POTENTIALITY AND BENEFITS OF ROBUST ENGINEERING AND THE TECHONOLOGICAL EXPERIMENTATION IN THE STEEL INDUSTRY

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New thermomechanical processing (TMP) and steels with exclusive properties are continuously designed and optimized through the development, extension and application of metallurgical models and/ or carrying out expensive programs of R&D. This paper highlights the benefits of concepts such as "robust engineering", "design of experiments (DOE)" and "process modeling" which are developed with a practical sorting for their better comprehension and effective industrial application. Improved process capability and performance in use of HSLA and high carbon steels, less number of industrial trials and lower costs of R&D are some of the advantages on applying this methodology.

KEYWORDS: DOE, statistical modeling, robust engineering, metallurgical modeling

OBJECTIVES OF THE TECHNOLOGICAL EXPERIMENTATION AND OF "ROBUST ENGINEERING"

The industry requires science to accomplish controlled transformations (variabilities), either to create new products and processes, or to improve the existent ones. An industrial process (Fig.1) can be defined as the set of rules and material conditioning for the production of a material good. Raw materials, equipments, workmen, operative practices (specification of the parameters, tolerances) form part of an industrial process. In order to control it, a certain number of basic parameters (called "control parameters" or "process parameters") must stay fixed to avoid important variabilities. Another number of parameters (the noise parameters) may vary between certain more or less defined limits and their control is not always convenient due to economical or material reasons.

A causality relationship does exist between the output variables and the input variables, Y= F(X, Z, W, …, T ; B1, B2, …, Br). Variations in the input variables (causes) will cause variations (effects) over the output variables. The main ob-

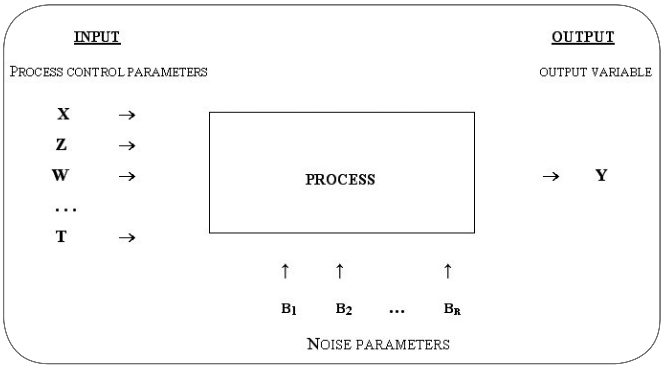

Fig. 1
Industrial process (schematic).
Processo industriale (schema).

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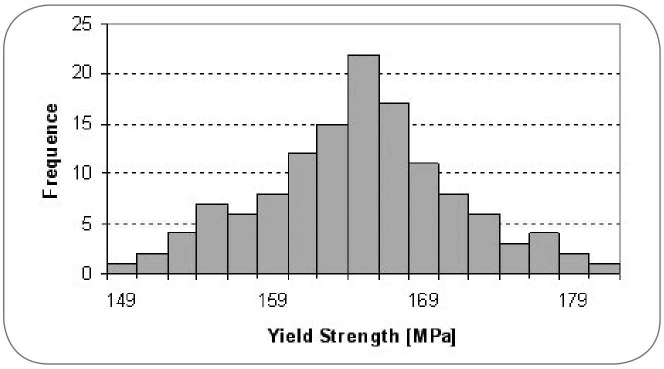

Fig. 2
Histogram of yield strength [MPa].
Istogramma di frequenza della tensione di snervamento [MPa].

jective of the experimental design (DOE) is to identify these relations of causality, measure and understand the effects of the processing parameters. For this objective, we will use experimental methods which allow us to set causality relations, and empirical models with stochastic components that will show the functional relation between the inputs and the outputs of the process.

Example (hot rolled steel strip)

The control parameters (inputs) are the chemical composition (C, Mn, N) and the coiling temperature. The noise parameters are: variations in chemical composition (inside the tolerance range) and variations in the rolling settings. The yield strength of the steel (YS) is the output to analyze, whose histogram is shown in Fig. 2. The centering of the process will be defined by the settings of some control parameters (or signal parameters). The spread of the process may be determined by the effects of some control parameters (or spread parameters) and by those of the noise parameters.

CLASIFICATION OF THE PROCESS PARAMETERS

Fig. 3 shows the effects of signal and the spread parameters on the Y process variable.

Signal parameters: have effect over the mean value of the process. Variations from these will cause changes in the mean value (centering of the process.)

Spread parameters: have effect over the variability of the process. The controls of these parameters allow us to reduce the impact of the noise parameters over the variability of the process.

ROBUST ENGENEERING

One of the essential objectives of robust engineering is the reduction of the output variability around the specified values. This means to center the process at the nominal value and to reduce its intrinsic variability.

In the past, the common practice was trying to reduce the intrinsic variability by eliminating the processing noises. This strategy can be economically unviable, as well as technically impossible. The proposed method by G. Taguchi (1985) and developed in the literature (Phadke, 1989) is to try to eliminate or minimize not the noises, but the effects of them. This means to identify the spread effects of the processing parameters, and to use these effects to minimize the impact of the noise factors on the overall variability.

