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# CLASSIFICATION OF SHORT CIRCUIT GMA WELDING USING ARTIFICIAL NEURAL NETWORK

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***Abstract.*** *Short circuit gas metal arc welding has an important role in manufacturing processes and is widely used in an industrial base. In order to achieve high quality control levels in weldments, investigations are carried out with the aim to find a way to monitor the quality of weldments in real time. The Laprosolda research group has created a criterion to quantify the metal transfer stability in short circuit process that is based on calculating the* $IV_{cc}$ *index and metal drop diameter - the two parameters used by Laprosolda criterion. The proposal in question makes use of measured data obtained from three different gas flow rate weld beads performed in laboratory. Observing such samples, this work introduces a classification for monitoring the gas flow rate in short circuit gas metal arc welding using a Multilayer Perceptron Artificial Neural Network fed by parameters of Laprosolda criterion and statistics from the electrical signal, for the purpose of classifying satisfactorily events in the abovementioned process. The results indicate that this proposal is suitable to be used in welding quality monitoring, generating benefits that will be discussed and thus providing solutions for users to achieve the top of operational excellence.*

***Keywords:*** *short circuit GMAW, artificial neural network, gas flow rate*

## 1. INTRODUCTION

Short circuit gas metal arc welding (GMAW) is widely present in manufacturing processes in the industry. Aiming at improving weldment quality, specially in online mode, laboratory experiments and computational methods are employed in this paper. In this context, Multilayer Perceptron Artificial Neural Network (MLP ANN) techniques have been applied to achieve interesting results.

Koleva, *et al*., (2010) proposes a methodology based on MLP ANN to construct nonlinear models, being able to predict the geometric characteristics of the obtained orbital arc welding joints. In the same way, Campbell, *et al*., (2012a) apply an MLP ANN to predict weld geometries produced using GMAW with alternating shielding gases. Cruz, *et al*., (2015) present a methodology to perform the modeling, optimization and control weld bead width, enabling the adjustment of process parameters in real time.

Another application for MLP ANN stands on defects detection. Mirapeix, *et al*., (2007) implemented an MLP ANN employed for welding defects identification task. It is able to detect four different kinds of defects along the weld seam: slight lack of penetration, lack of penetration, low welding current and inert gas flow reduction. Garcia-Allende, *et al*., (2008) propose a spectral processing technique for arc-welding quality monitoring based on MLP ANN. Furthermore, although several online monitoring solutions have been proposed in the literature to provide real time information, the classification of defects, in terms of their causes, is an important task in welding and its discussion is open in the literature. In this case, MLP ANN could be used by classifying defects into different groups, given that the system would have information regarding the welding parameter to be modified (e.g.: welding current, gas flow rate, distance between the electrode tip and the piece).

Those parameters mentioned above are commonly used as inputs for MLP ANN applied in welding. This work proposes other inputs: $IV_{cc}$ (Vilarinho Index of Regularity Transfer), $F_{cc}$ (short circuit frequency) and current and voltage statistics. De Rezende, *et al*., (2011) introduce a criterion (namely Laprosolda criterion) able to quantify the short circuit transfer mode stability. This criterion takes the following two assumptions: short circuit metal transfer stability is correlated with the regularity of both period of open arc and period of short circuit, as well as appropriate volume of the drop being transferred from the tip of electrode to the weld bead. The criterion is composed by two parameters. The first one is the $IV_{cc}$, is given by:

$$IV_{cc} = \frac{\sigma_{tsc}}{\mu_{tsc}} + \frac{\sigma_{toa}}{\mu_{toa}}, \quad (1)$$

where $\mu_{tsc}$ and $\mu_{toa}$ are the statistical average of short circuit and open arc period, respectively, whereas $\sigma_{tsc}$ and $\sigma_{toa}$ are the standard deviation of respective short circuit and open arc period. The second parameter is the estimated short circuit frequency $F_{cc}$:

$$F_{cc} = \frac{V_{feed}\, d^2}{(k\, d)^3}, \quad (2)$$

where $V_{feed}$ stands for wire feed rate, $d$ for the electrode diameter and $k$ is a constant that estimates the drop diameter.

The use of Laprosolda criterion as an adequate transfer mode stability index has been investigated recently, specially regarding the correlation between stability of transfer mode and welding defects. This paper discusses the capabilities of the presented MLP ANN for classifying short circuit GMA welds in different conditions of gas flow rate. The Laprosolda criterion together with other features obtained from the signal were used as an input for the MLP ANN.

