6.0000	0.5000	717
2	8.0000	0.5000	562
3	6.0000	0.8000	600
4	8.0000	0.8000	619
5	5.5858	0.6500	686
6	8.4142	0.6500	727
7	7.0000	0.4379	553
8	7.0000	0.8621	648
9	7.0000	0.6500	558
10	7.0000	0.6500	551
11	7.0000	0.6500	713

Table 7: Analysis of the variance of the response

Variance Source	**Sum of squared ($\times 10^4$)**	**Degrees of freedom**	**Mean squared ($\times 10^3$)**	**Ratio**	**Signif. %**
Regression	2.24446	5	4.48893	0.8050	59.2
Residues	2.78799	5	5.57598		
Validity	1.11072	3	3.7024	0.4415	74.8
Error	1.67727	2	8.38633		
Total	5.03245	10			

Table 8: Correlation coefficients and standard deviation of the response

Response standard deviation	74.672
R^2	0.446
R^2A	N.D

Table 9: Model effects of the answer

Name	**Coefficient**	**Significance %**
b_0	607.334	0.0135***
b_1	-9.752	72.5
b_2	9.924	73.6
b_{11}	42.334	23.5
b_{22}	-10.667	74.5
b_{12}	43.500	29.7

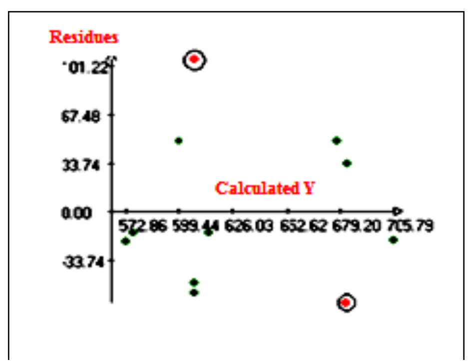

Fig. 5. Graph of residues

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Variance Source	Sum of squared	Degrees of freedom	Mean squared	Ratio	Signif. %
Regression	4.22686E+4	5	8.45373E+3	47.5302	0.0460
Residues	5.33580E+2	3	1.7786E+2		
Validity	5.09080E+2	2	2.5454E+2	1.0387	22.2
Error	2.45000E+2	1	2.4500E+2		
Total	4.28022E+4	8			

Response standard deviation	13.336
R^2	0.988
R^2A	0.967

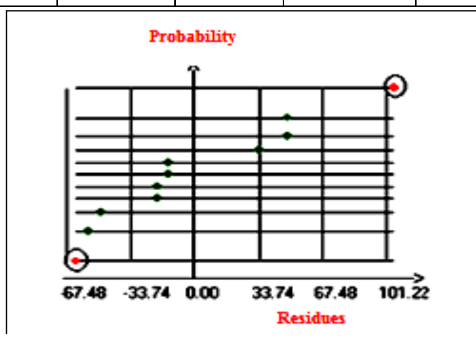
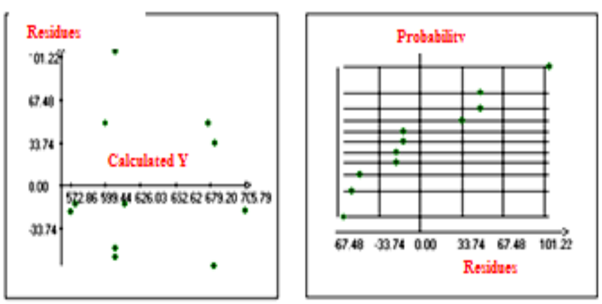


Fig. 6. Graph of the straight line of Henry

The table 10 shows the results of the analysis of variance of the response after the removal of the two points 4 and 11.

According to the table of the analysis of variance, one can conclude that:

The ANOVA 1 shows that the regression explains the phenomenon well studied since the meaning of risk is less than 5:



H_1 : Vreg>Vres ➔ Which shows that the regression is significant.

The ANOVA 2 shows that the model made fewer errors than testing since the significance of the risk is greater than 5%, so it is predictive.