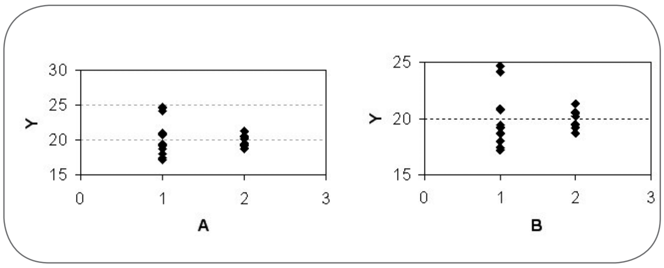

Fig. 3 ***Effects of the signal (A) and the spread (B) parameters on the Y variable.***
Effetto sulla variabile Y dei parametri segnale (A) e dispersione (B).

ROBUSTNESS AND BIAS MEASURES OF A PROCESS

The bias of a process which is under control can be estimated by the difference between its mean or average value (□) and its nominal value (T). The robustness of a process can be estimated by its variance (s^2) or by a monotonous function of its variance, and particularly by: S/N = - 10 Log10(s^2/k). K value is chosen so as S/N is always positive. It is clear that the process will be much more robust (less affected by the effects of noise) when lower the value of s^2 is [or 10 Log10(s^2/k)] and higher -10 Log10(s^2/k) is. The reason to measure the robustness by means of -10 Log10(s^2/k) resides a) in the statistical-mathematical properties of these random functions; and b) in the nonlinear character of the "metric of the quality ". In effect, the industrial effort to reduce the variance will be greater in the case of a relatively "good" process that in case of a "bad" one (like a long-distance runner that must provide a greater personal effort in the end to cross a same distance that at the beginning of the race).

Effects of the parameters

In several industrial situations, the relation Y = F(X, Z, W, …, T ; B1, B2, …, Br) can be by often approximated by a Taylor series as a function of the control parameters (X, Z,

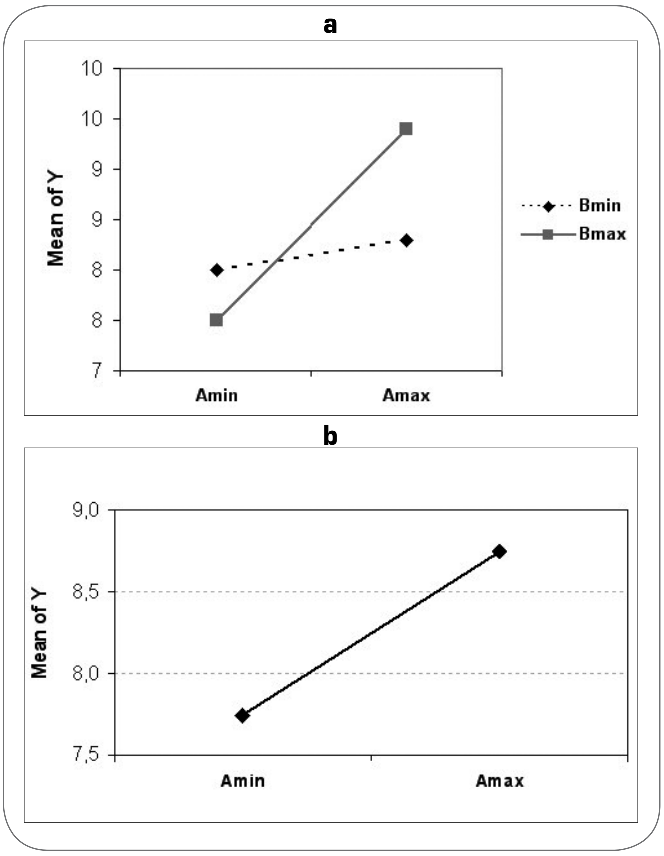

Fig. 4 ***Main effect of parameter A (XB = O).***
Effetto del parametro A (XB = O).

W, …, T). A stochastic term (ε) is added to represent the functional relationship between the output and the noise parameters (B1, B2, …, Br). If the experimental region is defined by a rectangle of industrially reasonable dimensions, the polynomial development can be reduced to a second-order one. In the case of two parameters (A and B), we have:

$Y = a0 + aA\ XA + aB\ XB + aAB\ XA\ XB + bA\ X^2A + bB\ X^2B + \varepsilon$
where XA y XB are standardized:
-1 if the parameter is in the minimum value
XA and XB =
+1 if the parameter is in the maximum value

The standardization is obtained with the followed transformation:

$XA = [2A - (Amaxi + Amini)] / (Amaxi - Amini)$
$XB = [2B - (Bmaxi + Bmini)] / (Bmaxi - Bmini)$

The given value by the deterministic component of the model, $f(XA, XB) = a0 + aA\ XA + aB\ XB + aAB\ XA\ XB + bA\ X^2A + bB\ X^2B$ represents the symmetry center of the process's histogram (its mean value). It is supposed that the random component ε has, according to the probability theory, a Gaussian distribution which zero mean and standard deviation σ (which measures the sum of the effects of noise parameters).
The effect of parameter A is the deterministic variation of the function caused by a variation Δ(XA) from A1 to A2.

