A multiobjective optimization of the welding process in aluminum alloy (AA) 6063 T4 tubes used in corona rings through normal boundary intersection and multivariate techniques

Eduardo Rivelino Luz 1 · Estevão Luiz Romão 1 · Simone Carneiro Streitenberger 1 · Leonardo Ribeiro Mancilha 1 · Anderson Paulo de Paiva 1 · Pedro Paulo Balestrassi 1

Received: 15 May 2021 / Accepted: 20 July 2021 / Published online: 9 August 2021
© The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2021

Abstract
The welding process in aluminum is a complex process that commonly presents several issues such as weld bead discontinuity, cracks, and lack of penetration. Thus, an accurate specification of the parameters in order to achieve optimal values for the investigated responses is aimed by the industry. The present paper proposes the application of a multiobjective optimization approach considering multivariate constraints based on the simultaneous confidence intervals and the elliptical region of the correlated data. Structured experiments for the welding process of aluminum alloy (AA) 6063 TA tubes used in corona rings were performed according to a face-centered composite design with 4 factors, wire feed rate (Wf), arc voltage (V), contact tip to the workpiece distance (Ct), and motor frequency (Fr), resulting in 31 experiments. Poisson regression was applied to model the values of yield (Y), dilution (D), reinforcement index (RI), and penetration index (PI), allowing to estimate the optimal individual values with regard to the multivariate constraints. Rotated factor scores were obtained in order to replace the original data, and therefore, the factor multivariate square error was used as objective functions to be minimized through normal boundary intersection method. A satisfactory weld bead with large values of PI, D, and Y and a small value of RI was reached as prespecified by the manager of the process.

Keywords Aluminum welding · Design of experiments · Multiobjective constrained optimization · Factor analysis · Simultaneous confidence intervals

1 Introduction
Corona rings are used to improve the performance of the insulator strings. Besides reducing corona discharges, the associated audible noise, and radio and television interference levels, they also improve the voltage distribution along the insulator string by reducing the percentage of the voltage on the nearest unit to the power transmission line. Moreover, corona rings also alleviate corona degradation of non-ceramic materials. Structurally, they are toroidal shaped metallic rings which are fixed at the end of bushings and insulator strings. Also called anti-corona rings, they can even be used to prevent corona discharge that occurs in high voltage power lines. This discharge, or corona loss, is a significant issue in very high voltage power lines, causing power loss [1, 2].

In order to increase the lifetime of a composite insulator, mainly when it carries high voltages like over 230 kV, a field stress control ring, such as the corona ring, is necessary. Furthermore, it is important that a great coherence between the insulator and the corona ring in terms of the design and construction exists; i.e., the dimensions of the corona ring should be well specified during the insulator construction [3].

Constraints and better operating conditions are applied for better efficiency and organizational effectiveness in the management of the gas metal arc welding (GMAW) process, better known as metal inert gas (MIG) welding, of anti-corona protection rings. Considering a project from a Brazilian company, these rings are manufactured using aluminum alloy (AA) 6063 T4. Specifically for this study, a tube with a diameter of 100 mm and thickness of 2 mm was chosen. The...
company manufactures other designs of anti-corona rings, with different diameters and thicknesses, but from the same material with the same characteristics and properties (AA6063 T4).

The use of aluminum is justified by its weight, since it is lighter when compared with other metals, and because AA 6063 presents an electrical conductivity that satisfies the projects of companies such as the electric energy segment, consumers of this kind of product.

Among published papers such as [4–7], special attention has been given to the welding of different aluminum alloys, whose usage by the energy industry is extremely intense due to good corrosion resistance, good mechanical properties, and excellent electrical conductivity.

Aluminum welding is a complex task that requires well-defined parameters to present a satisfactory result, with no defects such as porosity, cracks, lack of penetration, lack of fusion, and filling failures. Many researches regarding aluminum welding have been recently published in literature [8–12]. Miguel et al. in [13] established a control methodology for GMAW welding based on the response surface methodology (RSM) considering two parameters, penetration and length of the heat affected zone (HAZ). The experimental methodology for measuring both variables allowed to get better adjusted models than those obtained in the compared studies [13].

In [5], whose main objective was the optimization of the HAZ, RSM was exploited. This method allowed the optimization of the response function after modelling the influence of different independent variables through a minimum number of experiments. A sequential strategy was carried out in order to obtain the maximum amount of information with minimum effort. Once the variables influencing the response have been identified, the response surface was obtained and used as a reference to gradually vary the input variables that affect the response to improve its value.

Furthermore, in [14], an experimental design was presented for a GMAW welding process to maximize the amount of information with the following characteristics: response surface modelling (RSM) to quantify response variables of interest, statistical model selection to obtain the most informative models, statistical model checking for definitive models to ensure inference capabilities, and multiobjective optimization to identify the Pareto frontier of optimal solutions.

Several papers in literature [5, 6, 14–17] used techniques such as factor analysis, normal boundary intersection (NBI), and RSM for multiobjective optimization. However, they combined NBI and multivariate mean square error (MMSE), disregarding multivariate constraints.

In view of this, the present paper is motivated and justified by the need of obtaining better technical results, such as elimination of welding defects, optimization of the resources, and reduction of waste, in the MIG welding process in aluminum alloy (AA) 6063 T4 tubes, 100 mm in diameter with a 2-mm wall thick. As previously discussed, this is the main raw material for manufacturing anti-corona protection rings, used by several companies in the electric energy segment during the assembly of medium and high voltage circuit breakers. Thus, this work proposes a new approach of the methodology developed in [18] for multiobjective optimization in the MIG welding process of corona rings. Since the most important response had its range defined by the manager of the process, this directly influenced in stabilishing the range of the other correlated responses.

The fundamental idea is to optimize the use of necessary resources and find better welding parameters that ensure it, such as materials and energy consumption, quality improvement, and cost reduction related to the process. The research problem can be defined as how the combination of multivariate techniques, Poisson regression, and multiobjective optimization can help to encounter better operating conditions to give the necessary support for organizational efficiency in the management of the MIG welding production process in AA6063 tubes in the manufacture of anti-corona protection rings.

A face-centered composite design with 4 factors, wire feed rate ($W_f$), arc voltage ($V$), contact tip to the workpiece distance ($C_t$), and motor frequency ($F_r$), resulting in 31 experiments, is used. The values of yield ($Y$), dilution ($D$), reinforcement index ($R_I$), and penetration index ($P_I$) are modeled, allowing to estimate the optimal individual values. Hence, the methodology presented here incorporates simultaneous confidence intervals and elliptical constraints to the multiobjective optimization problem. Poisson regression technique is applied firstly to model the squared residuals generated by the ordinary least square (OLS) models of the original variables, and subsequently to model the original variables themselves.