## 2. METHODOLOGY

In the present work, the primary electrical signal analyzed is given by voltage and current originated in the welding process. Signal processing is required for the proper investigation of its features, which are then fed to an MLP ANN in order to investigate the influence and particular characteristics the gas flow variation induces. The valid portion of the signal was extracted and formatted for further analysis. Since the goal of signal processing in the current work is to produce material for the MLP ANN, each signal section used as a sample for the network input will further on be denominated as unit.

Regarding the numerical data processing, an important parameter to be set is the threshold that separates the period of short circuit from the rest of the drop deposition cycle, which was fixed to 10V for the voltage signal. Thus, after determining which part of the cycle belongs to the short circuit section, and which does not (thus being part of the open arc section), it is possible to define parameters which will be further used as inputs for the MLP ANN and should be effective in classifying the weld quality.

Let $\boldsymbol{r}$ be voltage and current signals. Figure 1 shows the paradigm used for the classification of short circuit GMA welding. The block "Features" provides the $IV_{cc}$ parameters, time derivative of voltage and, finally, voltage and current peak statistics. These calculated features are represented by $\boldsymbol{p_x}$ and will be presented in Subsection 2.1. The block "Classification" applies a classification technique based on MLP ANN to obtain the output vector $\boldsymbol{s}$, thereby identifying the pre-defined class of gas flow it belongs to.

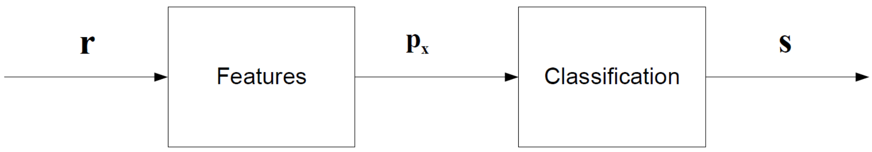


Figure 1. Block diagram of the scheme for classification of short circuit GMA welding

### 2.1 Features

This section will present the features obtained from the electrical signal which are used as input for the MLP ANN.

#### 2.1.1 Laprosolda criterion

Some of the key signal processing parameters that indicates the quality of arc welding are related to the time it takes for a short circuit to take place, and also its frequency on the weld bead signal. The present work makes use of the parameters developed by de Rezende, *et al.*, (2011), represented here by three variables. Firstly, the short circuit ratio $R_{tsc}$, corresponding to the first term of the sum in Eq. (1), is given by:

$$R_{tsc} = \frac{\sigma_{tsc}}{\mu_{tsc}} \quad (3)$$

Similarly, the open arc ratio $R_{toa}$, corresponding to the second term of the sum in Eq. (1), is given by:

$$R_{toa} = \frac{\sigma_{toa}}{\mu_{toa}} \quad (4)$$

Finally, the frequency with which short circuit takes place in the welding signal is given by the number of occurrences divided by the total period of active welding. Thus, these are the first three features obtained from the signal, related to the Laprosolda criterion.

#### 2.1.2 Time derivative of voltage

The samples analyzed indicated that substantial decrease in gas flow induced sudden voltage drops of up to 10V in the middle of the open arc period, that is, before reaching the next short circuit period, whereas a sufficient gas flow kept a much more stable decline on the voltage signal.

Experimental observation suggested including this sudden drop in voltage as the fourth feature for the MLP ANN. This can be accomplished by evaluating the minimum value of the time derivative of the voltage signal during the open arc section of each cycle and taking its average value. The central difference time march was applied for this purpose here, as given by Eq. (5) below, where $\dot{E}^n$ approximates the time derivative of voltage $E$ at time step $n$, and $\Delta t$ represents the time interval between two consecutive readings.

$$\dot{E}^n = \frac{E^{n+1} - E^{n-1}}{2\,\Delta t} \tag{5}$$

Since there is always a substantial variance in voltage in the initial passage from short circuit to open arc, the very first part of this transition was not included in this calculation, once it would naturally yield high values and reveals to be common for all gas flow rates measured. After several simulations, the optimal percentage of the leading part of the open arc signal to be ignored in the time derivative evaluation was found to lie in the range 5-10%. In this work, it was set to 10%. This assures that the atypical voltage drops are indeed located in the bulk of the open arc section, and not in the transition region.