Considering $f(xA,xB) = a0 + aA\ xA + aB\ xB + aAB\ xA\ xB + bA\ x^2A + bB\ x^2B$
We have : Effect of A $= \Delta A(f) = (aA + aAB\ xB)\ \Delta(XA) + bA\ [2\ xA1\ \Delta(XA) + \Delta^2(XA)]$

We take into account two cases: i) bA = 0 ; and ii) bA ≠ 0.

First case (bA = 0)

Effect of A $= \Delta A(f) = (aA + aAB\ xB)\ \Delta(XA)$
The effect of A is proportional to the slope (aA + aAB xB). The slope is constant if and only if aAB = 0.
If aAB ≠ 0 : i) the effect of A changes with the value of parameter xB; ii) the same thing happens with B (which effect will change with the value of A). Hence, an interaction between parameters A and B does exist. In this case, aA is the slope of the straight line which represents the effect of A when B takes the central value of its variation range (XB = 0) and the corresponding effect is named the main effect of A. Graphically, we have (Fig.4-a and 4-b):

Second case (bA ≠0)

Effect of A $= \Delta A(f) = (aA + aAB\ xB)\ \Delta(XA) + bA\ [2\ xA1\ \Delta(XA) + \Delta^2(XA)]$
$= [\{aA + bA^*\ \Delta(XA)\} + aAB\ xB + 2\ bA\ xA1]\ \Delta(XA)$

The slope changes with the A value. If we fix the value xB = 0, we obtain the main effect of A (graphically represented by a parabolic arc).

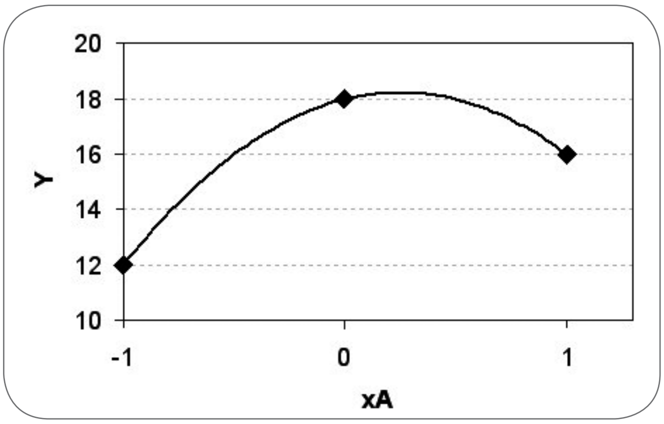

Fig. 5
Quadratic relationship between parameter A and Y variable.
Relazione quadratica tra parametro A e variabile Y.

Quadratic main effect
In this case (Fig. 5), the effect is a function of three factors: i) range of variation of the parameter, ii) initial value of the range of variation; and iii) complementary value of the interaction (if binary – or two-way – interaction is present).

This model may be generalized to any number of parameters:
$Y = a0 + \Sigma ai\ Xi + \Sigma\ aij\ Xi\ Xj + \Sigma\ bi\ X^2i + \varepsilon$ [model(1)]
where Xi is standardized:
-1 if the parameter is in the minimum value
Xi =
+1 if the parameter is in the maximum value

It is supposed that ε has a Gaussian distribution with a mean equal to 0 and standard deviation σ. Degree 3 and higher order terms are excluded. It is reasonable when the variation ranges of the parameters are not too wide.

DESIGN OF EXPERIMENTS

A design of experiments (DOE) is a list of trials (runs) that give place to linearly independent equations for the estimation of the parameters for the deterministic model, and hence, the estimation of the effect of the parameters. In the unreal and hypothetic case that the random component (ε) would have σ = 0, it would be enough to choose any group of K trials giving K linearly independent equations in order to estimate the k constants of the polynomial model. However, the presence in the model of aleatory component ε makes that two different groups of experiments (with the same number of trials) can give place to estimations with unequal precisions.
The art of DOE consists in choosing, for a given number of trials n, the group of n trials (runs) which allow us to estimate the constants of the model with the higher statistical precision as shown in Box and Draper (2007). We will exemplify the methodology with the aid of three case studies. In the first and second cases, linear effects and interactions are evaluated. In the third one, possible quadratic effects will be also evaluated.

	Design of experiments							Results	
	Design of experiments			Design of experiments					
RUN	A	B	C	AB	AC	BC	ABC	K	√k
1	-1	-1	-1	1	1	1	-1	0	0,00
2	-1	-1	1	1	-1	-1	1	0	0,00
3	-1	1	-1	-1	1	-1	1	0	0,00
4	-1	1	1	-1	-1	1	-1	0	0,00
5	1	-1	-1	-1	-1	1	1	1	1,00
6	1	-1	1	-1	1	-1	-1	2	1,41
7	1	1	-1	1	-1	-1	-1	9	3,00
8	1	1	1	1	1	1	1	17	4,12

Tab. 1
Full factorial design, A: Furnace temperature; B: Heating time; C: Cooling oil temperature.
Analisi fattoriale, A: Temperatura di riscaldamento; B: Tempo di riscaldamento; C: Temperatura di olio di raffreddamento.

