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Modeling and Optimization of Heat Treatment Process in Steel Wire Used in the Manufacture of Automotive Springs

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Abstract:
The aim of this work was the creation of a statistical modeling, able to override the process used for the preparation of hardening and tempering ovens, which traditionally is performed by means of adjustments from results of mechanical properties, tested in the laboratory and required on customer specifications. We sought to understand the influence of input variables (factors) in the limit mechanical properties tensile strength, hardness and yield, in SAE 9254 steel wires, to the diameters 2.00 mm and 6.50 mm, used in the manufacture of clutch and valve springs for automotive. The main variables were investigated the case diameter, speed, temperature of tempering and quenching medium concentration, for this, we used the methods of design of experiments with block and multiple regression Analysis. For optimization of the methods were used statistical models, Generalized Reduced Gradient Desirability (GRG), Genetic Algorithm (GA) and the Meta-heuristics Simulated Annealing. The results revealed that all variables considered to have significant influence and the models were validated using appropriate statistical methods. This modeling and its optimization, if implemented and applied correctly, can lead to scientific advances which would provide the automation of this process.

Keywords: *Heat Treatment, SAE 9254, Design of Experiments, Statistical Modeling; Meta-heuristic.*

1. Introduction

Currently, due to the high speed of scientific advances, increasingly required the application of statistical methods for the optimization of industrial processes, as these impact on minimization of experiments, on cost reduction for companies and through the use of statistical models it is possible to determine the best processing conditions impacting directly on quality and productivity.

The problem of the research is characterized by the absence of statistical models, in the literature, that represent the mechanical results in drawn steel wire SAE 9254, quenched in liquid polymer (means of quenching) and tempered in liquid lead, as steel mills have sought to develop these models to reduce the amount of laboratory tests and the setup time of the ovens, which would mean a reduction of costs for company.

In this article, the statistical methods were used to assist in the development of a statistical modeling to come replace the traditional way of error-attempt at adjusting the input variables of the heat treatment oven. In the case in question, the initial setting (setup) are accomplished through the testing of mechanical properties (tensile strength limit, yield and hardness) in a sample-pilot who, after going through all the stages of a heat treatment quenching and tempering, was sent for laboratory analysis.

The results of limit of tensile strength and hardness obtained in this step are used to setting of the oven inside which makes a second pilot sample, to confirm that the settings of the process were enough so that the product would achieve the mechanical specifications, while the values obtained from yield are only used for verification in relation to customer specifications. This implies considerable operating routine analysis and waiting time, reducing the productivity of the process due to low income, since the oven remains inoperable until it is configured.

2. Process of Heat Treatment and Testing

According to Callister (2012), quenching is related to sudden cooling after heating steel to the austenitizing temperature and aims to obtain a microstructure that gives mechanical properties, such as hardness and tensile strength limit for specific applications that require this condition. During the cooling stage in quenching the temperature drop promotes structural changes that result in the emergence of internal tensions and so it is necessary the realization of tempering.

The tempering involves a series of micro structural transformations that tend to thermodynamic equilibrium. It is, therefore, a thermally activated process and thus direct function of time and temperature. This process is performed in addition to quenching being particularly important in the manufacture of steel for springs. It consists of heating the quenched material between 250ºC to 650ºC for a certain time, to increase the ductility and elastic (CALLISTER, 2012).

According to Berger and Kaiser (2006), whereas the springs are used as structural elements that are subject to the limit of tensile or compression, the wire itself must be able to withstand the traction or compression stresses the coil springs respond to external compressive force with a torsion strain caused by torsion of active coils in spring. The wire in turn must be able to resist the torsional stresses arising, requiring the testing of tensile strength limit for this monitoring.

In a test of tensile strength limit the body of proof shall be on the head of a testing machine that applies an effort which tends to lengthen it up to the break, being measures the deformation by means of a device called a strain gauge. The test is performed on a body of proof with standardized dimensions, so that the results obtained can be compared, reproduced and measured on the machine itself. Usually the test occurs until the break of the material (what ranks as destructive) and allows you to measure the resistance of the material and the deformation as a function of applied voltage. This variation is extremely useful for engineering, and is determined by the route of the stress-strain curve. Above a certain level of tension, the materials begin to deform plastically until the break, at which point you get the limit of tensile strength (CHIAVERINI, 2012).

Steel industries are very used the universal testing machine of traction and it is common for the units of force used are kilogram-force per square millimeter (kgf/mm^2) or MegaPascal (MPa). The technical standards used for the execution of mechanical tests are elaborated by the ASTM (American Society for Testing and Materials).

Yield is the attribute presented by certain materials to suffer large plastic transformations before its breakup when subjected to tension. In specimens of steel the yield is measured by the reduction in cross-sectional area that occurs before the break. The yield is given by the ratio between the change in cross-sectional area of body of proof. The yield or area reduction is usually expressed as a percentage, showing how much of the cross-sectional area of the resistive body of proof section was reduced after the application of force (F) on the test of tensile strength, as shown in Figure 1.

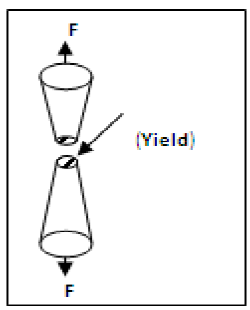

Figure 1: Area reduction after rupture of the body of proof.

The hardness is a measure of the resistance of a metal to penetration. The most common methods to determine the hardness of a metal are the Brinell, Vickers and Rockwell. In this project will only be used the method Brinell Hardness (CHIAVERINI, 2012).

Getting the values of Brinell Hardness (BH), as shown in Figure 2, is made by dividing the applied load by the area of penetration. The penetrator diameter (D) is a hardened steel ball to medium or low hardness materials, or tungsten carbide, for materials of high hardness. The test machine has a light microscope that makes measuring the diameter of the circle (d, in mm) that corresponds to the projection of the spherical Cap printed in the sample. Brinell hardness (BH) will be given by the applied load (P, in kg) divided by the print area as (1):

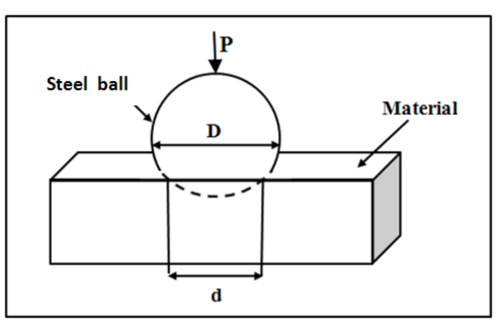

Figure 2: Illustration of the method of Brinell hardness (BH).

$$\text{Brinell hardness} = \frac{2P}{\pi D\left(D-\sqrt{D^2-d^2}\right)} \quad \left[\text{kgf}/\text{mm}^2\right] \tag{1}$$

3 Statistical Methods

3.1. Design of Experiments

The factorials "planning" are often used in experiments involving several factors and that "factorial" are the only way to discover interactions between process variables. In the design of experiments the first step is the choice of variables (factors) of the process that should be investigated. Are then chosen output variables that will be monitored. These input factors may be quantitative or qualitative, and the output variables, whenever possible, quantitative analyses should be to provide more precise statistics with the lowest cost (MONTGOMERY; RUNGER, 2009).