The next sections are organized according to the following: Section 2 presents a theoretical review of the main concepts involved in the optimization method; Section 3 illustrates the materials and methods applied; Section 4 details the main findings; and finally, Section 5 presents a conclusion about the work.

2 Optimization method

2.1 Multiobjective optimization

Industrial processes generally involve an expressive number of goals that are expected to be optimized simultaneously. Although this concurrent optimization is not always up to be reached, this characteristic must not need be neglected, since there is a pool of techniques available to perform a multiobjective optimization (MO) that allows the problem to be treated in a more lifelike behavior [19].
According to [20], the MO is a decision-making tool capable of dealing with situations where multiple characteristics of the process need to be optimized at the same time. A general way to describe it is shown in Eq. (1), where $a$ and $b$ ensure the solution space limitation and $h(x)$ is related to the equality constraint, whereas $g(x)$ refers to the inequality constraint.

$$
\min_{x \in \mathcal{C}} F(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_n(x) \end{bmatrix}, n > 2, \quad (MOP) \quad C
$$

$$
= \{x : h(x) = 0, g(x) \leq 0, a \leq x \leq b\}
$$

(1)

It is easy to infer that optimizing a scenario with multiple conflicting objectives will not lead to a single best solution, but to a set of possible solutions. Once there is a trade-off relationship between different characteristics of the system, one solution will be more connected with the better performance of determined answer, while a second one will be driven to another attribute and so on [20]. This whole group of solutions is called Pareto optimal [21].

NBI method, applied in [22, 23], generates an even spread feasible solutions—the Pareto curve [20]—that overcome the deficiencies from the least squares method, and through which it is possible to analyze the context in a more practical and visual way [16, 24]. A general manner for representing a NBI formulation is presented Eq. (2) [20], by means of a restricted nonlinear programming.

$$
\max_{x_i,t} \quad \begin{aligned}
\Phi \beta + Dn &= \Phi(x) \\
h_i(x) &= 0 \\
g_j(x) &\leq 0 \\
a \leq x \leq b
\end{aligned}
$$

(2)

where $\Phi$ indicates the normalized payoff matrix, $\beta$ is the vector of weights, $D$ represents a scalar that is perpendicular to the utopia line, and $\Phi(x)$ contemplates the vector of dimensioned objective functions [25].

The payoff matrix $\Phi$, as shown in Eq. (3), comes from the establishment of the individual minima for one objective function, so that this $i$-th optimal point $x^*_i$ is also applied in the remaining functions. This procedure is repeated until all the objective functions were examined. In this way, the position $\Phi_{ij}$ from all the matrix lines shows the optimal value of $f_i(x^*_j)$, while the remaining positions present the values of the other functions evaluated in $x^*_j$, line by line. The values from the main diagonal are then used to normalize the objective functions and this is a useful strategy when dealing with different variables scales or units [16, 20, 24, 26].

$$
\Phi = \begin{bmatrix}
\begin{array}{ccc}
\phi_1^*(x^*_1) & \cdots & \phi_1^*(x^*_m) \\
\vdots & \ddots & \vdots \\
\phi_n^*(x^*_1) & \cdots & \phi_n^*(x^*_m)
\end{array}
\end{bmatrix}
$$

(3)

To normalize the original values from the $\Phi$ matrix, two vectors are constructed, one containing the optimal values resulting from the individual optimization of all the objective functions and another composed by their worst possible values. The first vector is called Utopia while the second one is the Nadir, and they are represented by Eq. (4) and Eq. (5), respectively [16, 27].

$$
f^U = \begin{bmatrix} f_1^*(x^*_1), \ldots, f_1^*(x^*_m) \end{bmatrix}^T
$$

(4)

$$
f^N = \begin{bmatrix} f_2^N, \ldots, f_i^N, \ldots, f_m^N \end{bmatrix}^T
$$

(5)

Once theses vectors are available, the Eq. (6) can be applied to generate the normalized payoff matrix $\overline{\Phi}$ shown in Eq. (7).

$$
\overline{\Phi} = \begin{bmatrix}
\begin{array}{ccc}
\overline{\phi}_1(x^*_1) & \cdots & \overline{\phi}_1(x^*_m) \\
\vdots & \ddots & \vdots \\
\overline{\phi}_n(x^*_1) & \cdots & \overline{\phi}_n(x^*_m)
\end{array}
\end{bmatrix}
$$

(7)

where $\overline{\phi}_i(x)$ indicates the normalized version of the objective function $f_i(x)$.

The generic formulation presented in Eq. (2) can be simplified, leading to the formulation for bi-objective scenarios, as depicted in Eq. (8).

$$
\min_{x} F(x) = \overline{\phi}_1(x)
$$

$$
\begin{aligned}
s.t. & \quad \overline{\phi}_1(x) - \overline{\phi}_2(x) + 2\beta_1 - 1 = 0 \\
& \quad g_j(x) \leq 0 \\
& \quad h_{j+1}(x) = 0
\end{aligned}
$$

(8)

RSM can be applied to help on modelling and analyzing the objective function $f_i(x)$ capable of explaining one response of interest that is involved in the multiobjective optimization scenario and is influenced by several input variables. Since RSM is a type of design of experiment (DOE), it comprises a set of mathematical and statistical techniques that allow investigating and modelling complex problems from a relatively
small group of runs [28], making it widely spread in the industry, consequence of its easy and economical way to implement [29].

Diverse applications of RSM are available in the literature, including a wide range of industrial processes. The study performed in [30] applied the RSM, among other techniques, to characterize the ultrasonic-assisted drilling process of Aluminum 6061 that is known to be better when compared with conventional drilling, since it applies high-frequency vibrations with low amplitudes. Another study explored the squeeze casting process capability for casting AA2026 alloy, by investigating, through the RSM, the influence of squeeze pressure, die temperature and pouring temperature on surface roughness, ultimate tensile strength, and hardness [31].

Natarajan et al. in [32] combined RSM and desirability function approach to maximize metal removal rate while minimizing surface roughness, considering the spindle speed, feed rate, and depth of cut as the cutting parameters. In [33], RSM was applied jointly with the global criterion method to find the optimal parameters settings for the best surface roughness.

