NON QUALITY COSTS REDUCTION IN WELDING

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Abstract. *The objective of this work is to present an experimental optimization study in the welding field. The optimization was carried out based on the reduction of the non quality costs, which are the financial loss suffered by the client every time a response variable drifts away from its target value or presents variability. The costs reduction is fulfilled through the proper adjustment of the process parameters, in such a way that deviations from the target are minimized while robustness to noise and to process parameter fluctuations are maximized. Since this a multi-response, multi-objective problem, the optimum solution is a compromise. The optimization methodology used in this work is composed of five steps: problem identification, experimental design, response modeling, objective function definition and optimization. As an application example for the proposed methodology, it was successfully applied in the submerged arc welding of plain steel, 9.5 mm thick, butt joint.*

Keywords. *Experimental Optimization, Quality, Response modeling, Submerged Arc, Welding.*

1. Introduction

The quality of the welded material can be evaluated by many characteristics (or responses), such as bead geometric parameters (penetration, width and height). These characteristics are controlled by a number of welding parameters, and, therefore, to attain good quality, is important to set up the proper welding process parameters. But the underlying mechanism connecting then (welding parameters and quality characteristics) is usually not known.

In the optimization of a given welding process, the quality engineer is generally interested in achieve three objectives:

1) minimize target deviations;
2) maximize process robustness to noise factors (= minimize variability); and
3) maximize process robustness to process parameters oscillations.

The targets are the ideal values for each response. To minimize target deviations means to produce units with their responses as close as possible to the ideal values. The noise (variability) is caused by the effect of non-controllable factors, such as weather condition. To maximize robustness to noise means to produce units relatively insensitive to these non-controllable factors.

The process parameters are the controllable factors, i. e., the product or process variables that can be controlled. In the welding process under investigation, typical parameters are welding voltage, wire feed speed, welding speed, etc. The process parameters should be adjusted in order to achieve objectives 1 to 3. Unfortunately during the production phase, due to changes in setup, operators, raw material supply, etc, it may be difficult to hold the levels of some (or all) process parameters at fixed levels. Therefore, it is also desirable to develop robustness to process parameters fluctuations. This means that when the process parameters experience small variations from their optimal setting, the quality responses will not degrade.

To achieve these three, sometimes conflicting, objectives, Ribeiro & Elsayed (1995) proposed the following five steps optimization methodology:

1) Problem identification: list process parameters and quality characteristics of interest. For quality characteristics define target and priorities. Defining the proper targets is crucial. Engineer must be sure that the chosen targets are in harmony with the customer's requirements.

2) Experimental design: study the problem and choose the proper experimental design to collect data concerning mean and variability. The levels of the process parameters must be chosen carefully in order to properly investigate the region of interest. Also, it is important to collect enough data to allow modeling variability.

3) Response modeling: build mean and variance models for each response. To perform step 3 the engineer must be familiar with model building techniques. Building models for each response separately, the engineer has the opportunity to learn important facts about the process under study. Barbetta (1998) proposed an iterative technique for building models of mean and variance. At first, the variance modeling is built with a statistic made from the calculated variance and from the quadratic error (taken from the mean model). Then the mean model is recalculated using the variance statistic values as weights when finding the new mean regression parameters, in a technique known as Generalized Least Squares (GLS). This technique is a variation of the common Ordinary Least Squares (OLS). The procedure is

repeated at least twice or is finished by visual analysis of residual error and R^2 index.

4) Objective function definition: the gradient loss function is based on the function proposed by Taguchi (Phadke, 1989) to quantify the non quality costs. These costs may be defined as the financial loss suffered by the client every time a response variable drifts away from its target value or presents variability. Eq. (1) presents the objective function.

$$Z(i) = \sum_{j=1}^{Q} w_j \left[(Y_j^m - T_j)^2 + (\sigma_{Yj}^m)^2 + \sum_{k=1}^{P} (\sigma_{X_k}^m)^2 \cdot \left(\frac{\partial Y_j^m}{\partial X_k} \right)^2 \right] \tag{1}$$

where:

$Z(i)$	is the objective function to be minimized, i. e., the lower function values, the higher the process quality. For each parameter adjust (treatment "i"), a Z value can be obtained;
w_j	are weights to take into account units and the relative importance of each quality characteristic. Q is the total number of responses;
T_j	is the target, or the ideal value to, to the response j;
Y^m_j	is the predicted mean for each quality response j;
σ^m_{Yj}	is the predicted variance for each quality response j;
σ^m_{xk}	is the standard deviation estimate for each controllable factor k.