H_1 : VLOF = VPE ➔ The model does not present an adjustment default, it is predictive.

Name	Coefficient	Significance %
b_0	554.5	<0.01***
b_1	11.262	13.00
b_2	30.308	0.993**
b_{11}	79.258	0.0738***
b_{22}	26.257	2.44*
b_{12}	85.529	0.152**

The table 11 represents the standard deviation of the response and the two correlation coefficients.

The model coefficients for the response are summarized in the table 12.

There is a remarkable improvement in the coefficients.

Graphs of residues and the straight line of Henry confirmed the validity of the model for the studied response (See Figure 7).

Table 10: Analysis of the variance of the response

Table 11: Correlation coefficients and standard deviation of the response

Table 12: Model Effects of response

Fig. 7. Graphs of residues and the straight line of Henry

Since the majority of factors are significant, we will hold them all in the postulated model.

The model is the following (4):

$$Y = 554.5 + 11.262 * X_1 + 30.308 * X_2 + 79.258 * (X_1*X_1) + 26.257 * (X_2*X_2) + 85.529 * (X_1*X_2) \quad (4)$$

The priori postulated model is validated statistically. To verify it experimentally in order to exploit it for possible prediction, we will test this model via test points.

Experimental point coordinates		**Response : Strength**	
X_1	X_2	***Predicted Y***	***Experimental Y***
8.23	1.36	795±16.41	781

Table 13: Experimental and predicted value for the test item

In this regard, we conducted several trials. The table 13 gives the experimental results and the theoretical result given by this model. The results presented in Table 13 clearly show that there is no significant difference between the experimental response and that predicted.

The model applied was statistically and experimentally validated which gives it the descriptive quality of the phenomenon.

Comparing the experimental result and predicted one makes the model predictive.

So we recommend using this model with confidence to predict the response anywhere in the experimental field.

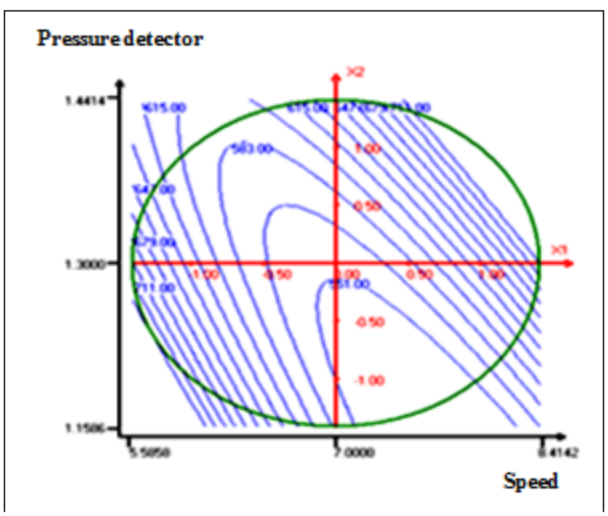


Fig. 8. Response surface

4. Conclusions

The DoE method is made up of safe, practical tools allowing the study to be carried out with the greatest possible efficiency in which many parameters are involved. Given these advantages, we have used this methodology to optimize the parameters influencing the resistance of drawn steel wires.
In our application, a screening study, a response surface design and an ANOVA analysis were used to optimize the resistance of the drawn steel wires. The six parameters affecting the resistance of the drawn steel wires were the subject of a screening study carried out to select the most influential parameters. These most influential parameters participated in the optimization study using the design of response surfaces. To guarantee the validity of the postulated model, we have developed the ANOVA analysis. The correlation coefficient for this model (developed at a 95% confidence interval) was calculated at 98.8%. This higher correlation coefficient shows great consistency between the experimental and estimated values. Consequently, the approach presented in this study can be considered as a paper method for optimizing the resistance of the drawn steel wires.
Future researches will be conducted to develop other models that could increase the accuracy for the strength of drawn steel wires estimation and predict optimum parameters that maximize this strength.

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