Usually, a second order polynomial is sufficient to represent the problems for the response surface. Its general equation, as depicted in Eq. (9), includes the response of interest (Y), the coefficients to be estimated (β), the l independent variables (x), and the associated errors (ε) [28, 35].

\[
Y = \beta_0 + \sum_{i=1}^{l} \beta_i x_i + \sum_{i<j}^{l} \beta_{ij} x_i x_j + \varepsilon
\]  

(9)

OLS is the regression method used to estimate the β coefficients [16]. The achievement of an analytical model with a high adequacy is intimately connected to the quality of the process real output data collected. On behalf of it, a good experimental design must be planned so that it can help guaranteeing these results through a minimal number of experiments [28].

The central composite design (CCD) consists of a \(2^k\) factorial design, \(n_c\) central runs, and \(2^k\) axial runs as exemplified in Fig. 1. The axial points are useful and necessary when the \(2^k\) design is not efficient on fitting a first-order model, since through them, it is possible to incorporate the quadratic terms into the model [28, 35]. The adequacy or not of the models can be ascertained through the \(R^2\) and \(R^2_{adj}\) coefficients, obtained by running an ANOVA test, and also the residues normality analysis [16, 27, 28, 35].

Basically, the region of operability and interest determines the value for the axial distance \(\alpha\) that may vary from 1 to \(\sqrt{k}\). Considering contexts where the ranges on the design variables are strict, making the region of the interest equals to the region of operability, the region for the design may be a square, a cube, or a hypercube, rather than the well-known spherical region. This characterizes a variation of CCD, called the face-centered cube (CCF), since the axial points lie at the centers of the faces, as shown in Fig. 2 where a CCF for \(k = 3\) is illustrated. It is easy to see that, in this variation \(\alpha = 1\), i.e., there is no experiments located outside the cube, but rather at the extremities of the region. The CCF meets effectively cases of cuboidal design region and it has no limitations regarding to the number of design variables. A crucial point on determining about the suitability of a CCF relies on checking whether the axial points outside the ranges are viable, and then if they must be considered or not for the region of interest [28, 35].

### 2.2 Poisson loglinear model

Poisson regression is an invaluable technique that should be applied when it comes to interest variables that are not normally distributed, representing a count of an event. A generalized linear model (GLM) states that a linear predictor is related to the mean (\(\mu_i\)) for a link function \(g\), that is, \(\eta_i = g(\mu_i)\), where \(\eta_i = \sum_{j=1}^{p} \beta_j x_{ij}\) or \(\eta_i = \mathbf{x}_i^T \beta\) [36].

The likelihood equations for a GLM as demonstrated in [36] is shown in Eq. (10) with \(j = 1, 2, \ldots, p\), where \(p\) is the number of variables.

\[
\frac{\partial L(\beta)}{\partial \beta_j} = \sum_{i=1}^{n} \left( y_i - \mu_i \right) x_{ij} \frac{\partial \mu_i}{\partial \eta_i} = 0
\]  

(10)

For a GLM that assumes a Poisson random component and uses the log link function, a link function commonly used for this type of models [37], the Poisson loglinear model, could be written as shown in Eq. (11).

\[
\log(\mu_i) = \sum_{j=1}^{p} \beta_j x_{ij} = \eta_i
\]  

(11)

This implies that \(\mu_i = \exp(\eta_i)\), and consequently that \(\frac{\partial \mu_i}{\partial \eta_i} = \exp(\eta_i) = \mu_i\), which means that \(\text{var}(y_i) = \mu_i\). Then, the likelihood equations in Eq. (10) can be simplified as in Eq. (12) with \(j = 1, 2, \ldots, p\) [36].

\[
\sum_{j=1}^{p} (y_i - \mu_i) x_{ij} = 0
\]  

(12)
Once the parameters are encountered, the predictions of a Poisson loglinear model can be calculated as shown in Eq. (13) [37].

\[
\hat{y}_i = g^{-1}(x_i^T b) = \exp(x_i^T b) \tag{13}
\]

### 2.3 Multivariate analysis

In dealing with correlated responses, it is important to consider the problem as a multivariate one [38]. This means that the variables vary concomitantly, and it is recommended to analyze them through simultaneous confidence intervals. A deeper explanation about this concept can be found in [18, 39].

In [39], a sophisticated way called the Bonferroni method is presented as an alternative approach to obtain these intervals as shown in Eq. (14).

\[
\bar{x}_p - t_{n-1}\left(\frac{\alpha}{2p}\right) \sqrt{\frac{S_{pp}}{n}} \leq \mu_p \leq \bar{x}_p + t_{n-1}\left(\frac{\alpha}{2p}\right) \sqrt{\frac{S_{pp}}{n}} \tag{14}
\]

where the mean value of the original variables is represented by \(\bar{x}_p\), and the term \(t_{n-1}\left(\frac{\alpha}{2p}\right)\) represents the \(t\) value associated with a distribution with \(n-1\) degree of freedom that leads to a probability equals to \(\alpha/2p\), where \(\alpha\) is the significance level, and \(p\) the number of considered components. Finally, \(S_{pp}\) is the variance associated with the \(p\) component and \(n\) is the number of observations.

For two correlated variables, it is possible to construct an ellipsoid for their means according to Eq. (15) [25]. It is worth mentioning that \(\mu_y\) is the mean of the variables, \(p\) is the number of variables being considered (in this case \(p = 2\), since the equation is used to construct a 2D ellipsoid), \(n\) is the number of observations of the variables, \(F\) is the statistic associated with significance level \(\alpha\) and two degree of freedom \((p \text{ and } n-p)\), \(\lambda_i\) and \(e_{ij}\) represent the eigenvalues and the elements of the matrix composed of the eigenvectors, respectively, and finally \(\theta\) is an angle that varies from 0 to \(2\pi\).

\[
\begin{bmatrix}
\mu_{y_1} \\
\mu_{y_2}
\end{bmatrix}
+ \frac{p(n-1)}{n(n-p)} F_{(p,n-p)}(\alpha) \times \begin{bmatrix}
\sqrt{\lambda_1} & 0 \\
0 & \sqrt{\lambda_2}
\end{bmatrix} \times \begin{bmatrix}
e_{11} & e_{12} \\
e_{21} & e_{22}
\end{bmatrix} \times \\
\begin{bmatrix}
\cos\theta \\
\sin\theta
\end{bmatrix} \tag{15}
\]
Similarly, an ellipsoid for the original data may also be constructed applying Eq. (16), which results in a larger ellipsoid than the one for the means.

\[
\begin{bmatrix}
\mu_1 \\
\mu_2
\end{bmatrix} + c \times \begin{bmatrix}
e_{11} & e_{12} \\
e_{21} & e_{22}
\end{bmatrix} \times \begin{bmatrix}
\sqrt{\lambda_1} & 0 \\
0 & \sqrt{\lambda_2}
\end{bmatrix}
\times \begin{bmatrix}
cos \theta \\
sen \theta
\end{bmatrix}
\] (16)

It is also possible to observe the Bonferroni confidence intervals in Fig. 3 in which is depicted the green ellipsoid constructed using Eq. (15) and the blue one using Eq. (16).