The objective function Z(i) has three terms. The first one accounts for deviations from target values. The last two terms account for two sources of variability: (1) variability due to non controllable factors (noise factors), and (2) variability due to fluctuations on "controllable" factors (process parameters).

However, Eq. (1) presents its results in dimensionless values, which have only comparative use. Caten (1995), in an optimization study for a chemical industry, suggests a procedure to find a constant that changes these dimensionless values into monetary ones. The cited industry has a production line set to fabricate a specific chemical. Depending on the final quality, the product may be classified into two categories (high or low quality), and is sold with different prices. The non quality cost for a class A product (high quality) is 64 units of Eq. (1) and its retail price is R$1.42/kg. The low quality product (B class) has a 179 units cost and a R$ 1.07/kg price. The constant was defined as the reason between the price and the quality differences. Once calculated this constant, the non quality monetary costs were found by multiplying the Z function by the constant.

Besides the advantage of putting the non quality costs into a more understandable base, the described procedure permits that the researcher adds a operational costs function to the Z function and performs an optimization to find the best compromise between quality and fabrication cost.

5) Optimization: this step refers to numerical optimization of the objective function and it may be accomplished by a number of methods (simulated annealing, genetic algorithm, augmented Lagrange multiplier method, etc.). The lowest value of the Z function presents the parameter adjusts that deliver the highest quality, i. e., the parameters that cause the responses to fulfill the three objectives previously cited.

The goal of this article is to demonstrate the viability of the above procedure in the welding field. More precisely, to optimize 2 parameters (gap between plates and contact tip work piece distance) in a submerged arc process application. These parameters were chosen because they are the most likely to fluctuate in a real production line, generating therefore non quality costs. The search for the optimum was based on the minimization of an objective function Z, which takes into account the geometric characteristics (penetration, p_{exp}, width, W_{exp}, and reinforcement, R_{exp}) of the bead.

2. Optimization Methodology

The Submerged Arc welding process is easily found in any industry whose products require metal joining in a large scale. It establishes an electric arc between a continuous filler metal electrode and the weld pool, with shielding from an externally supplied flux. The heat of the arc melts the surface of the base metal and the end of the electrode. The electrode molten metal is transferred through the arc to the work where it becomes the deposited weld metal (weld bead).

The optimization study experiments were obtained with an automatic welding equipment (electromagnetic power supply, wire feeder and traveling system) and the electric signals of the welding arc were acquired (voltage and current). The work piece to be welded was made of two 9.5 mm thick, 300.0 mm long and 50.0 mm wide mild steel plates, with a square-groove butt joint. Two passes were used to fill the joint (same welding conditions) and the combination filler metal/flux was AWS F7A2-EM12K, with 3.18 mm electrode diameter. The electrode angle was held in 90° to the work piece.

2.1 Problem identification

The targets for the evaluated responses were 5.5 mm for bead penetration, 9.0 mm for width and 2.0 mm for reinforcement and the respective importances were (from 0 to 5) 5 to penetration and 1 to the rest. These values were chosen by an industry interested in changing its current welding process (manual metal arc) for a new one with better quality and productivity. It should be noticed that these values were defined according to the industry experience with the manual metal arc process and, with the exception of the penetration, the others response values are not vital to the weld soundness. And the importance given to each response reflects this concern.

A previous set of experiments (pre-optimization) defined the values for the fixed parameters and the ranges for the two process parameters investigated (further details on the pre-optimization phase can be seen on Correia, 2003). The selected ranges are presented below:

Gap between plates (GAP) – 0.0 to 1.5 mm;
Contact Tip Work Piece Distance (CTWD) – 35 to 45 mm.