According to Rosa et al. (2009) and Robin et al. (2010) report that among the most appropriate statistical methods for investigation of influential variables there is the method Design of Experiments. This method is used to set the input factors and response variables, planning experiments and establish the order of trial in order to obtain results with greater statistical accuracy at the lowest possible cost.

Design of experiments (DOE) is very suitable to study various process factors and the complexity of their interactions, in order to troubleshoot through statistical analyses (GRANATO et al., 2011).

To perform a factorial planning, you must specify the levels at which each factor should be studied and the more important of these special cases is called 2^k factorial planning, which uses two-level factors each (NETO et al., 2007).

Blocking is a design technique used to improve the accuracy of the comparison between factors of interest. It can be employed in factorial plannings when there is the need to control the variability from disturbing sources known, which may affect the results (MONTGOMERY, 2013).

3.2. Multiple Regression

According to Benyounis and Olabi (2008), multiple regression technique when used in addition to the design of experiments, is very efficient to develop statistical models that quantify the influence of process input variables for prediction of output variables (BENYOUNIS; OLABI, 2008).

According to Montgomery and Runger (2009), multiple regression is used for situations involving more than one regressor, as (2):

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \varepsilon \tag{2}$$

In this expression Y represents the dependent variable, independent variables are represented by x_1, x_2, …, x_n and ε is the random error term. The unknown parameters β_0, β_1, β_2 and β_n. In this model, the parameter β_0 is the intersection of the plan. The terms β_1, β_2 and β_n are partial regression coefficients.

The models that include interaction effects, according to Montgomery and Runger (2009), can be analyzed by multiple regression method. An interaction between two variables can be represented by a term, because if we concede that $x_3 = x_1x_2$ and $\beta_3 = \beta_{12}$, so the model including interaction terms, use (3):

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + ... + \varepsilon \tag{3}$$

3.3. Methods for Optimization

The Desirability method is very effective in optimizing processes that have multiple answers, which should be optimized simultaneously. As a result of the geometric, the Desirability value (D) evaluates, in General, the levels of the combined set of responses. Is an index which also belongs to the interval [0,1] and is maximized when all the answers get close as possible to your specifications. The closer one is D, closer to the original answers will be their respective specification limits. The good general point of the system is the great point achieved by maximizing the geometric mean, calculated from the individual desirability functions. States that the advantage of using the geometric mean is to have the comprehensive settlement is achieved in a manner that is balanced, allowing all answers meet the expected values and forcing the algorithm to approximate the specifications imposed (WU, 2005).

The desirability method is a method of bonding, used for the determination of the best conditions for process adjustments, making possible the simultaneous optimization of multiple responses. With that, the best conditions of the responses are obtained simultaneously minimizing, maximizing, or seeking nominal values, depending on the situation more convenient for the process (WANG; WAN, 2009).

Each of the answers (Y_1, Y_2 ... Y_K) of the original set is transformed, such that d_i belonging to the range $0 \leq d_i \leq 1$. The value of d_i increases when the response approaches the limits imposed. To meet the global index D, from the combination of each of the replies processed through a geometric mean, it is used (4):

$$D = \left(d_1(Y_1) \times d_2(Y_2) ... \times d_k(Y_k)\right)^{\frac{1}{k}} \tag{4}$$

The optimization will depend on the type of response desired (maximization, standardization or minimization), desired limits within the specification and of the amount (weights) of each of the responses, which identifies the main features of the different types of optimization (DERRINGER; SUICH, 1980). As follows:

a) Minimize function: the value of the desirability function increases while the value of the original response approaches a minimum target value;
b) Normalize function: when the response moves towards the target, the desirability function value increases;
c) Maximize function: the desirability function value increases when the response value increases.

According to WU (2005) state that when the maximization of a reply, the transformation formula as (5):

$$di = \begin{cases} 0 & \hat{Y}_i < LSL \\ \left[\dfrac{\hat{Y}_i - Li}{Ti - Li}\right]^R & L_i \leq \hat{Y}_i \leq T_i \\ 1 & \hat{Y}_i > T_i \end{cases} \tag{5}$$

Being: L_i, T_i and H_i respectively, the values of the major, minor and acceptable target for the answer.

The value of R indicates the preponderance of upper limit. Values greater than the units should be used when the answer (Y_i) grows rapidly above L_i. So d_i increase slowly while the response value is maximized. Soon to maximise (D), the response must be much larger than L_i. You can choose R<1, while it is not critical if find values for the response under limits set (6).

In cases where the goal is to reach a target value, the formulation of transformation ceases to be one-sided to be bilateral. The bilateral formulation occurs when the response of interest has two constraints: a maximum and a minimum as (6):

$$d_i = \begin{cases} 0 & \hat{Y}_i < L_i ou\, \hat{Y}_i > H_i \\ \left[\dfrac{H_i - \hat{Y}_i}{Hi - Ti}\right]^R & T_i \leq \hat{Y}_i \leq H_i \\ \left[\dfrac{\hat{Y}_i - Li}{Ti - Li}\right]^R & L_i \leq \hat{Y}_i \leq T_i \end{cases} \tag{6}$$

There are some disadvantages in the use of the Desirability method, such as:

a) In the transformation, variance and covariance structure of responses is ignored. Ignoring this information can lead to an unrealistic solution, the answers have significantly different levels of variance;
b) Disregard the correlation between the answers;
c) Disregard the estimates of uncertainty of model parameters;
d) The increase of the non-linearity of D to the extent that it is considered a larger number of variables to responses, which can lead to great location places only.

The Generalized Reduced Gradient method (GRG) has its structure based on an algorithm for solving nonlinear programming problems with constraints. Basically, the method provides only the use of linear or non-linear constraints of equality. However, for situations where the constraints are inequalities, solves the problem by introducing slack variables (if the constraint is of type ≤), or excess variables (in the case of restrictions of the type ≥).

The GRG is an algorithm applied to optimization problems and was developed by Leon Lasdon, University of Texas at Austin, and Allan Waren, Cleveland State University. For optimization through the Generalized Reduced Gradient Algorithm (GRG), you can use Microsoft Excel Solver, which is used for optimizing nonlinear problems, through this method. Microsoft Excel Solver uses iterative numerical methods involving assessment values for the adjustable cells and observes the results calculated by cells of restrictions. Each attempt is called an interaction. Because in a trial-and-error approach would require an extremely long time (especially for problems involving several adjustable cells and constraints). However, the Microsoft Excel Solver performs comprehensive analysis of observed results and change fees as are varied to guide the selection of new evaluation values.

Inspired by the Natural selection of Darwin in 1859, the evolutionary computation is an emerging research branch of Artificial intelligence that proposes a new paradigm for troubleshooting. With that, the evolutionary computation comprises a set of search and optimization techniques to create a population of individuals who are going to play and compete for survival (RODRIGUES et al., 2004). Currently, the techniques of evolutionary computation include: Evolutionary Programming, Evolutionary Strategies, Genetic Algorithms (designed in 1960 by John Holland) and genetic programming (HOLLAND, 1975).

The Genetic Algorithms (GA) have a wide application in many scientific areas, among which may be mentioned problems solutions optimization, machine learning, developing strategies and mathematical formulas, analysis of economic models, engineering problems, diverse applications in biology as simulation of bacteria, immune systems, ecosystems, discovery of format and properties of organic molecules.