Nevertheless, in some situations, it is preferable to work with uncorrelated variables instead of the original correlated ones. Principal component analysis (PCA) and factor analysis are indicated for these cases. According to [39], factor analysis can be considered an extension of PCA, since both strategies attempt to estimate the variance-covariance matrix (\(\Sigma\)) of a multivariate dataset. However, factor analysis provides a more elaborated approximation of \(\Sigma\). In addition, in PCA each principal component is written as a function of the original variables, whereas in factor analysis, each original variable is written as a function of the latent variables, that is, the factors.

The orthogonal factor model, in which \(p\) distinct variables are well explained by \(m\) factors, where \(m < p\), can be observed in Eq. (17) in matrix notation. \(X\) is a random vector \((p \times 1)\) with \(p\) components, \(\mu\) is its mean vector \((p \times 1)\), and \(\Sigma\) is its variance-covariance matrix \((p \times p)\). \(L\) indicates the vector of loadings \((p \times m)\), whose values \(l_{ij}\) represent the correlation of the \(i\)-th variable with the \(j\)-th factor, \(F\) represents the vector of unobservable variables (common factors) \((m \times 1)\), and finally, \(\varepsilon\) is the source of variation, which means the vector of errors \((p \times 1)\).

\[
X = \mu + LF + \varepsilon
\] (17)

It is worth mentioning that \(E(F) = 0\), \(\text{Cov}(F) = I\) and \(E(\varepsilon) = 0\), \(\text{Cov}(\varepsilon) = \Psi\), where \(\Psi\) is a diagonal matrix. In addition, the model previously shown in Eq. (17) implies that the covariance structure for \(X\) can be written as in Eq. (18) [39].

\[
\Sigma = \text{Cov}(X) = E(X-\mu)(X-\mu)^T = LE(FF^T)L^T + E(eF^T)L + LE(F\varepsilon^T) + E(\varepsilon\varepsilon^T) = LL^T + \Psi
\] (18)

In view of this, it is possible to work with uncorrelated rotated factor scores instead of the original correlated variables in an optimization problem. However, in some cases, a factor explains different variables with distinct optimization direction. This conflict in the optimization direction can be overcome by using Eq. (19), which presents the factor mean square error (FMSE) developed in [40] as an extension of the multivariate mean square error (MMSE) proposed in [41].

\[
\text{FMSE}_i = \left(\bar{F}_i(x) - T_i\right)^2 + \lambda_i
\] (19)

where \(\bar{F}_i\) indicates the fitted value for the \(i\)-th factor, \(T_i\) represents the target, and \(\lambda_i\) is the variance associated with the factor. The target of the \(i\)-th factor can be obtained through the product \(Z^T L_i\), where \(L_i\) is the loading vector of the factor \(i\) and \(Z\) is calculated subtracting the individual target of each original variable from its mean and dividing this result by the standard deviation of the variable, as shown in Eq. (20).
\[ Z_j = \left( \frac{\zeta_j - \mu_j}{\sigma_j} \right) \]  

(20)

3 Materials and methods

The present paper aims to optimize the welding process of AA6063 tubes that take part in corona rings, regarding some variables such as \( Y, D, RI, \) and \( PI. \) The chemical composition of AA6063 is shown in Table 1. It is important to highlight that \( RI \) was obtained as the ratio between the height of the weld bead and its width. \( D \) was the ratio between penetration area or internal area (\( IA \)) and total area, which is defined by the sum of \( IA \) and the reinforcement area or external area (\( EA \)) of the weld bead. Finally, \( PI \) was the ratio between the penetration height and the thickness of the material being welded.

To calculate the actual deposition yield, \( Y, \) it was necessary to weigh 1 meter of ER4043 wire (linear mass), with 1.2 mm in diameter, used to calculate the total mass. The specimens were weighed before and after the completion of each weld, obtaining the value of the initial mass (\( IM \)), that is the mass of the specimen before welding, and the final mass (\( FM \)), i.e., the mass of the specimen after welding and after cleaning to remove spatter.

Some factors that have great influence on the welding process are stated in Table 2 after some research in the literature [5, 13, 43, 44]. Their levels were also established not only according to the values found in literature, but mainly according to some experiments performed by the authors.

Next, a CCF with 31 runs was applied in order to perform the experiments. The MIG welding process of the specimens was carried out with an Aristo Power 460 welding machine—ESAB brand—with an external wire feeder. Some devices were used to hold the torch and the part, as depicted in Fig. 4. It is possible to state that the MIG welding process was performed in a semi-automatic way, since the torch and the part were static and a person was responsible just for triggering the torch.

The experiments were performed as homogeneous as possible, that is, using the same machine, the same welding inputs, the same person triggering the torch, and the same structure. Only the welding parameters (controllable variables) were possible to be changed.

The machine was created to weld parts that have the same profile as the object of this study. An aluminum plate was machined and an axis was welded to it with the inner diameter of the 100mm tube, so that this tube could remain fixed during the welding process. In addition, a frequency inverter was connected to the machine’s motor, in order to start the motor and control the welding speed. The rotation of the part to be welded was due to interlocking pulleys and belts that made the plate rotate. As can be seen in Fig. 4, the arm that supports the torch and a clamp fixed the torch using allen screws. With these measures, it was possible to maintain the distance parameters and the best possible regulation for carrying out the experiments.

The specimens were welded randomly according to CCF. Next, they were cut, treated, and submitted to metallographic analysis of images in the laboratories from the Federal University of Itajubá, under the supervision of specialized personnel.

Regarding the welding process, the upper and lower parts of the tube were put over a small cylindric piece consisted of the same base metal (aluminum) aiming to hold these parts of the tube, making them concentric, allowing more accurate weld as in a bushing process. It is possible to observe the internal part of the tube in Fig. 5.