Source of variability	Effect estimation	Coefficient estimation
Constant	-	1,19
A	2,38	1,19
B	1,18	0,59
C	0,38	0,19
AB	1,178	0,59
AC	0,38	0,19
BC	-0,18	-0,09
ABC	-,018	-0,09

Tab. 2
Effects and coefficients estimations, A: Furnace temperature; B: Heating time; C: Heating time.
Valutazione dell'effetto e del coefficiente relativo
A: Temperatura di riscaldamento; B: Tempo di riscaldamento; C: Temperatura di olio di raffreddamento.

Number of parameters	Number of linear main effects	Number of binary interactions
2	2	1
3	3	3
4	4	6
5	5	10
6	6	15
7	7	21
8	8	28
9	9	36
10	10	45
11	11	55

Tab. 3
Number of main effects and binary interactions as a function of the number of parameters.
Valutazione dell'effetto e del coefficiente relativo
Numero dei principali effetti e delle interazioni binarie in funzione del numero dei parametri.

THE CHOICE OF THE EXPERIMENTAL DESIGN AND THE NUMBER OF RUNS

The minimum number of required trials must be strictly higher to the number of effects to be estimated. If, in a first step, quadratic effects are not likely to be estimated, the Tab. 3 shows the number of main effects and the binary interactions as a function of the number of parameters.
The higher the number of parameters, the higher the number of interactions is. If all these are to be estimated the experimental cost increases dramatically. Because of the Pareto principle only few interactions are really (statistically and physically) significant. To solve this problem, when the number of parameters $k \geq 4$, it is desirable to estimate "aliases" (sums) of binary interactions instead of individual estimations.
Tab. 4 includes the number of runs for the usual experimental designs (Nomaksteinsky, 2005) that by allows the estimation of main linear effects and binary interactions as a function of the number of parameters.
Beside its usefulness, the interest on the two blocks-divided designs resides on the fact that the analysis of results from the first block allows, in certain cases, to extract enough information in order to avoid making the second block of experiments. On the other hand, the estimation of sums or aliases of interactions (and not individual estimations) shows big advantages and no major problems. In fact, these designs permit us to leave the presence of a significant quantity of interactions aside, achieving a great economy of experiments. In addition the presence of a sum of interactions statistically significant can result in several alternatives:
- Technical analysis on each one of the interactions included in the sum allow to discard some of them;
- The discarding of interactions between two continuous

Number of parameters	Number of runs	Effects to be estimated		Results
		Main effects	Binary interactions	
2	4	A, B	AB	Carry out at least two
3	8	A, B, C	all	repetitions for each run
4	8	A, B, C, D	AB+CD, AC+BD, AD+BC	
4	12	A, B, C, D	all	
5	16	A, B, C, D, E	all	
5	16 16	A, B, C, D, E	AB, AC, AD, AE, BC+DE, BD+CE, BE+CD	Design divided in two consecutive blocks of 8 runs each one
6	22 16 16 9	A, B, C, D, E, F	AB+EF, AC+DF, AD+CF, AE+BF, AF+BE+CD, BC+DE, BD+CE	Design divided in two consecutive blocks of 8 runs each one
6	12	A, B, C, D, E, F	all	
7	12 12	A, B, C, D, E, F, G	AB+DG+EF, AC+DF+EG, AD+BG+CF, AE+BF+CG AF+BE+CD, AG+BD+CE, BC+DE+FG	Design divided in two consecutive blocks of 8 runs each one
8		A, B, C, D, E, F, G, H	AB+CD+EF+GH, AC+BD+EG+FH, AD+BC+EH+FG, AE+BF+CG+DH AF+BE+CH+DG, AG+BH+CE+DF, AH+BG+CF+DE	
8		A, B, C, D, E, F, G, H	none	Exploratory design
9		A, B, C, D, E, F, G, H, I	none	Exploratory design
10		A, B, C, D, E, F, G, H, I, J	none	Exploratory design
11		A, B, C, D, E, F, G, H, I, J, K	none	Exploratory design

▲ Tab. 4 ***Number of runs for the usual DOE to evaluate main linear effects and binary interactions (or aliases of binary interactions) as a function of the number of parameters.***
Numero delle simulazioni DOE per la valutazione dei principali effetti lineari e le interazioni binarie in relazione al numero di parametri.

parameters when none of them shows main effects ;
- Additional trials to dissipate doubts

CASE STUDIES

Case I: hardenable boron steel

It is well known that solute boron can segregate to the austenite grain boundary and can delay the pro-eutectoid ferrite formation during continuous cooling. For this reason hardenable boron steel are usually chosen for the farming tools production. Good balance between hardness and toughness is required after quenching process, especially for avoiding tempering as a second treatment and hence reducing the costs. In this sense the control of austenite grain size and of cooling stop temperature is very important.
This example is related to the design of an oil quenching treatment of a medium carbon boron steel (0.30%C, 1.3%Mn, 30ppmB, Ti/N > 4) used for plow discs (Bruna et al, 2002). The estimation of the effects of three parameters on the robustness of the process is needed in order to obtain the lowest frequency of plow discs with shape defect (twisting) after quenching. One hundred (100) plow discs of 2.5 mm thickness x 406 mm diameter for each run are analyzed.