According to Holland (1975), the fittest individuals have a greater number of descendants, unlike those individuals least able. The requirements for the implementation are:

a) Representations of possible solutions of the problem in the form of a genetic code;
b) Initial population containing diverse enough to allow the algorithm to combine features and produce new solutions;
c) Existence of a method to measure the quality of a potential solution;
d) A combination of solutions to generate new individuals in the population;
e) A choice of solutions that will remain in the population or it will be removed;
f) A procedure to introduce periodically changes to some solutions. In this way the diversity of the population and the possibility to produce innovative solutions to be evaluated on criteria of selection of the fittest.

The basic idea of Genetic Algorithms is to treat the possible solutions of the problem as individuals of a population, which will evolve each interaction or generation. For this it is necessary to build a development model in which individuals are solutions of a problem (HOLLAN, 1975). The execution of the algorithm can be summarized in the following steps:

a) Choose an initial population comprised individuals randomly created;
b) Evaluate the entire population of individuals according to some criteria, determined by a function that evaluates the quality of the individual (fitness function);
c) Through the selection operator, choose the individuals best value (given by the fitness function) as the basis for the creation of a new set of possible solutions, called new generation;
d) This new generation is obtained by applying on the individuals selected to operations that blend their characteristics (genes), through the intersection operators and mutation;
e) These steps are repeated until an acceptable solution is found, until the predetermined number of steps is reached or until the algorithm does not get more improve the solution I've found.

The basic principle of genetic operators is to transform the population through successive generations, extending the search to reach a satisfactory result. Genetic operators are necessary for the population if diversify and keep the adaptation features acquired by previous generations. Through the crossing are created new individuals, mixing characteristics of two parents. This mixture is done trying to imitate the reproduction of genes into cells and the result of this operation is an individual that potentially combine the best features of individuals used as base (HOLLAN, 1975).

During the last decades, classical heuristics have been developed in different stages, and in the decade of 80 became the most popular proposals for solution of practical problems. Due to the major scientific advances of the last few years, the heuristics have been revised and improved, resulting in the new class of so-called meta-heuristics.

The Meta-heuristics are advanced methods that manage interactions between local refinement procedures and high-level strategies to create a process able to escape from great local situations, and provide a search optimal solutions (SILVA, 2013).

Meta-heuristics techniques are fundamental tools for solving complex optimization problems whose search spaces of optimal solutions are very large so you can determine them accurately through a deterministic method with acceptable processing time (CHAVES, 2007).

Heuristic methods for improvement, gets a home solution and subsequently through some interactive procedure (usually involving exchange of positions of the tasks following) seeks to obtain a sequence of tasks better than the current as the performance measure adopted. For this, search method was developed in the vicinity of greater complexity (Simulated Annealing) which have been the subject of great interest in the scientific community on the basis of successful applications and met in literature (BUZZO; MOCCELLIN, 2000).

The algorithm of Simulated Annealing, derives from the observation that the solution of large scale combinatorial problems is analogous to the annealing of solids in the field of condensed matter physics. The goal of this process is to reduce the temperature of a system, leading to the minimum energy State. Such energy can be seen as a cost function to be optimized (DIOGENES, 2009).

The Meta-heuristics Simulated Annealing is a meta-heuristics proposed by Kirkpatrick et al. (1983), a probabilistic search technique that is based on an analogy with thermodynamics, to simulate the cooling of a set of heated atoms. Its origin is related to the adjustment of mechanical properties through a controlled cooling process, in which the product is heated to a certain temperature and then cooled in cooling, according to the desired result. If the goal is to obtain hardness and rigidity, the temperature is decreased abruptly. If, on the contrary, we want flexibility, the reduction is made slowly, until the ambient temperature.

The use of Simulated Annealing is justified by the ability to perform movements "up the Hill" in the space of feasible solutions of the problem, exploring the "valleys" in an attempt to obtain a global optimal solution to the problem. The Simulated Annealing can be considered a generalization of the method "descendant", in which the search is extended to a global minimum is completed after a local minimum be obtained, and may be classified as heuristic random search method in the neighborhood (BARROS; MOCCELLIN, 2004).

3.4. Materials and Basic Flow of the Process

The material used in this study was the SAE 9254 cold drawn steel, used for the manufacture of Springs valves and clutch Springs applied to the automotive segment, with diameters 2.00 mm and 6.50 mm, subjected to the process of hardening and tempering.

The spring steel SAE 9254, has chemical composition equivalent to DIN 54SiCr6 and steel is a steel chrome-silicon, which is hardened and tempered and subsequently cold deformed.

The chemical analysis of the SAE 9254 material used in the study is presented in table 1.

Chemical Elements	C	Mn	Si	P	S	Cr	Ni	Mo	Cu	Al	V
(percentage)	0.554	0.64	1.22	0.022	0.018	0.58	0.04	0.03	0.01	0.009	0.005

Table 1-Chemical Composition (SAE 9254).

Afterwards, will be given a brief description of the operation of the heat treatment process in question.
At the entrance of the tempering furnace there are twelve coupling to which channels are the coils of wire. In this first stage of the process, called "input", has steel wire drawing gross structure (ferrite fine perlite). In the second phase, known as "thermic conditioning furnace", the material goes through five temperatures ranging around 900° C, in which occurs the austenitization. In the third step of the process, the steel wire is dipped in liquid polymer (quenching medium) in which your structure is transformed into martensite and then dipped in liquid lead to be tempered, with temperatures ranging from 400ºC to 650ºC, with the purpose of removal of surface tensions and transformation of its structure to tempered martensite. In the last phase of the process the steel wire is dipped in a tank of anticorrosive oil (antioxidant).

4. Results and Discussion
The factors investigated were:

a) Speed of passage of wire inside the oven (meters per second)- Factor A;
b) Lead in tempering temperature (in° C)- Factor B;
c) Concentration of the polymer (in percentage)- Factor C.

The diameter of the steel wire was also regarded as an important factor, because there was a chance that its mass could influence the results of mechanical properties have been investigated. In this step, however, was used to block analysis methodology. For 1 block related experiments were allocated only to the diameter of 2.00 mm, and for block 2, experiments related to diameter of 6.50 mm.
The speed factors, lead temperature and concentration of the polymer, were experienced by means of factorial planning, using the array called 2^3 and reduced variables (table 2).

Input variables	Values (physical units)	Values (standardized variables)
Speed (meters per second)	Minimum / Maximum	-1 / 1
Lead temperature (ºc)	Minimum / Maximum	-1 / 1
Polymer concentration (in percentage)	Minimum / Maximum	-1 / 1

Table 2 : Physical variables and standardized variables (multiple responses)

In the experimentations were carried out every 1 block and related replicas, then the corresponding to the block 2. Six replicates were used for each experimental condition. The replicates were aleatorizadas and sequenced using a numbering of 1 to 9, corresponding to the order of realization of each experiment, for each block individually. This string of experimentation is presented in parentheses and in subscript format alongside the obtained values of mechanical properties as shown in tables 3, 4 and 5. You can see even though for each experimental condition was determined the values of three mechanical properties studied, corresponding to each replica.