Each cylindric specimen, as depicted in Fig. 5, was cut into four quadrants that were, afterwards, subdivided into small parts. One of these parts from each quadrant was selected to go through the resin mounting process, resulting in a final mounted specimen consisting of four parts as shown in Fig. 6. Still in Fig. 6, it is possible to observe part of the welded tube and the weld bead (upper), the cylindric metal piece (lower), and an empty space between the tube and this piece. This empty space is not a welding defect as it does not interfere in the construction of the corona ring.

| Table 1 | Chemical composition of AA6063 [42] |
|---|---|
| **Element** | **%** |
| Al | 98.05% |
| Si | 0.20% |
| Fe | 0.35% |
| Cu | 0.10% |
| Mg | 0.90% |
| Mn | 0.10% |
| Cr | 0.10% |
| Zn | 0.10% |
| Ti | 0.10% |

| Table 2 | Parameters considered in the welding process and their respective levels |
|---|---|---|---|
| Factor | Abbreviation | Level -1 | Level +1 |
| Wire feed rate (m/min) | \( Wf \) | 3.0 | 3.4 |
| Arc voltage (V) | \( V \) | 20 | 23 |
| Contact tip to the workpiece distance (mm) | \( Ct \) | 8 | 16 |
| Rotation frequency (Hz) | \( Fr \) | 1.8 | 2.2 |
Fig. 4  Semi-automatic MIG welding process structure. a Aristo Power 460 welding machine—ESAB brand. b Structure used to attach the torch of the welding machine and the aluminum part and a top view of the frequency inverter connected to the machine’s motor.

Fig. 5  a Top view of the specimen and the cylindric piece; b MIG welding process.

Fig. 6  Specimen obtained in the runs 01, 07, and 20 of the CCF.
The specimen shown in Fig. 6 were sanded and put in a Keller solution composed of 190 mL H₂O + 5 mL HNO₃ (65%) + 3 mL HCl (32%) + 2 mL HF (40%), making possible to see the area where the metal was deposited. Fig. 7 shows some images of the weld bead and the measurements of the penetration (P), reinforcement (R), internal area (IA), external area (EA), width (W), and height (H = R + P).

The analysis of the results followed mainly a recent methodology published in [18]. However, an improvement was done in step G. The methodology applied in this paper is presented bellow in 9 steps.

A. Evaluate the correlation structure of the dataset.
B. Perform factor analysis.
C. Generate the models for all of the original responses using OLS.
D. Generate full quadratic models using General Linear Models (Poisson regression) for the square residuals.
E. Generate Poisson models for the original variables.
F. Perform individual optimization.
G. Establish constraints based on simultaneous confidence intervals.
H. Adapt the Payoff matrix.
I. Apply NBI method for the factor mean square error.

The next section presents the results obtained in each step of this methodology.

4 Results

The data obtained through the execution of the 31 experiments are shown in Table 3, where the following abbreviations Y, D, RI, and PI stand for yield, dilution, reinforcement index, and penetration index, respectively.

4.1 Evaluate the correlation structure of the dataset

The correlation structure of the original variables considered in this paper can be seen in Table 4, where the correlation values are associated with a p-value in italics. A p-value less than 0.05 indicates a significant correlation.

4.2 Perform factor analysis

Factor analysis was performed and the rotated scores of the factors were stored. It is important to highlight that varimax rotation was chosen since it presents satisfactory results as shown in [45]. Table 5 shows the scores considering 3 factors and 4 original variables. These factors are able to explain 88.2% of the variability of the data.

4.3 Generate models for all of the original responses using OLS

The original variables and the rotated scores of the factors were initially modeled through OLS method and their residuals were stored and squared to be used in step D.

4.4 Generate full quadratic models using General Linear Models (Poisson regression) for the square residuals

Poisson regression was used to model the 4 sets of square residuals from step C (each set corresponds to the residuals obtained from the initial modelling of each original variable). The fitted value (\( \hat{\varepsilon} \)) was stored, and the weight, \( W = 1/\hat{\varepsilon}^2 \), was calculated.

4.5 Generate Poisson models for the original variables

Poisson models weighted by W were obtained for all the original variables. Some variables did not present suitable values for \( R^2 \), \( R^2_{adj} \), and \( R^2_{pred} \) in the first interaction of the method. Thus, the steps C and D had to be repeated. These models are presented in equations from Eq. (21) to Eq. (24).
\[ Y = \exp \left( Y' \right) \]
\[ Y' = -0.1885 - 0.03875 \times Wf + 0.01604 \times V - 0.00084 \times Ct - 0.03980 \times Fr + 0.1159 \times Wf^2 - 0.0377 \times V^2 - 0.0129 \times Ct^2 + 0.0251 \times Fr^2 + 0.0042 \times Wf \times V + 0.00106 \times Wf \times Ct - 0.00577 \times Wf \times Fr + 0.0108 \times V \times Ct + 0.0159 \times V \times Fr - 0.0102 \times Ct \times Fr \]
\[ R^2 = 93.66\% \]
\[ R^2_{adj} = 89.59\% \]

(21)

\[ D = \exp \left( D' \right) \]
\[ D' = 4.1765 - 0.0301 \times Wf + 0.069 \times Fr - 0.0415 \times Wf \times Fr \]
\[ R^2 = 95.77\% \]
\[ R^2_{adj} = 81.58\% \]