2.2 Experimental design

The ranges were distributed over a full factorial design 3^2 (two factors on three levels) plus a central point and each test had two replications in order to build a model of variance (total of 3 tests for each experimental condition).

Table 1 presents the welding parameters in codified and actual levels. The codification is done in order to put the parameters in a dimensionless way and in the same scale, so the effects of each parameter can be evaluated by the terms in the regression model. From this moment on the subscript "c" close to a parameter name means that the correspondent value is codified (further details on codification may be seen on Eq. (2)). It must also be said that experiments in Table 1 were conducted in an random way, in order to minimize the influence of the non-controllable factors of the process.

$$CL = \frac{AL - M}{(HL - LL)/2} \tag{2}$$

where: CL: Codified Level; AL: Actual Level; M: Range Mean; Higher Level: Higher Limit from the range and LL: Lower Limit from the range.

Table 1. Experimental design (Submerged Arc Process)

Test	Codified Levels		Actual Levels	
	GAP_c	$CTWD_c$	GAP (mm)	CTWD (mm)
1	-1	-1	0.0	35
2	-1	0	0.0	40
3	-1	1	0.0	45
4	0	-1	0.8	35
5	0	0	0.8	40
6	0	1	0.8	45
7	1	-1	1.5	35
8	1	0	1.5	40
9	1	1	1.5	45

Table 2 presents the current and voltage signal acquired during the tests, as well as the mean of the measured values for each response. In this table, U_m and I_m stands, respectively, for mean arc voltage and mean arc current.

Table 2. Experimental results

Test	U_m (V)	I_m (A)	Penetration (mm)			Width (mm)			Reinforcement (mm)		
1	34.5	533	5.0	4.8	4.9	12.7	12.7	12.7	1.8	2.1	1.9
2	35.5	514	4.5	4.2	4.5	12.8	12.8	12.7	1.9	2.1	1.9
3	35.4	495	4.2	3.9	4.1	12.8	12.7	12.8	1.7	1.8	1.8
4	35.1	528	5.4	5.6	5.5	12.9	13.0	12.9	1.6	1.6	1.6
5	35.0	519	5.0	5.0	4.9	13.0	13.0	12.8	1.8	1.7	1.6
6	35.1	510	5.1	4.7	4.7	12.9	13.0	12.8	1.9	1.8	1.6
7	34.5	519	5.9	6.0	6.0	12.8	12.8	12.7	1.3	1.1	1.1
8	35.0	500	5.3	5.3	5.4	12.9	12.8	12.8	1.0	1.0	1.0
9	35.4	499	5.9	5.5	5.8	12.9	12.5	12.7	1.0	1.1	0.9

The analysis of the Table 2 shows that some tests were able to achieve the target values for the penetration and some others were very close to the target values for the reinforcement. And no test delivered the desired value for the width. With the response modeling and optimization steps, it is attempted to locate a non tested experimental point with a better compromise between the responses.

2.3 Response modeling

Before applying the modeling technique proposed by Barbetta (1998), the data shown in Table 2 should be transformed to a –1 to +1 range for each response. The reason for this procedure is as follows. The actual objective function to be optimized is composed by three blocks, each of then with Eq. (1) filled with data relative to the evaluated responses (penetration, width and reinforcement). Each block has four functions and these function refer to the three objectives of non quality: minimize target deviations, maximize process robustness to noise factors and maximize process robustness to process parameters oscillations.

As seen in the Introduction, the blocks are multiplied by weights and these weights have a dual purpose: keep responses with high numerical values from "heading" the optimization process and provide a relative hierarchy for the responses. However, it may occur that inside each block there are terms with scale differences and them the weights will have no effect. For instance, inside the penetration block, the term relative to target deviation can be substantially higher than the term relative to variance. In this case, the optimization algorithm will "forget" the variance and "concentrate" only in the target during the search for the optimum. In other words, the optimization may be carried out only concerning means (usually higher) and ignoring the other terms relative to variance (Osyczka, 1984).