Experiments	Repetition 1	Repetition 2	Repetition 3	Repetition 4	Repetition 5	Repetition 6
1/block 1	$2149_{(1)}$	$2148_{(9)}$	$2146_{(2)}$	$2161_{(8)}$	$2167_{(1)}$	$2160_{(6)}$
2/ block 1	$2157_{(4)}$	$2155_{(7)}$	$2157_{(3)}$	$2151_{(7)}$	$2157_{(4)}$	$2157_{(2)}$
3/ block 1	$1924_{(3)}$	$1922_{(3)}$	$1920_{(1)}$	$1921_{(5)}$	$1920_{(6)}$	$1918_{(4)}$
4/ block 1	$1924_{(2)}$	$1924_{(8)}$	$1922_{(8)}$	$1943_{(6)}$	$1945_{(8)}$	$1945_{(5)}$
5/ block 1	$2108_{(6)}$	$2106_{(5)}$	$2108_{(7)}$	$2104_{(2)}$	$2102_{(9)}$	$2109_{(8)}$
6/ block 1	$2136_{(5)}$	$2127_{(4)}$	$2127_{(4)}$	$2136_{(3)}$	$2134_{(3)}$	$2127_{(3)}$
7/ block 1	$1927_{(7)}$	$1926_{(2)}$	$1944_{(5)}$	$1935_{(4)}$	$1946_{(2)}$	$1947_{(7)}$
8/ block 1	$1946_{(8)}$	$1946_{(6)}$	$1946_{(6)}$	$1953_{(1)}$	$1951_{(5)}$	$1946_{(9)}$
1/ block 2	$1968_{(9)}$	$1974_{(1)}$	$1962_{(3)}$	$1971_{(4)}$	$1971_{(9)}$	$1974_{(5)}$
2/ block 2	$1980_{(7)}$	$1976_{(4)}$	$1988_{(6)}$	$1978_{(2)}$	$1980_{(3)}$	$1988_{(2)}$
3/ block 2	$1771_{(3)}$	$1764_{(3)}$	$1763_{(7)}$	$1773_{(5)}$	$1771_{(5)}$	$1764_{(4)}$
4/ block 2	$1796_{(8)}$	$1784_{(2)}$	$1797_{(8)}$	$1781_{(9)}$	$1796_{(2)}$	$1784_{(9)}$
5/ block 2	$1949_{(5)}$	$1963_{(6)}$	$1947_{(1)}$	$1951_{(1)}$	$1949_{(4)}$	$1947_{(6)}$
6/ block 2	$1992_{(4)}$	$1980_{(5)}$	$1976_{(9)}$	$1994_{(8)}$	$1980_{(7)}$	$1992_{(7)}$
7/ block 2	$1760_{(2)}$	$1768_{(7)}$	$1766_{(5)}$	$1763_{(7)}$	$1766_{(6)}$	$1763_{(8)}$
8/ block 2	$1787_{(6)}$	$1793_{(8)}$	$1785_{(2)}$	$1784_{(6)}$	$1784_{(1)}$	$1785_{(1)}$

Table 3: Limit results to limit of tensile strength (in MPa).

Experiments	Repetition 1	Repetition 2	Repetition 3	Repetition 4	Repetition 5	Repetition 6
1/ block 1	50 $_{(1)}$	51 $_{(9)}$	51 $_{(2)}$	50 $_{(8)}$	50 $_{(1)}$	50 $_{(6)}$
2/ block 1	50 $_{(4)}$	50 $_{(7)}$	50 $_{(3)}$	50 $_{(7)}$	50 $_{(4)}$	50 $_{(2)}$
3/ block 1	58 $_{(3)}$	58 $_{(3)}$	58 $_{(1)}$	58 $_{(5)}$	58 $_{(6)}$	58 $_{(4)}$
4/ block 1	58 $^{(2)}$	58 $_{(8)}$	58 $_{(8)}$	56 $_{(6)}$	56 $_{(8)}$	56 $_{(5)}$
5/ block 1	53 $_{(6)}$	53 $_{(5)}$	53 $_{(7)}$	53 $_{(2)}$	53 $_{(9)}$	53 $_{(8)}$
6/ block 1	51 $_{(5)}$	52 $_{(4)}$	52 $_{(4)}$	51 $_{(3)}$	51 $_{(3)}$	52 $_{(3)}$
7/ block 1	58 $_{(7)}$	58 $_{(2)}$	56 $_{(5)}$	58 $_{(4)}$	56 $_{(2)}$	56 $_{(7)}$
8/ block 1	56 $_{(8)}$	56 $_{(6)}$	56 $_{(6)}$	55 $_{(1)}$	56 $_{(5)}$	56 $_{(9)}$
1/ block 2	42 $_{(9)}$	41 $_{(1)}$	42 $_{(3)}$	42 $_{(4)}$	42 $_{(9)}$	41 $_{(5)}$
2/ block 2	41 $_{(7)}$	41 $_{(4)}$	40 $_{(6)}$	41 $_{(2)}$	41 $_{(3)}$	40 $_{(2)}$
3/ block 2	47 $_{(3)}$	46 $_{(3)}$	46 $_{(7)}$	47 $_{(5)}$	47 $_{(5)}$	46 $_{(4)}$
4/ block 2	44 $_{(8)}$	45 $_{(2)}$	44 $_{(8)}$	45 $_{(9)}$	44 $_{(2)}$	45 $_{(9)}$
5/ block 2	56 $_{(5)}$	42 $_{(6)}$	56 $_{(1)}$	56 $_{(1)}$	56 $_{(4)}$	56 $_{(6)}$
6/ block 2	40 $_{(4)}$	41 $_{(5)}$	41 $_{(9)}$	40 $_{(8)}$	41 $_{(7)}$	40 $_{(7)}$
7/ block 2	46 $_{(2)}$	47 $_{(7)}$	47 $_{(5)}$	46 $_{(7)}$	47 $_{(6)}$	46 $_{(8)}$
8/ block 2	44 $_{(6)}$	44 $_{(8)}$	45 $_{(2)}$	45 $_{(6)}$	45 $_{(1)}$	45 $_{(1)}$

Table 4 : Yield results (in percentage).