(22)
Table 5 Rotated factor scores for each designed experiment

| Run | Wf  | V   | CT  | Fr  | F₁  | F₂  | F₃  |
|-----|-----|-----|-----|-----|-----|-----|-----|
| 1   | 3.00| 20.00| 8.00| 1.80| -0.8286| -0.0590| -1.2966|
| 2   | 3.40| 20.00| 8.00| 1.80| 0.1592 | -0.7504| -0.9590|
| 3   | 3.00| 23.00| 8.00| 1.80| 0.1672 | -0.1648| -1.2167|
| 4   | 3.40| 23.00| 8.00| 1.80| 2.9331 | -0.2198| -0.9940|
| 5   | 3.00| 20.00| 16.00| 1.80| 0.3945 | -0.7208| -1.9338|
| 6   | 3.40| 20.00| 16.00| 1.80| 2.2376 | -1.4006| -0.4800|
| 7   | 3.00| 23.00| 16.00| 1.80| -0.3512| -1.1151| 0.8347|
| 8   | 3.40| 23.00| 16.00| 1.80| -0.8463| -0.8566| -0.1451|
| 9   | 3.00| 20.00| 8.00| 2.20| -0.1320| -0.2234| 1.9763|
| 10  | 3.40| 20.00| 8.00| 2.20| 0.3633 | -0.1339| 0.1471|
| 11  | 3.00| 23.00| 8.00| 2.20| -1.0997| -0.4504| 0.8533|
| 12  | 3.40| 23.00| 8.00| 2.20| -0.8384| -0.1763| -1.2577|
| 13  | 3.00| 20.00| 16.00| 2.20| 0.2681 | 0.2309 | 0.8091|
| 14  | 3.40| 20.00| 16.00| 2.20| -0.3477| -0.3315| 0.3285|
| 15  | 3.00| 23.00| 16.00| 2.20| -0.3085| -0.3151| 1.0733|
| 16  | 3.40| 23.00| 16.00| 2.20| -1.2200| -0.1377| -0.0859|
| 17  | 3.00| 21.50| 12.00| 2.00| -0.0007| -0.6969| -1.1056|
| 18  | 3.40| 21.50| 12.00| 2.00| 0.6949 | -0.6539| 1.1560|
| 19  | 3.20| 20.00| 12.00| 2.00| 0.9165 | 2.8736| 0.7319|
| 20  | 3.20| 23.00| 12.00| 2.00| 0.3239 | 0.7898 | 0.5842|
| 21  | 3.20| 21.50| 8.00| 2.00| 0.5736 | -0.3561| -0.6602|
| 22  | 3.20| 21.50| 16.00| 2.00| 0.5947 | 0.1718| 1.4411|
| 23  | 3.20| 21.50| 12.00| 1.80| -0.0929| 3.4257| -1.6378|
| 24  | 3.20| 21.50| 12.00| 2.20| 1.4600 | 1.2374| 1.0764|
| 25  | 3.20| 21.50| 12.00| 2.00| -0.4973| 0.1935| 0.9194|
| 26  | 3.20| 21.50| 12.00| 2.00| -0.6555| 0.1601| 0.6704|
| 27  | 3.20| 21.50| 12.00| 2.00| -1.1457| 0.2431| -0.0551|
| 28  | 3.20| 21.50| 12.00| 2.00| -2.0142| 0.4141| -0.8084|
| 29  | 3.20| 21.50| 12.00| 2.00| -0.6161| 0.1197| -0.0815|
| 30  | 3.20| 21.50| 12.00| 2.00| 0.3661 | -0.8557| 0.4638|
| 31  | 3.20| 21.50| 12.00| 2.00| 0.0783 | -0.2419| -0.3480|

4.6 Perform individual optimization

From the models for the original variables, it is possible to perform their individual optimization. It is important to highlight that \( Y, D, \) and \( PI \) are variables to be maximized, whereas the \( RI \) is to be minimized, since the reinforcement is removed from the final structure. In view of this, the payoff matrix shown in Table 6 was constructed.

4.7 Establish constraints based on simultaneous confidence intervals

At this point, it is essential to perform some multivariate analyses. Initially, the ellipsoids for the means of each pair of significantly correlated variables were generated using Eq. (15). These ellipsoids and the Bonferroni intervals are shown in Fig. 8 and Fig. 9. However, distinctly from the previous article where this methodology was published, here, a range for the most important variable was established. \( PI \) was chosen as the most relevant variable, since the larger the penetration, the better the quality of the final product. A range from 1.19 to 1.25 was defined by specialists, and therefore, all the other variables had to vary according to this range, considering their correlation. Hence, the constraints to the variation of the original variables are the variation established as the intersection of the green and yellow lines in Fig. 8 and Fig. 9 that are highlighted in red on both axes.

4.8 Adapt the payoff matrix

In order to adapt the payoff matrix, an elliptical constraint was set according to Eq. (25) in addition to the constraints established in step G. The adapted payoff matrix can be seen in Table 7.

\[
\begin{align*}
RI &= \exp(R'I') \\
R' &= -0.45577 \times Wf' - 0.0319 \times V - 0.0145 \times CT + 0.0042 \times Fr \\
&- 0.3150 \times Wf^2 + 0.1186 \times V^2 - 0.0780 \times CT^2 + 0.0474 \times Fr^2 \\
&- 0.0025 \times Wf \times V - 0.0336 \times Wf \times CT - 0.0124 \times Wf \times Fr - 0.0005 \times V \times CT \\
&+ 0.0092 \times V \times Fr + 0.0390 \times CT \times Fr \\
R^2 &= 99.93\% \\
R^2_{adj} &= 99.90\% \\
\end{align*}
\]

\[
\begin{align*}
PI &= \exp(P'I') \\
P' &= -0.1865 \times Wf' - 0.0017 \times V + 0.01946 \times CT - 0.0644 \times Fr \\
&- 0.0310 \times Wf^2 - 0.0292 \times V^2 + 0.0144 \times CT^2 - 0.0103 \times Fr^2 \\
&+ 0.0113 \times Wf \times V - 0.0216 \times Wf \times CT - 0.0604 \times Wf \times Fr \\
&- 0.04462 \times V \times CT - 0.0357 \times V \times Fr + 0.0218 \times CT \times Fr \\
R^2 &= 99.99\% \\
R^2_{adj} &= 99.99\% \\
\end{align*}
\]

Table 6 Payoff matrix considering individual optimization

| Response | Payoff matrix |
|----------|---------------|
| Y        | 100.00        | 95.81        | 90.52 | 89.41 |
| D        | 61.1235       | 74.8885      | 62.6405 | 61.592 |
| RI       | 0.5045        | 0.5143       | 0.3864 | 0.5087 |
| PI       | 1.2367        | 1.2274       | 1.2904 | 1.5118 |
4.9 Apply NBI method for the factor mean square errors

Finally, the factor’s targets were defined according to Eq. (19) and Eq. (20), and the FMSE functions for the three rotated score of the factors were modeled. Matrix NBI method was applied, since 3 functions were being considered. A simplex lattice mixture design, with degree of lattice 10, was applied to generate a matrix containing 70 distinct combinations of weights to be used in the NBI, ranging from 0.00001 to 0.99998.

All the objective functions were to be minimized, since they corresponded to the FMSE values for the three factors. The results are summarized in Table 8 and Table 9.