Parameters:
A: Furnace temperature, (880 ~ 920 °C)
B: Heating time (3.7 ~ 4.4 min)
C: Cooling oil temperature (40 ~ 70°C)

Output variable: amount (frequency) of discs with twist defect

A full factorial design (Tab. 1) with eight runs was chosen. It results of the 23 combinations from the maximum and minimum of the range of variation of the three parameters. The AB column is obtained by multiplying, one to one, the cells of the A and B columns. The same procedure is applied to obtain the AC, BC and ABC columns. It is admitted that the results have a Poisson distribution. Therefore, the result of the test is a frequency, and frequencies represent a

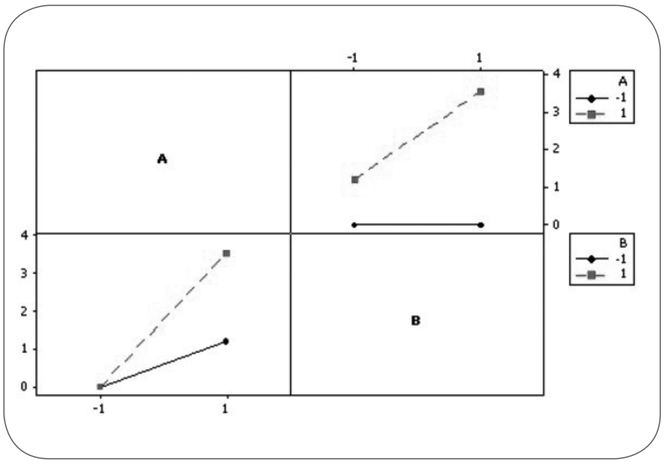

Fig. 6

AB Interaction plot (data means) for √k, A: Furnace temperature; B: Heating time.

Grafico della interazione A B (medie di dati) per √k, A: Temperatura di riscaldamento; B: Tempo di riscaldamento.

small proportion of the total. For the analysis of the results, we will work then with the square root of the frequency. Let us call A-1 the average of the 4 results corresponding to the trials with xA = -1; and A+1 the average of the 4 results corresponding to the trials with xA = +1. The least square estimation of the coefficient aA is obtained calculating (A+1 - A-1)/2.
Least squares estimations of the coefficients aB, ... , aABC are obtained by similar calculations from the respective columns of the matrix. The effects estimations are obtained multiplying by 2 the least squares estimations of the coefficients. In the following Tab. 2, the estimations of the model coefficients are shown, as well as the effects estimations. The effects that stand out are the main ones of A and B, as well as the AB interaction.

Modelization

Estimation of the average of √k = 1,19 + 1,19 * Furnace temp. (A) + 0,59 * Heating time (B) + 0,59 * Furnace temp. (A) * Heating time (B)
Fig. 6 is the graphic of Furnace temperature*Heating time (AB) interaction.

Conclusions

The only parameters with effects on the shape problem (twist) of discs are the furnace temperature and the heating time. At low furnace temperature (880 °C), the variations of the heating time (between 3.7 and 4.4 min) are without effect. In these conditions, the estimation of the average of √k = 1,19 + 1,19 * (-1) + 0,59 * Heating time + 0,59 * (-1) * Heating time = 0. At high Furnace temperature (920 °C), the variations of the heating time (between 3.7 and 4.4 min) causes variations in the frequency of plow disks with twist defect. In these conditions, the estimation of the average of √k = 2,38 +1,18 * Heating time.

Case II: C-Mn-V steel for welded pipes

This case deals with the development of thermo-mechanical rolling of hot strips for the production of J55 grade welded pipes (ERW, 6.9 mm thickness x 140mm ∅) without making full body normalizing treatment. Therefore, strict control of the mechanical properties on the hot strip is necessary to avoid rejected tubes.
We tried to evaluate both signal and dispersion effects, of k = 4 parameters on the mechanical properties (yield strength, which we wish to decrease, and tensile strength, that is desired to maximize) of hot rolled strip as studied by Bruna et al (1996). The parameters were selected taking into account their possible influence over amount and type of microstructural constituents (pearlite, vanadium precipitates)

	FACTORIAL EFFECT							Results							
	EXPERIMENTAL DESIGN				Interactions										
RUN	A	B	C	D	AB + CD	AC + BD	AD + BC						YS average (MPa)	s	S/N
1	-1	-1	-1	-1	-1	-1	-1	369	379	406	396	388	387,6	12,88	7,80
2	-1	-1	1	1	-1	1	1	373	356	370	366	371	367,2	6,05	14,37
3	-1	1	-1	1	1	-1	1	387	382	381	404	395	389,8	8,66	11,25
4	-1	1	1	-1	1	1	-1	425	397	402	408	406	407,6	9,48	10,47
5	1	1	1	1	-1	-1	-1	387	378	389	407	406	393,4	11,32	8,92
6	1	1	-1	-1	-1	1	1	457	449	414	410	412	428,4	20,28	3,86
7	1	-1	1	-1	1	-1	1	399	415	400	404	416	406,8	7,30	12,73
8	1	-1	-1	1	1	1	-1	416	375	381	386	375	386,6	15,27	6,33

Tab. 5

Fractional factorial design (8 runs), S/N = -10 * log10(s²/1000), A: Carbon; B: Manganese; C: Nitrogen; D: Coiling Temperature.