In order to avoid this situation, it is suggested to normalize the data of the responses to the range of –1 to +1. The algorithm used to perform such transformation is presented in Eq. (3).

$$nv = 2 * (ac - minvr) / (maxvr - minvr) - 1 \quad (3)$$

where:

nv = normalized value;
ac = actual value;
minvr = minimum value in the set of values "ac";
maxvr = maximum value in the set of values "ac".

The algorithm shown in Eq. (3) was used to transform the data from Table 2. Table 3 presents the results, i. e., the normalized data, including the transformed target values.

Table 3. Normalized experimental results

	Penetration (target = 0.52)			**Width (target = -1.00)**			**Reinforcement (target = 0.83)**		
1	0.05	-0.14	-0.05	0.85	0.85	0.85	0.50	1.00	0.67
2	-0.43	-0.71	-0.43	0.90	0.90	0.85	0.67	1.00	0.67
3	-0.71	-1.00	-0.81	0.90	0.85	0.90	0.33	0.50	0.50
4	0.43	0.62	0.52	0.95	1.00	0.95	0.17	0.17	0.17
5	0.05	0.05	-0.05	1.00	1.00	0.90	0.50	0.33	0.17
6	0.14	-0.24	-0.24	0.95	1.00	0.90	0.67	0.50	0.17
7	0.90	1.00	1.00	0.90	0.90	0.85	-0.33	-0.67	-0.67
8	0.33	0.33	0.43	0.95	0.90	0.90	-0.83	-0.83	-0.83
9	0.90	0.52	0.81	0.95	0.75	0.85	-0.83	-0.67	-1.00

Applying the iterative modeling technique proposed by Barbetta (1998) on the data shown in Table 3, the following models are found.

$$\text{Penetration} = 0.12 + 0.58 \cdot GAP_c - 0.26 \cdot CTWD_c + 0.15 \cdot GAP_c \cdot CTWD_c \quad (4)$$
$$\text{VAR-pen} = \exp(-4.01 - 0.02 \cdot GAP_c + 0.11 \cdot CTWD_c + 0.05 \cdot GAP_c \cdot CTWD_c) \quad (5)$$

$$\text{Width} = 0.91 + 0.00 \cdot GAP_c - 0.02 \cdot GAP_c \cdot CTWD_c \quad (6)$$
$$\text{VAR-width} = \exp(-6.11 + 0.07 \cdot GAP_c + 0.08 \cdot CTWD_c + 0.07 \cdot GAP_c \cdot CTWD_c) \quad (7)$$

$$\text{Reinforcement} = 0.07 - 0.69 \cdot GAP_c - 0.04 \cdot CTWD_c - 0.00 \cdot GAP_c \cdot CTWD_c \quad (8)$$
$$\text{VAR-reif} = \exp(-3.51 - 0.03 \cdot GAP_c + 0.05 \cdot GAP_c \cdot CTWD_c) \quad (9)$$

The models found with the Barbetta (1998) technique are superior than the ones obtained with ordinary least squares. The only problematic response was the width, where the regression equation did not succeed in explaining the data variation. But a simple visual analysis in Table 2 shows that the values for this response are very much alike. And it is believed that this low level of variance was responsible for the bad results, since the GLS efficiency related to OLS is better when the variance between experimental points is great. Table 2 shows that the width varies only between 12.7 to 13.0 mm, which is very little in practical. However, the width model was included in the Z function, since it has a small importance in the optimization.

2.4 Objective Function Definition

The objective function used in the optimization of the submerged arc process is based on Eq. (1) and its complete characterization needs, aside the prior presented models, the weights "w" and the estimatives "σ". The weights "w" take into account the utility and the relative importance of each response. And the values "σ" are estimatives of the standard deviation for each control parameter.

The weights used in this article are presented below.

Penetration Weight: $w_{pen} = 5$
Width Weight: $w_{larg} = 1$
Reinforcement Weight: $w_{ref} = 1$

The estimatives for the standard deviation "σ" are related with the expectative of parameter fluctuation in a real production line. First, it is assumed a variation coefficient (VC) for each parameter. Then the estimative "σ" is calculated as shown below (with supposed variation coefficients of 90% for the GAP and 10% for the CTWD).