The values of the factors for each combination of weights were normalized subtracting the utopia and dividing the result...
by the difference between Nadir and Utopia. The plot of normalized factors and their respective weights can be seen in Fig. 10.

In order to choose the best combination of weights, it applied the ratio ($R$) between the entropy ($E$) and the Mahalanobis’ distance ($Mh$), that is $R = \frac{E}{Mh}$. Mahalanobis’ distance was calculated using Minitab software via PCA, which generated three principal components and stored this distance. The entropy value was calculated according to Eq. (26), where $w_i$ represents the weight.

| Response | Payoff matrix |
|----------|---------------|
| $Y$      | 0.8729 0.8286 0.8464 0.8729 |
| $D$      | 62.4427 64.9201 64.3064 62.4427 |
| $RI$     | 0.5183 0.5183 0.5183 0.5183 |
| $PI$     | 1.2500 1.1900 1.1953 1.2500 |

Table 7 Adapted Payoff matrix considering elliptical constraints and Bonferroni intervals constraints

Table 8 Results of the NBI method part I
\[-\sum_{i=1}^{n} w_i \times \ln(w_i)\]  

The maximal value for \( R \) was selected, since it was expected a small value for the \( Mh \) and a large value for \( E \). The optimal values for \( w_1, w_2, \) and \( w_3 \) were 0.3333, 0.3333, and 0.3333, respectively. For these weights, the optimized coded values for \( Wf, V, Ct, \) and \( Fr \) were 0.215, 0.269, 0.536, and \(-0.380\), respectively. The uncoded values for the same factors were 3.243 m/min, 21.904 V, 14.143 mm, and 1.924 Hz, respectively. Therefore, the original variables \( Y, D, RI, \) and \( PI \) were, respectively, equal to 84.14\%, 63.28\%, 0.5953, and 1.2387 according to the model developed in this paper. It is an interesting result, since it allows satisfactory yield and values related to the geometry of the weld bead.

### 5 Validation experiment

In order to validate whether the results obtained in the previous section were really practicable, a validation experiment was performed and the specimen is shown in Fig. 11.
Table 10 shows the results obtained with the specifications for the parameters, and the percentage of error associated.

Figure 12 shows some microscopical images of the validation specimen, each one of them representing one quadrant.

### 6 Conclusion

The present paper proposed the application of a methodology based on Poisson regression, multivariate constraints to optimize, through normal boundary intersection method, a multiobjective problem considering the MIG welding process of aluminum alloy (AA) 6063 T4 tubes used in corona rings. Although there are difficulties of welding aluminum alloys, the paper proved that it is possible to obtain satisfactory results through an accurate adjustment of the most significant parameters and identification of their ranges. Thirty-one experiments structured according to a face-centered composite design with 4 factors, wire feed rate, arc voltage, contact tip to the workpiece distance, and motor frequency, were carried out. Poisson regression was used to model the objective functions that were correlated and could not be considered separately. In view of this, multivariate constraints were applied.
Additionally, it was possible to observe that using factors to represent the original variables and factor mean square errors as objective functions was suitable, since the problem could be solved through normal boundary intersection. This was also confirmed via validation experiment that reached 86.00%, 66.50%, 0.5034, and 1.3762 for the yield, dilution, reinforcement, and penetration indices, respectively. These values were really near the estimated values from the mathematical model. It is important to highlight that the real values were obtained considering the optimal values 3.243 m/min, 21.904 V, 14.143 mm, and 1.924 Hz for the wire feed rate, arc voltage, contact tip to the workpiece distance, and rotation frequency, respectively. Hence a weld bead with satisfactory characteristics was reached as prespecified by the manager of the process, even though the process complexity.

Acknowledgements The authors would like to thank the Brazilian agencies of CAPES, CNPq, and FAPEMIG for supporting this research.

Author contribution L.R.M., A.P.P., P.P.B., resources; A.P.P., E.R.L., S.C.S., E.L.R., data curation; S.C.S., E.R.L., E.L.R., writing—review and editing; A.P.P., E.R.L., S.C.S., E.L.R., P.P.B., visualization; A.P.P., P.P.B., supervision. All of the authors have read and agreed to publish this version of the manuscript.

Data Availability All the data are available in the paper.

Declarations
Ethical approval Not applicable.
Consent to participate Not applicable.
Consent for publication Not applicable.
Competing interests The authors declare no competing interests.

References
1. Murawwi EA, Mohammed A, Alip Z, Ei-Hag A (2013) Optimization of corona ring design for a 400KV non-ceramic insulator. 2013. IEEE Electr Insul Conf EIC 2013:370–373. https://doi.org/10.1109/EIC.2013.6554269
2. Abderrazzaq MH, Abu Jalgaf AM (2013) Characterizing of corona rings applied to composite insulators. Electr Power Syst Res 95:121–127. https://doi.org/10.1016/j.epsr.2012.08.010
3. Farhad N, Asaad S, Pourya K (2020) Modeling and optimization of dimensions of corona rings on high-voltage composite insulators using FEM. Adv Sci Eng Med 12:1204–1207. https://doi.org/10.1166/asem.2020.2677
4. Rezaei A, Ehsanifar M, Wood DA (2019) Reducing welding repair requirements in refinery pressure vessel manufacturing: a case
study applying six sigma principles. Int J Interact Des Manuf 13: 1089–1102. https://doi.org/10.1007/s12008-019-00573-8

5. Meseguer-Valdenebro JL, Martínez-Conesa EJ, Serna J, Portoles A (2016) Influence of the welding parameters on the heat affected zone for aluminum welding. Therm Sci 20:643–653. https://doi.org/10.2298/TSCI140503106M

6. Braguine TB, de Alcântara DS, Castro CAC, dos Santos GHR (2017) A new multiobjective optimization with elitist constraints approach for nonlinear models implemented in a stainless steel cladding process. Int J Adv Manuf Technol 113: 1469–1484. https://doi.org/10.1007/s00170-020-06581-3

19. De Motta RS, Afonso SMB, Lyra PRM (2012) A modified NBI and NC method for the solution of N-multiobjective optimization problems. Struct Multidiscip Optim 46:239–259. https://doi.org/10.1007/s00158-011-0729-5

12. Kang SG, Shin J (2021) The effect of laser beam intensity distribution on weld characteristics in laser welded aluminum alloy (AA5052). Opt Laser Technol 142:107239. https://doi.org/10.1016/j.optlastec.2020.107239