*Disegno fattoriale frazionato (8 simulazioni), S/N = -10 * log10(s²/1000)A: Carbonio; B: Manganese; C: Azoto; D: Temperatura di avvolgimento.*

Source of variability	Effect estimation	Coefficient estimation
A	15,75	7,88
B	17,75	8,88
C	-4,35	-2,18
D	-23,35	-11,68
AB+CD	-3,55	-1,78
AC+BD	-3,05	-1,53
AD+BC	-4,25	-2,13

Source of variability	Effect estimation	Coefficient estimation
A	-3,01	-1,51
B	-1,68	-0,84
C	4,31	2,16
D	1,50	0,75
AB+CD	-1,46	-0,73
AC+BD	1,42	0,71
AD+BC	-2,17	-1085,00

Tab. 6

Analysis of signal effects (left) and dispersion effects (right) on Yield Strength, A: Carbon; B: Manganese; C: Nitrogen; D: Coiling Temperature.

Analisi degli effetti sulla tensione di snervamento dovuti al segnale (grafico a sinistra) e alla dispersione (grafico a destra), A: Carbonio; B: Manganese; C: Azoto; D: Temperatura di avvolgimento.

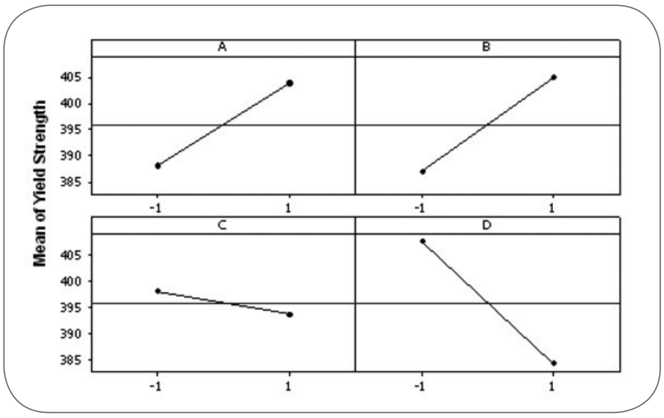

Fig. 7

Main effects plot for average Yield Strength [MPa], A: Carbon; B: Manganese; C: Nitrogen; D: Coiling Temperature.

Grafico degli effetti principali per la tensione di snervamento media [MPa] A: Carbonio; B: Manganese; C: Azoto; D: Temperatura di avvolgimento.

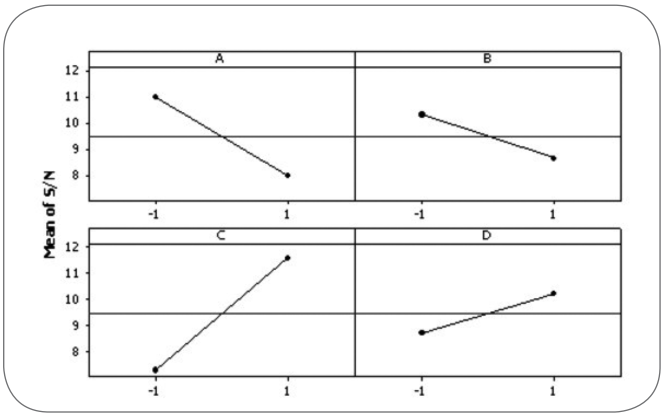

Fig. 8

Main effects plot for dispersion parameters (S/N) on Yield Strength, A: Carbon; B: Manganese; C: Nitrogen; D: Coiling Temperature.

Grafico degli effetti principali per il parametro dispersione media (S/N) relativo alla tensione di snervamento, A: Carbonio; B: Manganese; C: Azoto; D: Temperatura di avvolgimento.

Parameters :
A: Carbon, C (0.14 ~ 0.18 %wt)
B: Manganese, Mn (1.00 ~ 1.30 %wt)
C: Nitrogen, N (35 ~ 80 ppm)
D: Coiling temperature, CT (580 ~ 650°C)

Output variable: mechanical properties

An eight run fractional factorial design was selected (Tab. 5). Five repetitions were carried out by experimental setting. The average and standard deviation of yield strength and tensile strength were calculated (only the results for yield strength are shown). The robustness seeked concerns the intra-trial as well as the inter-trial variability (repeatability and reproducibility)

AB and CD columns are identical; therefore, both effects are «aliased» and the calculation carried out from the column is an estimation of the sum of both effects. The same happens with the other two columns belonging to the aliases AC+BD and AD+BC. Tab. 6 shows the analysis of signal (I) and dispersion (II) on yield strength

Analysis of signal effects on yield strength

Significant effects can be assigned to the A,B and D parameters (Fig. 7). Other effects can be assumed as noises of the process (Pareto principle). The manganese and carbon contents have a positive effect on the mean yield strength whereas the coiling temperature has a negative effect and the nitrogen content has no influence on the yield strength. These conclusions are valid for the evaluated experimental range.