Experiments	Repetition 1	Repetition 2	Repetition 3	Repetition 4	Repetition 5	Repetition 6
1/ block 1	608 $_{(1)}$	606 $_{(9)}$	606 $_{(2)}$	611 $_{(8)}$	611 $_{(1)}$	611 $_{(6)}$
2/ block 1	608 $_{(4)}$	608 $_{(7)}$	608 $_{(3)}$	608 $_{(7)}$	608 $_{(4)}$	608 $_{(2)}$
3/ block 1	544 $_{(3)}$	542 $_{(3)}$	542 $_{(1)}$	542 $_{(5)}$	542 $_{(6)}$	542 $_{(4)}$
4/ block 1	544 $_{(2)}$	544 $_{(8)}$	542 $_{(8)}$	550 $_{(6)}$	550 $_{(8)}$	550 $_{(5)}$
5/ block 1	594 $_{(6)}$	594 $_{(5)}$	594 $_{(7)}$	594 $_{(2)}$	594 $_{(9)}$	594 $_{(8)}$
6/ block 1	603 $_{(5)}$	600 $_{(4)}$	600 $_{(4)}$	603 $_{(3)}$	603 $_{(3)}$	600 $_{(3)}$
7/ block 1	544 $_{(7)}$	544 $_{(2)}$	550 $_{(5)}$	547 $_{(4)}$	550 $_{(2)}$	550 $_{(7)}$
8/ block 1	550 $_{(8)}$	550 $_{(6)}$	550 $_{(6)}$	553 $_{(1)}$	550 $_{(5)}$	550 $_{(9)}$
1/ block 2	556 $_{(9)}$	558 $_{(1)}$	556 $_{(3)}$	556 $_{(4)}$	556 $_{(9)}$	558 $_{(5)}$
2/ block 2	558 $_{(7)}$	558 $_{(4)}$	561 $_{(6)}$	558 $_{(2)}$	558 $_{(3)}$	561 $_{(2)}$
3/ block 2	500 $_{(3)}$	497 $_{(3)}$	497 $_{(7)}$	500 $_{(5)}$	500 $_{(5)}$	497 $_{(4)}$
4/ block 2	508 $_{(8)}$	503 $_{(2)}$	508 $_{(8)}$	503 $_{(9)}$	508 $_{(2)}$	503 $_{(9)}$
5/ block 2	550 $_{(5)}$	556 $_{(6)}$	550 $_{(1)}$	550 $_{(1)}$	550 $_{(4)}$	550 $_{(6)}$
6/ block 2	564 $_{(4)}$	558 $_{(5)}$	558 $_{(9)}$	564 $_{(8)}$	558 $_{(7)}$	564 $_{(7)}$
7/ block 2	497 $_{(2)}$	500 $_{(7)}$	500 $_{(5)}$	497 $_{(7)}$	500 $_{(6)}$	497 $_{(8)}$
8/ block 2	506 $_{(6)}$	506 $_{(8)}$	503 $_{(2)}$	503 $_{(6)}$	503 $_{(1)}$	503 $_{(1)}$

Table 5 : Brinnel Hardness results (in BH).

The significance of the factors was tested at a level of confidence 95 percent ($p < 0.05$). This analysis was performed separately so that it could be verified the significance of the factors for each one of the results of mechanical properties studied, as shown in tables 6, 7 and 8.

Due to the significance test for mechanical property limit of tensile strength (shown in Table 6), it was found that the significant factors are: wire diameter (represented by the letter d and tested through blocks), speed (represented by the letter A), lead temperature (represented by the letter B), polymer concentration (represented by the letter C) , second-order interactions between speed and concentration of the polymer, temperature and concentration of the polymer and a third-order interaction between speed, temperature and concentration of the polymer.

Terms	Effect	Coefficient	p
Factors		1955.29	0.000
(d)	165.62	82.81	0.000
(A)	17.42	8.71	0.000
(B)	-198.54	-99.27	0.000
(C)	-8.04	-4.02	0.000
(A)(B)	-0.54	-0.27	0.805
(A)(C)	5.62	2.81	0.012
(B)(C)	14.08	7.04	0.000
(A)(B)(C)	-6.25	-3.13	0.005

Table 6 : Significance test to the limit of tensile strength (in MPa).

When you analyze the test of significance for the mechanical yield property (shown in Table 7), you can see that the influential factors are: wire diameter (tested by means of blocks), speed, temperature, concentration of the polymer, second-order interactions between speed and temperature, speed and concentration of the polymer, temperature and concentration of the polymer and a third-order interaction between speed, lead temperature and concentration of the polymer.

Terms	Effect	Coefficient	p
Factors		49.458	0.000
(d)	9.426	4.713	0.000
(A)	-2.750	-1.375	0.000
(B)	3.583	1.792	0.000
(C)	1.750	0.875	0.001
(A)(B)	1.250	0.625	0.012
(A)(C)	-1.667	-0.833	0.001
(B)(C)	-2.250	-1.125	0.000
(A)(B)(C)	1.667	0.833	0.001

Table 7 : Test of significance for the yield (in percentage).

Analyzing the test of significance for the mechanical property hardness (shown in Table 8), it is possible to afirm that the influential factors are: wire diameter (tested by means of blocks), speed, temperature, concentration of the polymer, second-order interactions between speed and concentration of the polymer, temperature and concentration of the polymer and a third-order interaction between speed, lead temperature and concentration of the polymer.

Terms	Effect	Coefficient	p
Factors		552.09	0.000
(d)	46.86	23.43	0.000
(A)	4.85	2.43	0.000
(B)	-55.81	-27.91	0.000
(C)	-2.19	-1.09	0.001
(A)(B)	0.10	0.05	0.877
(A)(C)	1.65	0.82	0.016
(B)(C)	4.06	2.03	0.000
(A)(B)(C)	-2.35	-1.18	0.001

Table 8 : Significance test for hardness (in BH).

Using the coefficients calculated through a significance test, contained in tables 6, 7 and 8, it was possible to build models using interaction terms that represent the relationship between the factors and interactions with the mechanical properties. These statistical models are defined as (7, 8 and 9):

$$LTS = 1955.29 + 82.81(d) + 8.71(A) - 99.27(B) - 4.02(C) + 2.81(A)(C) + 7.04(B)(C) - 3.13(A)(B)(C) \quad (7)$$

$$Y = 49.458 + 4.713(d) - 1.375(A) + 1.792(B) + 0.875(C) + 0.625(A)(B) - 0.833(A)(C) - 1.125(B)(C) + 0.833(A)(B)(C) \quad (8)$$

$$H = 552.09 + 23.43(d) + 2.43(A) - 27.91(B) - 1.09(C) + 0.82(A)(C) + 2.03(B)(C) - 1.18(A)(B)(C) \quad (9)$$

Being:

a) LTS: corresponds to results of limit of tensile strength;
b) Y: corresponds to results of yield;
c) H: corresponds to results of hardness.

4.1. Application of Function Desirability for Optimization

Process optimization through the use of the desirability function, first, it was necessary to define the specifications required for mechanical properties studied. For this, the blocks were analyzed separately optimizing the variables responses. Firstly, to the wire with diameter 2.00 mm and subsequently the same procedure for the 6.50 mm diameter. This entailed the use of a statistical model without the diameter. The use of the desirability function was made in Minitab Software.

Specifications (minimum, nominal and maximum) are related to a specific customer of this product, for the diameter 2.00 mm and they are presented in table 9. In this case, sought nominal values (target) to mechanical properties limit tensile strength and hardness and mechanical property yield, searching the maximization because the higher value is better for the product.

Limit of tensile strength (MPa)			**Yield (percentage)**			**Hardness (BH)**		
Minimal	average (target)	Maximum	Minimal	average (target)	Maximum	Minimal	average (target)	Maximum
1930	2040	2150	40	≥ 45	55	545	572	600

Table 9 : Specifications for diameter 2.00 mm.

The desirability (D) is the global index calculated from the combination of each of the variables responses processed through a geometric mean and this index is responsible for showing the best condition for optimization of all variables responses at the same time. To achieve the greatest possible value for D, which reflects, in the best of condition variables responses in relation to the attendance of their specifications (presented in Figure 3), the best settings, using standardized variables to of the factors are:

a) Speed, adjusted in -1.0;
b) Lead temperature adjusted in -0.0909;
c) Polymer concentration adjusted in 1.0.