13. Cao X, Yi Z, Xu C, Luo Z, Duan J, Zhou Y (2021) Influence of laser beam intensity distribution on weld characteristics in laser welded aluminum alloy (AA5052). Opt Laser Technol 142:107239. https://doi.org/10.1016/j.optlastec.2020.107239

10. Liu B, Liu K, Villavicencio R, Dong A, Guedes Soares C (2021) Experimental and numerical analysis of the penetration of welded aluminum alloy panels. Ships Offshore Struct 16:492–504. https://doi.org/10.1080/17445302.2020.1736856

17. Ro C-S, Kim K-H, Bang H-S, Yoon H-S (2021) Joint properties of stainless steel cladding process. Int J Adv Manuf Technol 113: 1469–1484. https://doi.org/10.1007/s00170-020-06581-3

16. Senthil SM, Parameshwaran R, Raghu Nathan S, Bhuvanesh Kumar (2021) Study on laser/DP-MIG hybrid welding-brazing of aluminum to Al-Si coated boron steel. J Mater 154:105307. https://doi.org/10.1016/j.jmrmat.2021.07.163

15. Miguel V, Marín-Ortiz F, Manjabacas MC, Martínez-Conesa EJ, Martínez-Martínez A, Coelho J (2015) Optimización multiobjetivo del proceso de soldadura GMAW de la aleación AA 6063-T5 basado en la penetración y en la zona afectada térmicamente. Rev Metal 51: 1–10. https://doi.org/10.3989/revmetalm.037

14. Martínez-Conesa EJ, Egea JA, Miguel V, Toledo C, Meseguer-Valdenebro JL (2017) Optimization of geometric parameters in a welded joint through response surface methodology. Constr Build Mater 154:105–114. https://doi.org/10.1016/j.conbuildmat.2017.07.163

11. Kang SG, Shin J (2021) The effect of laser beam intensity distribution on weld characteristics in laser welded aluminum alloy (AA5052). Opt Laser Technol 142:107239. https://doi.org/10.1016/j.optlastec.2020.107239

18. Luz ER, Romão EL, Streitenberger SC, Gomes JHF, da Paiva AP, Balestrassi PP (2021) A new multiobjective optimization with elitist constraints approach for nonlinear models implemented in a stainless steel cladding process. Int J Adv Manuf Technol 113: 1469–1484. https://doi.org/10.1007/s00170-020-06581-3

8. Liu B, Liu K, Villavicencio R, Dong A, Guedes Soares C (2021) Experimental and numerical analysis of the penetration of welded aluminium alloy panels. Ships Offshore Struct 16:492–504. https://doi.org/10.1080/17445302.2020.1736856

32. Ali MA, Ishaq K, Jawad M (2019) Evaluation of surface quality and mechanical properties of squeeze casted AA2026 aluminum alloy using response surface methodology. Int J Adv Manuf Technol 103:4041–4054. https://doi.org/10.1007/s00170-019-03836-6

33. Natarajan U, Periyanan PR, Yang SH (2011) Multiple-response optimization for micro-endmilling process using response surface methodology. Int J Adv Manuf Technol 56:177–185. https://doi.org/10.1007/s00170-011-3156-2

31. Ali MA, Ishaq K, Jawad M (2019) Evaluation of surface quality and mechanical properties of squeeze casted AA2026 aluminum alloy using response surface methodology. Int J Adv Manuf Technol 103:4041–4054. https://doi.org/10.1007/s00170-019-03836-6

30. Moghaddas MA (2021) Modeling and optimization of thrust force, torque, and surface roughness in ultrasonic-assisted drilling using surface response methodology. Int J Adv Manuf Technol 112: 2909–2923. https://doi.org/10.1007/s00170-020-06380-w
34. Saad MS, Nor AM, Baharudin ME, Zakaria MZ, Aiman AF (2019) Optimization of surface roughness in FDM 3D printer using response surface methodology, particle swarm optimization, and symbiotic organism search algorithms. Int J Adv Manuf Technol 105:5121–5137. https://doi.org/10.1007/s00170-019-04568-3
35. Myers RH, Montgomery DC, Anderson-Cook CM (2016) Response Surface Methodology Process and product optimization using designed experiments. Fourth. John Wiley & Sons, Inc., Hoboken, New Jersey
36. Agresti A (2015) Foundations Linear Generalized Linear Models
37. Meyers RH, Montgomery DC, Vining GG, Robinson TJ (2005) Generalized Linear Models with Applications in Engineering and the Sciences, Second. John Wiley & Sons, Inc., Hoboken, New Jersey
38. De Paiva AP, Gomes JHF, Peruchi RS et al (2014) A multivariate robust parameter optimization approach based on Principal Component Analysis with combined arrays. Comput Ind Eng 74: 186–198. https://doi.org/10.1016/j.cie.2014.05.018
39. Johnson RA, Wichern DW (2007) Applied multivariate statistical analysis. Sixth. Pearson Education, Inc., Upper Saddle River, New Jersey
40. Leite RR (2019) Método de interseção normal à fronteira para modelos quadráticos de escores fatoriais rotacionais. Federal University of Itajubá
41. Paiva AP, Paiva EJ, Ferreira JR, Balestrassi PP, Costa SC (2009) A multivariate mean square error optimization of AISI 52100 hardened steel turning. Int J Adv Manuf Technol 43:631–643. https://doi.org/10.1007/s00170-008-1745-5
42. Sakthivel P, Manobbalava V, Manikandan T, Mohammed Arman Salik Z, Rajkamal G (2020) Investigation on mechanical properties of dissimilar metals using MIG welding. Mater Today Proc 37: 531–536. https://doi.org/10.1016/j.matpr.2020.05.488
43. Meseguer-Valdenebro JL, Portoles A, Óñoro J (2016) Numerical study of TTP curves upon welding of 6063-T5 aluminium alloy and optimization of welding process parameters by Taguchi’s method. Indian J Eng Mater Sci 23:341–348
44. Paiva AP, Costa SC, Paiva EJ, Balestrassi PP, Ferreira JR (2010) Multi-objective optimization of pulsed gas metal arc welding process based on weighted principal component scores. Int J Adv Manuf Technol 50:113–125. https://doi.org/10.1007/s00170-009-2504-y
45. de Almeida FA, Streitenberger SC, Torres AF, de Paiva AP, Gomes JHDF (2020) A gage study through the weighting of latent variables under orthogonal rotation. IEEE Access 8:183557–183570. https://doi.org/10.1109/ACCESS.2020.3019031

Publisher’s note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.