Analysis of dispersion effects on the yield strength

Carbon and nitrogen effects are remarkable. The carbon content has a negative effect over robustness of the process and nitrogen has a positive effect. Manganese and the coiling temperature do not have effects on the robustness of the process. These conclusions are valid for the variations within the defined intervals. Therefore, the robust-

run	A	B	C	D	E	F	YS
1	-1	-1	-1	-1	-1	-1	465
2	-1	-1	-1	1	-1	1	478
3	-1	-1	-1	1	1	-1	442
4	-1	-1	1	-1	-1	1	473
5	-1	-1	1	-1	1	-1	442
6	-1	-1	1	1	-1	-1	464
7	-1	-1	1	1	1	1	447
8	-1	1	-1	-1	1	1	489
9	-1	1	-1	1	-1	-1	572
10	-1	1	1	-1	-1	-1	572
11	-1	1	1	1	-1	1	588
12	-1	1	1	1	1	-1	476
13	1	-1	-1	-1	1	1	469
14	1	-1	-1	1	-1	-1	520
15	1	-1	1	-1	-1	-1	505
16	1	-1	1	1	-1	1	534
17	1	-1	1	1	1	-1	527
18	1	1	-1	-1	-1	1	638
19	1	1	-1	-1	1	-1	560
20	1	1	-1	1	1	1	497
21	1	1	1	-1	1	1	494
22	1	1	1	1	-1	-1	645
23	-1	0	0	0	0	0	488
24	1	0	0	0	0	0	555
25	0	-1	0	0	0	0	501
26	0	1	0	0	0	0	581
27	0	0	-1	0	0	0	517
28	0	0	1	0	0	0	519
29	0	0	0	-1	0	0	519
30	0	0	0	1	0	0	517
31	0	0	0	0	-1	0	562
32	0	0	0	0	1	0	515
33	0	0	0	0	0	-1	482
34	0	0	0	0	0	1	500

Tab. 7

Design of Experiments. YS [MPa] values are predicted by metallurgical model.
A: Niobium; B: Manganese; C: rF4; D: rF5; E: Finisihing Temperature; F: Coiling temperature.
DOE. I valori della tensione di snervamento YS [MPa] sono stati predetti mediante modello metallurgico,
A: Niobio; B: Manganese; C: riduzione di spessore in finitore F4; D: riduzione di spessore in finitore F5; E:Temperatura finale fi laminazione; F: Temperatura di avvolgimento.

ness of the process can be optimized tending to maximize the level (ppm) of nitrogen and to diminish the content of carbon; and the yield strength levels can be minimized by minimizing the manganese content and maximizing the coiling temperature.

Conclusions

These results allowed us to implement a dynamic control system during the secondary metallurgy and hot rolling processes that aims at the optimal values of the parameters. The process capability (measured by the Cpk coefficient), after the modifications indicated by the analysis, was improved from 1.02 to 1.25 value.

Case III: HSLA steel

It is well known the synergy between microalloying elements (MAE) and thermo-mechanical controlled rolling processing (TMCP) to achieve the mechanical properties in microalloyed steels (HSLA). Grain refinement and precipitation hardening are mechanisms which require both steel alloy designs using different MAE (Nb, V, Ti, Mo, etc.) and an optimized rolling practice. Therefore, this work was aimed to set a robust design by using an experimental design combined with metallurgical deterministic models to predict microstructural evolution and mechanical properties of high strength steels. The obtained results using this methodology were validated in industrial production (Bruna et al, 2004).

Parameters:
A: Niobium, Nb (0.030 ~ 0.060 %wt)
B: Manganese, Mn (1.00 ~ 1.30 %wt)
C: Thickness reduction at the 4th finisher stand, rF4 (> 23%)
D: Thickness reduction at the 5th finisher stand, rF5 (> 20%)
E: Finishing temperature, FT (840 ~ 900 °C)
F: Coiling temperature, CT (550 ~ 650°C)
Strip thickness: 6.35 mm

Output variable: mechanical properties

Tab. 7 shows the experimental normalized matrix design used and the predicted tensile properties obtained by simulation. The 34 experimental runs permitted us to determine the linear and quadratic main effects and the binary interactions for the six chosen design variables. This experimental matrix has excellent statistical properties. The factorial part of the design (with $X_i = \pm 1$) results from a quasi-optimal design in 22 runs able to estimate 6 main linear effects and 15 binary interactions. The last 12 experimental runs result to carry out two experiments for each parameter with the ± 1 value whereas the other parameters take cero value. The outputs variables are YS (yield strength), UTS (ultimate tensile strength), YS/UTS x 100 (elastic ratio). Only the results regarding YS are shown. The term ε of the model (1) does not designate in this example a random component, as it does not represent the variations caused by the noise parameters of the process, but a) the lack of adjustment of the model by means of the polynomial development, and b) possible variations of the parameterization of the method to obtain the results of the metallurgical deterministic model.