Analyzing the Figure 3, you can see that the value of D, belonging to the range fron 0 until 1, is maximized when all the answers are approaching their specifications, because the nearest one is D, closer to the original answers will be their respective specification limits. The great general point of the system is the great point achieved by maximizing the geometric mean, calculated from the individual desirability functions (d), which in this case are the values for each of the variables responses the following data:

a) For response variable tensile strength limit, we have d=0.90455;
b) For response variable yield, we have d=1.0;
c) For response variable hardness, we have d=0.96916.

The values obtained for the compound desirability (D) and individual desirability (d) demonstrate that the process was well optimized, because these indices are very close to the condition great (1.0). Thus, it was found that the values obtained for this condition optimized meet the required specifications and they are:

a) For response variable tensile strength limit, we have (y= 2029.5 MPa);
b) For response variable yield, we have (y= 54.8182 percent);
c) For response variable hardness, we have (y= 572.8636 BH);

Analyzing the Figure 3, it was found that the speed factor, when it is increased, causes also the increase of the values of the variables responses limit of tensile strength (MPa) and hardness (BH). Also, the speed increase impacts in reducing response variable yield (percent) and reduced desirability compound (D).

In relation to the temperature factor of lead with increasing temperature, reducing the values of the variables responses limit of tensile strength (MPa), hardness (BH) and desirability compound (D). On the other hand, increases the value of the yield (percent).

Noting the increase in the polymer concentration factor, it is possible to perceive that there will be fall of the values of the variables responses limit of tensile strength (in MPa) and hardness (in BH), increasing the yield (in percent) and the desirability (D).

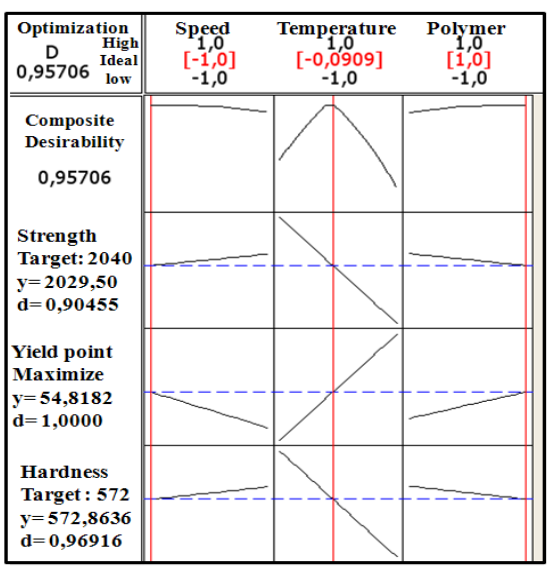

Figure 3: Desirability function applied in multiple responses (diameter 2.00 mm).

In table 10 are shown the specifications (minimum, nominal and maximum) for the 6.50mm diameter. Also if you're seeking nominal values (target) to mechanical properties limit tensile strength and hardness and mechanical property for yield, searching the maximization.

Limit of tensile strength (MPa)			Yield (percent)			Hardness (BH)		
Minimal	average (target)	Maximum	Minimal	average (target)	Maximum	Minimal	average (target)	Maximum
1770	1875	1980	40	≥ 48	56	500	530	560

Table 10: Specifications for diameter 6.50 mm.

As shown in Figure 4, to obtain the largest possible value for the compound desirability (D), the best settings of factors are:

a) Speed, adjusted in -1.0;
b) Lead temperature adjusted in -0.1919;
c) Polymer concentration adjusted in 1.0.

Through the analysis of Figure 4, you can see that:

a) For response variable tensile strength limit, we have d=0.99448;
b) For response variable yield, we have d=1.0;
c) For response variable hardness, we have d=0.99293.

Also you can see that the values obtained for this condition optimized meet the required specifications and they are:

a) For response variable tensile strength limit we have y= 1875.5791 MPa;
b) For yield we have y= 50.7710 percent;
c) For hardness we have y= 529.7879 BH;

Regarding to the speed factor, when you increase the speed you get increased values of variables responses limit of tensile strength (in MPa) and hardness (in BH). Also, with the increase of the speed factor, reducing the response variable yield (in percentage) and the compound desirability of reduction (D).

In relation to the temperature factor, the increase causes the reduction of all variables responses, including the desirability compound (D).

Noting the polymer concentration factor, it was found that the increase will cause a fall of the variables responses limit of tensile strength and hardness, increasing the yield and the desirability (D).

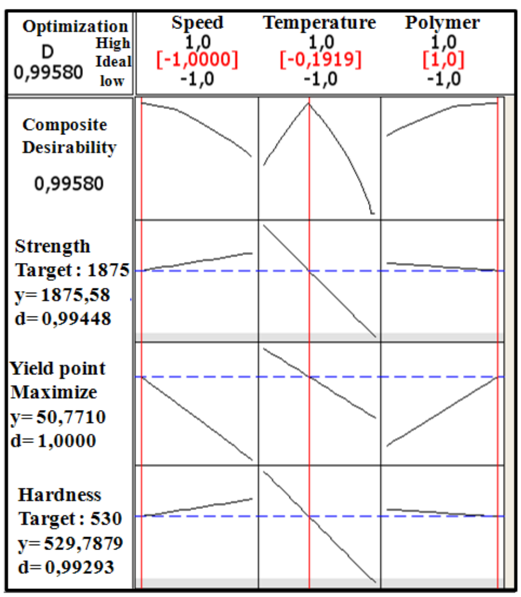

Figure 4: Desirability function applied in multiple responses (diameter 6.50 mm)

The red line (vertical) contained in Figure 4 can be interpreted as follows: if it is busy, will change the values of the responses, and this will directly affect the desirability compound values (D) and individual desirability (d). For example, if you move the red line, contained in the space for the temperature factor of lead, to the right side, will provide fall, in the compound desirability (D), and of all the answers (shown in Figure 29). You can see the fall, in the compound desirability (D), observing the inclination of the line contained in the location indicated previously. This drop in D would be the reduction of the optimization of multiple responses and, consequently, the non-utilization of answers in his best position to adjust the factors.

4.2. Application of Generalized Reduced Gradient Method (GRG) for Optimization

4.2.1. Application for Diameter 2.00 mm

In this step, we sought to process optimization by Generalized Reduced Gradient method, through the use of Solver tool contained in Excel software, version 2010.

For the application of this method was necessary the definition of:

a) Specifications: To optimization of the diameter 2.00 mm (table 9); the search for the response variable limit of tensile strength values between 1930 to 2150 MPa, to yield values between 40 to 55 (in percentage) and hardness values between 545 BH to 600 BH. These specifications will be inserted in the form of restrictions, in the field "subject to restrictions" on Solver tool.

b) Decision variables: in this case, refers to the values of the settings of the factors A, B and C, to be provided the best condition of meeting the specifications of the multiple responses of mechanical properties. The decision shall be entered in the field "changing cells", as using the Solver tool;

c) Objective function: For the objective function was used the distance Average Percentage (DAP), which is the average distance of the predictions of responses, that is, for each response predicted by the model subtracts the value "target"; so if it gets a error unit between the prediction and the nominal specification, which shall be multiplied by one hundred, for use in percentage (in percentage). In this case, the objective function is the minimization of the average of those "errors", seeking a condition that reduces to the maximum values of the distances of the variables answers simultaneously, seeking a balance between the best fit of the answers. The objective function is inserted in field "set target cell", using the Solver tool.