Intermediary Level factor

Step between factor levels

$VC_{GAP} = 90\ \%$ $\sigma_{GAP} = (0,9 * 0.8) / 0.8 = 0.9$

$VC_{CTWD} = 10\ \%$ $\sigma_{CTWD} = (0.1 * 40) / 5.0 = 0.8$

Where:
VC_{GAP} – GAP variation coefficient;
VC_{CTWD} – CTWD variation coefficient;
σ_{GAP} – GAP standard deviation estimative;
σ_{CTWD} – CTWD standard deviation estimative.

The models, weights and partial derivatives (obtained from the models) were included in the Eq. (1). The resulting function can be seen below (GAP and CTWD were replaced by X1 e X2, respectively).

Z =

$$5 \cdot \left\{ \begin{array}{l} [0.12 + 0.58 \cdot X1 - 0.26 \cdot X2 + 0.15 \cdot X1 \cdot X2 - 0.52]^2 + \\ [\exp(-4.01 - 0.02 \cdot X1 + 0.11 \cdot X2 + 0.05 \cdot X1 \cdot X2)]^2 + \\ \left[0.9^2 \cdot (0.58 + 0.15 \cdot X2)^2\right] + \\ \left[0.8^2 \cdot (-0.26 + 0.15 \cdot X1)^2\right] \end{array} \right\} +$$

$$1 \cdot \left\{ \begin{array}{l} [0.91 + 0.00 \cdot X1 - 0.02 \cdot X1 \cdot X2 + 1.00]^2 + \\ [\exp(-6.11 + 0.07 \cdot X1 + 0.08 \cdot X2 + 0.07 \cdot X1 \cdot X2)]^2 + \\ \left[0.9^2 \cdot (-0.02 \cdot X2)^2\right] + \\ \left[0.8^2 \cdot (-0.02 \cdot X1)^2\right] \end{array} \right\} +$$

$$1 \cdot \left\{ \begin{array}{l} [0.07 - 0.69 \cdot X1 - 0.04 \cdot X2 - 0.83]^2 + \\ [\exp(-3.51 - 0.04 \cdot X1 + 0.05 \cdot X1 \cdot X2)]^2 + \\ \left[0.9^2 \cdot (-0.69)^2\right] + \\ \left[0.8^2 \cdot (-0.04)^2\right] \end{array} \right\} \tag{10}$$

The results delivered by the Eq. (10) are relative to the non quality costs of the submerged arc welding process. And they are in dimensionless units, which have only comparative value. The optimization step (number 5) was taken with Eq. (10) and in the end of this article it will be proposed a way to change this dimensionless units into monetary values.

2.5 Optimization

The minimization of Eq. (10) was made through an algorithm based on the “simulated annealing” technique (Saramago et al, 1999). The minimum value found was 5.6 and the Table 4 presents the correspondent optimum adjusts (these values are the same of the experimental condition 4 in Table 1).

Table 4. Optimum values for the welding parameters

Parameter	Codified Levels	Actual Levels
FOLGA	0	0.8 mm
DBCP	-1	35 mm

3. Sensibility Analysis

After defining the best values for the welding parameters, it is also important to know how the quality responses react to parameter fluctuations. In other words, to have an idea of the process sensibility (quality loss due to fluctuations). This is so because in any production line, no matter how controlled it is, there are always little accidental variations that may corrupt the optimum adjustments. And depending on the situation, it may be necessary to alter the optimum settings in order to minimize this effect.

The sensibility analysis is made holding one of the parameters constant in the optimal setting and calculating the Z function (Eq. 1) for all the experimental range of the other parameter. With this technique, two graphics were built. They can be seen in Figures (1) and (2).