The application of statistical software (Minitab ®) of linear regression provides the following results:

The regression analysis has been carried out with the standardized data. Estimated regression to YS

Effect	Coef.	Er-T Coef	T	P
Constant	**521,85**	**3,963**	**131,683**	**0,000**
A	**24,79**	**2,463**	**10,063**	**0,000**
B	**37,59**	**2,463**	**15,260**	**0,000**
C	-1,54	2,463	-0,623	0,556
D	0,21	2,463	0,087	0,933
E	**-33,04**	**2,463**	**-13,415**	**0,000**
F	-4,14	2,463	-1,681	0,144
A*A	-0,35	7,366	-0,047	0,964
B*B	**19,15**	**7,366**	**2,600**	**0,041**
C*C	-3,85	7,366	-0,522	0,620
D*D	-3,85	7,366	-0,522	0,620
E*E	**16,65**	**7,366**	**2,261**	**0,064**
F*F	**-30,85**	**7,366**	**-4,187**	**0,006**
A*B	0,30	2,587	0,117	0,911
A*C	1,77	2,587	0,682	0,520
A*D	4,05	2,587	1,564	0,169
A*E	0,07	2,587	0,027	0,980
A*F	**-7,13**	**2,587**	**-2,756**	**0,033**
B*C	-2,65	2,587	-1,023	0,346
B*D	-4,12	2,587	-1,591	0,163
B*E	**-21,27**	**2,587**	**-8,220**	**0,000**
B*F	-2,22	2,587	-0,857	0,424
C*D	**6,55**	**2,587**	**2,530**	**0,045**
C*E	0,59	2,587	0,227	0,828
C*F	0,54	2,587	0,208	0,842
D*E	-0,88	2,587	-0,341	0,745
D*F	0,32	2,587	0,123	0,906
E*F	**-8,20**	**2,587**	**-3,170**	**0,019**

S = 11,34 R^2 = 99,1% R^2(adjust) = 95,0%

ANOVA for YS

Source	DF	SQ	MS	F	P
Regression	27	84723,5	3137,9	24,41	0,000
Linear	6	63948,3	10658,0	82,93	0,000
Quadratic	6	3295,1	549,2	4,27	0,050
Interaction	15	14378,2	958,5	7,46	0,010
Residual error	6	771,2	128,5		
Total	33	85494,6			

Reducing the model on the basis of previous results and of metallurgical evaluation, we obtain:

The regression analysis has been carried out with the standardized data. Estimated regression coefficients to YS

Effect	Coef.	Er-T Coef	T	P
Constant	521,07	3,740	139,324	0,000
A	26,12	2,293	11,389	0,000
B	37,41	2,293	16,312	0,000
E	-32,54	2,291	-14,202	0,000
B*B	17,08	6,511	2,623	0,015
E*E	14,58	6,511	2,239	0,035
F*F	-32,92	6,511	-5,056	0,000
A*F	-8,86	2,402	-3,688	0,001
B*E	-21,00	2,402	-8,744	0,000
E*F	-8,99	2,405	-3,738	0,001

S = 10,96 R^2 = 96,8% R^2(adjust) = 95,4%

Modelization

Estimation of the average of YS (MPa) = 521,1 + 26,12 * Nb + 37,41 * Mn – 32,54 *
 * FT + 17,08 * Mn² + 14,58 * FT² - 32,92 * CT² - 8,86 * Nb* CT - 21 * Mn* FT –
- 8.99 * FT* CT

Conclusions

Parameter Niobio (A) has a linear main effect and an interaction effect with parameter Coiling temperature (F). The Manganese (B), Finishing temperature (E) and Coiling temperature (F) parameters have quadratic main effects, and there are B*E and E*F interactions. This methodology, combining the use of metallurgical models with an efficient experimental matrix, allowed to obtain an optimized steel alloy and rolling practice. The effectiveness of the method and the robustness of the design were verified in industrial production.

FINAL CONCLUSIONS

Concepts such as "robust engineering", "experimental design" and "process modeling" were developed with a practical sorting for their better comprehension and effective industrial application. The experimental methodology was introduced with the aid of three case studies. The linear and quadratic main effects and the interactions for the chosen design variables were determined. Empirical models, which show the functional relationships between the inputs and the outputs of the process, were obtained. The examples allowed us to draw conclusions about ideal conditions for the processing of hardenable boron steel to reduce a shape defect in farming tool, an optimized alloy steel for API grade with higher process capability (Cpk), and the design of a high strength low alloy steel (HSLA) and of its thermo-mechanical process. The less number of industrial trials and lower costs of R&D are some of the additional advantages on applying this methodology.

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ABSTRACT

POTENZIALITA' E VANTAGGI DEL "ROBUST ENGINEERING" E DELLA SPERIMENTAZIONE TECNOLOGICA NELL'INDUSTRIA SIDERURGICA

Keywords:

Acciai con proprietà uniche e nuovi processi termo-meccanici (TMP) sono progettati e ottimizzati in modo continuo mediante lo sviluppo, l'estensione e l'applicazione di modelli metallurgici e/o la realizzazione di costosi programmi di ricerca e sviluppo.
In questo lavoro si sottolineano i benefici di metodi come "robust engineering", "design of experiments (DOE)" e "modellistica di processo" che sono stati sviluppati da un punto di vista pratico per una migliore comprensione e una più efficace applicazione industriale.
Migliorate capacità di processo e prestazioni in servizio di acciai HSLA e ad alto carbonio, minor numero di prove industriali e minori costi della ricerca e sviluppo sono alcuni dei possibili vantaggi derivanti dalle applicazioni di queste metodologie.