With the use of solver it became possible to allocate all the constraints of the decision variables and objective function. In this way, we can obtain the results presented in table 11, containing the best answers of the optimization. For this, we used the statistical model previously obtained by means of multiple regression.

It is possible to observe that to adjust of the factors in the settings shown in table 11, being: A=1; B=0.042 and C=-1; might get variables responses that meet their respective specifications and the average error obtained was 0.23 (in percentage).

Response	constant model	Factors									
		A	B	C	AB	AC	BC	ABC	Answers obtained	Error percent	Medium error percent
Tensile strength	2036	6.1	– 101	– 5.3	- -	2.8	13	–3.4	2040	0.00	0.23
Yield	54.08	- 0.5	2.875	0.25	- -	- - -	–0.7917	- - -	53.5	0.00	
Hardness	574.92	1.75	– 28.17	– 1.54	- -	0.87	3.79	–1.21	576.1	0.71	
Best fit		1	0.042	-1	- -	- -	- - - - - -	- - - -	- - - - - - - - - - - - - -	- - - -	- - - -

Table 11: Simulation using model with interaction terms (diameter 2.00 mm)

4.2.2. Application for Diameter 6.50 mm

The Generalized Reduced Gradient method was also applied to the 6.50 mm diameter and specifications used are in Table 10.

For the application of this method was necessary to the definition of:

a) Specifications: To optimization of the diameter 6.50 mm, if you search for the response variable limit of tensile strength values between 1770 MPa to 1980 MPa, for yield values between 40 to 56 (in percentage) and hardness values between 500 BH to BH 560. The specifications have been entered in the solver as previously executed procedure.

b) Decision variables: in this case, the decision variables are the same as those used earlier to 2.00mm diameter and its insertion in the solver follows the same procedure performed earlier.

c) Objective function: the objective function was the same performed for other diameter studied and the insertion procedure solver followed the same procedure detailed previously. It is possible to observe that to adjust the factors in the settings are shown in table 12, being: A=-0.46; B=0.8973 and C=-0.1; might get variables responses that meet their respective specifications and the average error obtained was 0.03 (in percentage).

Response	constant model	Fators									
		A	B	C	AB	AC	BC	ABC	Answers obtained	Error percent	Medium error percent
Tensile strength	1874.54	11.29	– 97.54	– 2.71	- - -	2.87	- - - -	–2.88	1875.24	0.013	0.03
Yield	44.833	-2.250	0.708	1.5	1.29	–1.5	–1.458	–1.542	48	5.23_x10^{-8}	
Hardness	529.27	3.10	– 27.65	– 0.65	- - -	0.77	0.27	–1.15	529.6	0.08	
Best fit		-0.46	-0.1	0.8973	- - -	- - -	- - -	- - -	- - - - - -	- - - - -	- - - - - -

Table 12: Simulation using model with interaction terms (diameter 6.50 mm)

4.3. Application of the Genetic Algorithm (GA) method for optimization

4.3.1. Application for Diameter 2.00 mm

The application of the Genetic Algorithm method (AG) was performed using CrystalBall software, which is a complementary to Excel software, version 2010.

First it was necessary to define the decision variables, that is, the settings of the factors that will be optimized inside the range -1 to 1 (reduced variables).

Then it was necessary the definition of " cell forecast". The cell in which is inserted the objective function to be minimized. In this case, the objective function is the average distance that was achieved in the prediction of each response variable compared to their nominal specification, in percentage, that is, for each response predicted by the model subtracts the value "target", so if it gets a error unit between the prediction and the nominal specification. The objective function is the minimization of the average of those "errors", seeking thus a condition that reduces to the maximum values of the distances simultaneously and then used the OptQuest optimizer, which is contained in the tool CrystalBall.
To use the optimizer "OptQuest" is necessary to the definition of the objectives. Configured to "Minimize" the objective function and set a maximum value to be reached, in which the objective function should not achieve an error greater than 10, between the predicted values of the variables responses.

a) The variable tensile strength limit, should be between 1930 to 2150 MPa;
b) The variable yield should be between 40 to 55 (in percentage);
c) The variable hardness should be between 545 BH to 600 BH.

It was necessary to determine the amount of cycles of simulations using the Genetic Algorithm method (AG). In the first simulation, using genetic algorithm (GA), the configuration was 5 minutes (approximately 700 simulations with random numbers) and all specifications were met. The objective function was minimized with 4.28 (in percentage), being the average of the difference between the predicted values of the variables and the specified values (nominal) was 4.28 (in percentage).
After the completion of the first simulation, the values found for the multiple responses were: for the limit of tensile strength of 2040 MPa, for the yield of 53.5 (in percentage) and for the hardness 576 BH.
The best settings for these values are: factor A=1.0; B=0.042 factor; factor C=-1.
Then it was made two more simulations where the first was made in 10 minutes (equivalent to 950 simulations) and the second with 20 minutes (equivalent to 1100 simulations), but it was not obtained no improviment for optimization of the objective function, then, remained the first simulation.

4.3.2. Application for Diameter 6.50 mm

The application of the Genetic Algorithm method (AG) for the 6.50 mm diameter was the same way that the application for the diameter 2.00 mm. There followed the same steps for inserting of the data, but the specifications were used the values presented in table 10. In this case, the restrictions were:

a) The variable limit of tensile strength should be between the 1770 MPa to 1980 MPa;
b) The variable yield should be between 40 to 56 (in percentage);
c) The variable hardness should be between 500 BH to BH 560.

After the completion of the simulation (configured for 5 minutes, approximately 1000 cycles), to 6.50 mm diameter, revealed that the best answers were: limit of tensile strength of 1875 MPa, 48 for yield and hardness of 530 BH. The best settings for these values are: factor A=-0.45; factor B =-0.1; factor C=1.
All nominal specifications were met and the objective function was minimized with 0.3 (in percentage), being the average the difference between the predicted values of the variables and the nominal values specified.
Two more simulations were made, the first one with 10 minutes (equivalent to 1600 simulations) and the second with 20 minutes (equivalent to 1800 simulations), but they were not obtained best results for optimization of the objective function, then, remained the first simulation.

4.4. Application of Simulated Annealing for Meta-heuristics optimization

In addition to the optimization by means of Generalized Reduced Gradient (GRG), Desirability methods and Genetic Algorithm (GA), was also used the Simulated Annealing heuristic, in order to find the best fit possible for optimization factors of multiple responses (limit of tensile strength, yield and hardness). The Simulated Annealing method was applied using Scilab software Enterprises, well-known in the field of numerical computation.
The simulation using Simulated Annealing was performed primarily for the diameter 2.00 mm (in table 13), in which were held 2245 simulations, until it was achieved the best condition for obtaining adjustments of answers. In table 13, was presented in summary form, containing the first two simulations, the last two and the values of mechanical properties studied.