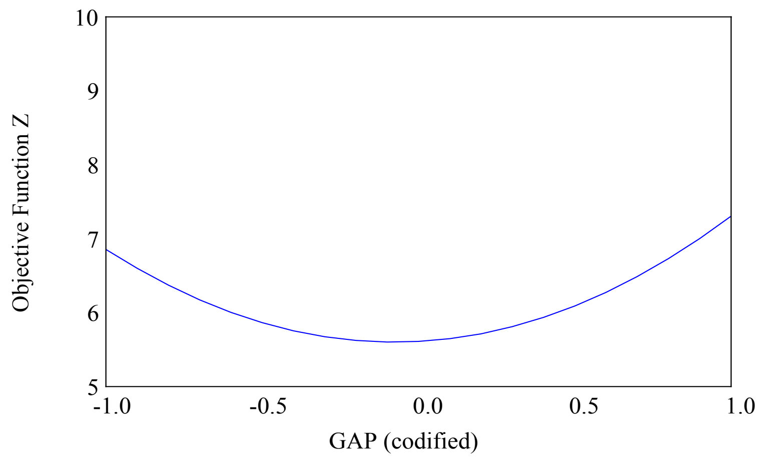

Figura 1. GAP effect on the objective function Z (CTWD fixed in its optimal setting)

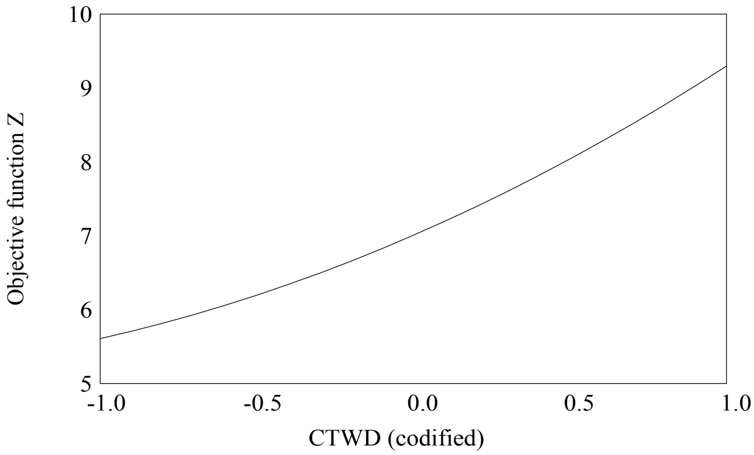

Figura 2. CTWD effect on objective function Z (GAP fixed in its optimal setting)

The comparison between the Figures (1) and (2) reveals that the welding parameter most likely to cause impact in the process quality is the CTWD. This result implies that the CTWD values should receive, in a real production line, more attention by engineers than the GAP ones, since its variation can cause higher quality loss.

There is also another way of analyzing the influence of the GAP and CTWD on the process sensibility. The objective function can be divided in its individual components, or several intermediary Z's, each one related to a line in Eq. (10). These terms are discriminated below and Table 5 presents the partial values of Z and their percentages, considering the optimum adjusts.

Z1a – related to penetration target deviation;
Z1b – related to penetration variance;
Z1c – related to the effect of GAP fluctuations on the penetration;
Z1d – related to the effect of CTWD fluctuations on the penetration;

Z2a – related to width target deviation;
Z2b – related to width variance;
Z2c – related to the effect of GAP fluctuations on the width;
Z2d – related to the effect of CTWD fluctuations on the width;

Z3a – related to reinforcement target deviation;
Z3b – related to reinforcement variance;
Z3c – related to the effect of GAP fluctuations on the reinforcement;
Z3d – related to the effect of CTWD fluctuations on the reinforcement.

Table 5. Z function Discrimination

Partial Z's	Quality loss with the optimum adjustment	% of Z
Z1a	0.1	1.8
Z1b	0.0	0.0
Z1c	0.7	13.2
Z1d	0.2	3.9
Z2a	3.7	65.1
Z2b	0.0	0.0
Z2c	0.0	0.0
Z2d	0.0	0.0
Z3a	0.5	9.1
Z3b	0.0	0.0
Z3c	0.4	6.9
Z3d	0.0	0.0
Total	**5.6**	100.0

The analysis of the values shown on Table 5 shows that more than 70% of the quality loss is due to target deviation by two responses: width (65%) and reinforcement (9%). Another relevant contributing factor is also the term related to the effect of GAP fluctuations on the penetration (13%). So, the major problem with quality loss is about the final width of the optimum weld bead, around 13 mm, when the chosen target was 9 mm (section 2.1, problem identification). There are basically two ways of dealing with this situation: new tests or target revision. The first option should be chosen if the value of 9 mm for the width were vital for weld bead. Since the bead width of 13 mm could be used on the given application without any kind of problem, it was decided to review the target and change it to the 13 mm value. Regarding the penetration, which is the most important response, the target was well achieved. And the industry also agreed on the value found for the reinforcement (low importance response, as the width). These considerations allow maintaining the settings presented on Table 4 as being the optimum.

4. Operational costs

The operational costs for the submerged arc welding process were not modeled, but only calculated for the optimum point presented in Table 4. Because of that, there is no need of a new optimization regarding non quality and operational costs. However, the values found for then are also important on the determination of the constant K, which changes the dimensionless non quality costs into monetary ones. Table 6 presents the calculated costs for submerged arc process, considering two passes.

Table 6. Operational costs for the submerged arc welding process

Welding cost	R$/m
Consumables (filler metal + flux)	0.33
Labor	0.90
Investment	0.12
Depreciation	0.13
Maintenance	0.08
Electric power	0.17
Total	1.73

5. Non Quality Monetary Costs

As it was said before, the values presented by the Eq. (10) are dimensionless and have only comparative utility. They are useful when comparing different processes and the researcher is interested in defining which one has the best quality (i. e., which one has their responses closer to the pre-chosen targets). However, it is possible to change these relative values into absolute ones (monetary costs), by a constant K. The methodology used to find this constant considers that there is a region where the quality loss exists, but not in the sense of reworking the weld bead. This region begins on the 5.6 value of the objective function Z (optimum value, i. e., minimum value of the objective function Z) and ends on the 16.7 value (worse condition inside the experimental region investigated, i. e., maximum value of the objective function Z). Beyond this region, any weld bead deposited would have to be removed from the plate and welded again. The cost of reworking the weld bead is calculated as the cost of a unitary pass (1.73 / 2 = 0.87 R$/m), plus the removal cost (0.64 R$/m) and plus the operational cost of depositing a single new bead (0.87 R$/m), which gives 2.37 R$/m.

The constant K is defined as the difference between beads costs (reworked bead cost and optimum bead cost) divided by the difference between the correspondents Z function values. Mathematically, the K constant is defined as below.

$$K = \frac{2.37 - 1.73}{16.7 - 5.6} = 0.058$$

The K Constant, when multiplied by the Z function value, gives the quality loss costs in monetary values. Considering the Z function optimal value, 5.6, the monetary quality loss costs are:

$$\text{Monetary quality loss costs} = K \cdot Z = 0.058 \cdot 5.6 = 0.32 \text{ R\$/m}$$

This value corresponds to, approximately, 18% of the operational costs (1.73 R$/m). The total cost for the submerged arc welding process is:

$$\text{Total Cost (non quality + operational)} = 0.32 + 1.73 = 2.05 \text{ R\$/m}$$

This final value should be used mainly to compare the costs of the submerged arc with other possible welding processes, i. e., processes that can substitute the manual metal arc with advantages in the given application, such as the GMAW. The best process would be the one with the smallest total costs.

6. Conclusions

The proposed optimization methodology can be considered effective in providing a representative value of the total costs involved in welding applications (operational costs and non quality costs). Therefore, it can be used to compare different processes options and help choosing the most suitable.

In the present submerged arc case, the proposed methodology was able to define the parameter adjustments that deliver the evaluated responses the closest possible of the their targets.

The targets should be chosen with great care, since a poor defined target can lead the remaining quality responses to undesirable values. In this article the major target problem was related with the bead width. Its value on the end of the optimization was very far of the desired one. But there was an agreement that the previous defined 9 mm was incorrect, since the normal widths achieved with the manual metal arc process are generally smaller than the ones achieved with the submerged arc.

Regarding the costs involved in the submerged arc, the monetary value found for non quality costs is not totally absolute, since it depends on the procedure used to calculate the constant K. Further work is needed in order to define better methods to relate rework, customer dissatisfaction and other non quality items with monetary values for the Z function.

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