SCILAB\ application for model with interaction terms 2.00 mm			
Enter the largest value of X =1			
Enter the lowest value of X =-1			
Enter the temperature value =1d10			
Enter the value of the cooling rate =0.95			
Enter the number of repetitions =500			
Enter the number of solutions =100			
1.	**Factor A**	**Factor B**	**Factor C**
3.	- 0.0187595	0.0012887	- 0.0411094
2243.	- 0.0790005	- 0.3038075	- 0.5909943
2245.	- 0.0790005	- 0.3038075	- 0.5909943 **(best fit)**
Limit of tensile strength (y1)= 2072 MPa			
Yield (y_2) = 53 percent			
Hardness (y_3) = 585 BH			

Table 13: Results of Simulated Annealing (Scilab), diameter 2.00 mm.

The same procedure was performed for the simulations for the diameter 6.50 mm (in table 14). Were also made 2245 simulations until it was achieved the best condition for obtaining adjustments of mechanical responses.

SCILAB\ application for model with interaction terms 6.50 mm			
Enter the largest value of X =1			
Enter the lowest value of X =-1			
Enter the temperature value =1d10			
Enter the value of the cooling rate =0.95			
Enter the number of repetitions =500			
Enter the number of solutions =100			
1.	**Factor A**	**Factor B**	**Factor C**
3.	- 0.0187595	0.0012887	- 0.0411094
2243.	0.2619011	0.6254999	- 0.5018487
2245.	0.2619011	0.6254999	- 0.5018487 **(best fit)**
Limit of tensile strength (y1) = 1818 MPa			
Yield (y_2) = 45 percent			
Hardness (y_3) = 513 HB			

Table 14: Results of Simulated Annealing (Scilab), diameter 6.50 mm.

4.5. Comparative Analysis between the Methods of Optimization

In table 15 according to 2.00 mm diameter are shown the best settings of factors achieved with the application of four methods: Desirability, Generalized Reduced Gradient (GRG), Genetic Algorithm (GA) and Simulated Annealing (SA). You can see that the best settings for the Generalized Reduced Gradient methods and Genetic Algorithm (GA), are absolutely the same to the diameter 2.00 mm, differing from the best configuration achieved by Desirability and Simulated Annealing methods.

Factors/ Adjustments	**(Minitab-*Desirability*)**	**(Solver- GRG)**	**(CrystalBall- GA)**	**(Scilab- SA)**
A	-1	1	1	-0.0790
B	-0.0909	0.042	0.042	-0.3038
C	1	-1	-1	-0.5909

Table 15 : Adjustments for factors for different optimization methods (diameter 2.00 mm).

Analyzing the table 16, we can note that to model by interactions, of the 2.00 mm diameter, the differences among the methods Generalized Reduced Gradient (GRG), Desirability and Genetic Algorithm (GA) was not significant, because all of these methods have achieved average errors very close approximately 0.23 (in percentage). However, the error obtained in the application of Meta-heuristics Simulated Annealing, proved to be a little bigger for model of the interactions with average error value of 1.28 (in percentage).

Response (Scilab- Simulated Annealing)	Hardness (BH)	585	545	600	572	2.27	1.28
	Yield (percent)	53	40	55	≥45	0.0	
	Tensile strength (MPa)	2072	1930	2150	2040	1.5	
Response (CrystalBall -AG)	Hardness (BH)	576	545	600	572	0,7	0.23
	Yield (percent)	53,5	40	55	≥45	0.0	
	Tensile strength (MPa)	2040	1930	2150	2040	0.0	
Response (Solver- GRG)	Hardness (BH)	576	545	600	572	0,7	0.23
	Yield (percent)	53,5	40	55	≥45	0.0	
	Tensile strength (MPa)	2040	1930	2150	2040	0.0	
Response (Desirability-GRG)	Hardness (BH)	572.86	545	600	572	0.15	0.22
	Yield (percent)	54.82	40	55	≥45	0.0	
	Tensile strength (MPa)	2029.5	1930	2150	2040	0.52	
		Predição (by model statistics)	Min. specification	Max. specification	specification (target)	Error (percent)	Error Average (percent)

Table 16 : Results of predictions by different methods of optimization (diameter 2.00 mm).

In table 17 according to diameter 6.50 mm, are shown the best settings of factors achieved with the use of four methods of optimization. You can see that the settings of the best adjusts to the Desirability, Generalized Reduced Gradient methods (GRG) and Genetic Algorithm (GA), they have reasonably close values, differing from the best configuration achieved by Simulated Annealing method. Also it was noticed (in table 18) that the differences (average errors) concerning the optimization, among the methods Generalized Reduced Gradient (GRG), Desirability and Genetic Algorithm (AG) also was not significant to the diameter 6.50 mm. Those methods achieved very small errors in relation to the nominal specification of approximately 0.02 (in percentage) on average. However, the Simulated Annealing heuristic got error 4.16 (in percentage) average, which was considered a significant error, compared to other methods.

Factors/ Adjustments	**(Minitab-*Desirability*)**	**(Solver- GRG)**	**(CrystalBall- GA)**	**(Scilab- SA)**
A	-1	-0.46	-0.45	0.2619
B	-0.1919	-0.10	-0.1	0.6255
C	1	0.8973	1	-0.5018

Table 17 : Adjustments for factors for different optimization methods (diameter 6.50 mm).

Response (Scilab- Simulated Annealing)	Hardness (BH)	513	500	560	530	3.2	4.16
	Yield (percent)	45	40	56	≥48	6.25	
	Tensile strength (MPa)	1818	1770	1980	1875	3.0	
Response (CrystalBall -AG)	Hardness (BH)	529.6	500	560	530	0.08	0.02
	Yield (percent)	48.2	40	56	≥48	0.0	
	Tensile strength (MPa)	1875.0	1770	1980	1875	0.0	
Response (Solver- GRG)	Hardness (BH)	529.6	500	560	530	0.08	0.02
	Yield (percent)	48	40	56	≥48	0.0	
	Tensile strength (MPa)	1875.2	1770	1980	1875	0.0	
Response (Desirability-GRG)	Hardness (BH)	529.8	500	560	530	0.04	0.02
	Yield (percent)	50.77	40	56	≥48	0.0	
	Tensile strength (MPa)	1875.6	1770	1980	1875	0.03	
		Predição (by model statistics)	Min. specification	Max. specification	specification (target)	Error (percent)	Error Average (percent)

Table 18 : Results of predictions by different methods of optimization (diameter 6.50 mm).

5. Conclusion

It was concluded through experimental analyses all factors (speed, temperature and concentration of the polymer), are influential in the process of hardening and tempering in steel drawn wires SAE 9254 and that these factors interact with each other, significantly, being the lead temperature factor of greatest impact on increasing or reducing the mechanical values obtained.

It was also, after being analysed the results concerning the Desirability, Generalized Reduced Gradient methods (GRG) and Genetic Algorithm (GA), that all the methods described previously obtained good efficacy in the optimization of multiple responses simultaneously and that the Simulated Annealing heuristic did not get the same performance for modeling using interaction terms.

The implementation of this process modeling, from simulations and the use of optimization methods studied, can mean the automation of tempering furnaces, causing potential productivity gains, the reduction of waiting for laboratory results, less sampling for checks, shorter stops in furnaces because of waiting for results of mechanical tests and can also contribute to quality gains, raised by predetermined adjustments to better meet the customers ' specifications.
For future work, it is suggested the experimentation through the application of response surface Methodology to be tested the modeling quadratic and their optimization through the same optimization methods previously tested.

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