#### 2.1.3 Voltage and current peak statistics

It its known that the typical voltage signal for this welding configuration reaches a peak right after the short circuit period, when the electric arc is open again. It was perceived however that the value of this peak, along with its variance, were different when the gas flow was modified. Lower gas flow tended to promote higher voltage peaks, with a higher variance. Therefore, the voltage peaks average and standard deviation for every unit was calculated and stored for the MLP ANN. The same study was performed for the current signal. A sensible difference regarding current peak average and its standard deviation along the signal was also apparent.

Therefore, four more features (two from voltage statistics and two from current statistics) can be obtained from the signal, summing eight features in total, which will be used in the classification process.

### 2.2 Classification based on MLP ANN

Given vectors $\boldsymbol{x}_{p,i}$, with $i = 1,2,\ldots,N_x$ samples, then the equations of an MLP ANN with $K_p$ inputs, $N_\mathrm{q}$ hidden layers and one output layer, are the following:

$$\mathbf{s}_i = \mathbf{A}^T \begin{bmatrix} \mathbf{x}_{p,i} \\ 1 \end{bmatrix} \mathbf{q}_i = \varphi(\mathbf{s}_i) \tag{6}$$

and

$$y_{rn,i} = \varphi\left( \mathbf{B}^T \begin{bmatrix} \mathbf{q}_i \\ 1 \end{bmatrix} \right), \tag{7}$$

where $\mathbf{A} \in \Re^{(K_p+1)\times N_q}$ and $\mathbf{B} \in \Re^{(N_q+1)\times 1}$ represent the weights between the input and hidden layers and between the hidden and output layers, respectively; $N_\mathrm{q}$ is the number of processors in the hidden layer and $y_{rn,i}$ is the output of the MLP ANN associated to the vector $\boldsymbol{x}_{p,i}$. In addition, $\varphi(\cdot)$ is a monotonically increasing function, which is considered here as a hyperbolic tangent sigmoid.

By concatenating the column vectors of matrices **A** and **B**, the following weight vector is obtained:

$$\mathbf{w} = [\mathbf{a}^T\,\mathbf{b}^T]^T, \tag{8}$$

where $\boldsymbol{a}^T$ and $\boldsymbol{b}^T$ are the results for the concatenation of column vectors of matrices $\boldsymbol{A}$ and $\boldsymbol{B}$, respectively. The optimal vector $\boldsymbol{w}$, given by $\boldsymbol{w_o}$, can be obtained by solving:

$$\mathbf{w}_o = \min_{\mathbf{w}} J(\mathbf{w}), \tag{9}$$

where

$$J(\mathbf{w}) = \frac{1}{2N_x}\sum_{i=1}^{N_x}\left(y_{rn,i} - y_{d,i}\right)^2 \tag{10}$$

is the cost function, and $y_{d,i}$ is the $i$th desired output of the MLP ANN. Note that $y_{d,i} = 1$ means that the parameter vector $\boldsymbol{x}_{p,i}$ is associated with a successful gas flow classification. On the other hand, $y_{d,i} = -1$ states that the parameter vector $\boldsymbol{x}_{p,i}$ is associated with an unsuccessful classification. The scaled conjugate gradient backpropagation training method (Moller, 1993) has been adopted for MLP ANN.

## 3. EXPERIMENTAL SETUP

Measured data was collected from signals produced by bead-on-plate welds deposited on ABNT 1020 (3.2 mm thick) carbon steel plates using ER 70S-6 wire, 1.0 mm diameter. The power source was the DIGIPLUS A7 450 (IMC soldagem), constant voltage mode, set on 19.0 V (nominal). Voltage, current and gas flow rate were measured by the data acquisition system SAP-4 with the sampling rate set on 5 kHz, which provides necessary resolution for the analysis. Distance from contact tube to the workpiece stand on 12 mm, wire-feed speed, 3.5 m/min and travel speed, 30 cm/min (nominal). The shielding gas used was pure Argon. Scotti and Ponomarev (2008) state that an adequate flow for almost whole welding conditions must lie within 10 and 16 L/min. Therefore, the experiments were performed in three different gas flow rates: 16, 8 and 2 L/min, in order to guarantee welds to be both inside and outside the classical range.

## 4. RESULTS

This section presents both the laboratory results for the welding setting chosen for the study, along with the numerical simulations carried out to classify the signal, embracing both a convergence and performance analysis.

### 4.1 Laboratory results

The weld beads obtained for the three gas flow variations are shown in Fig. 2.

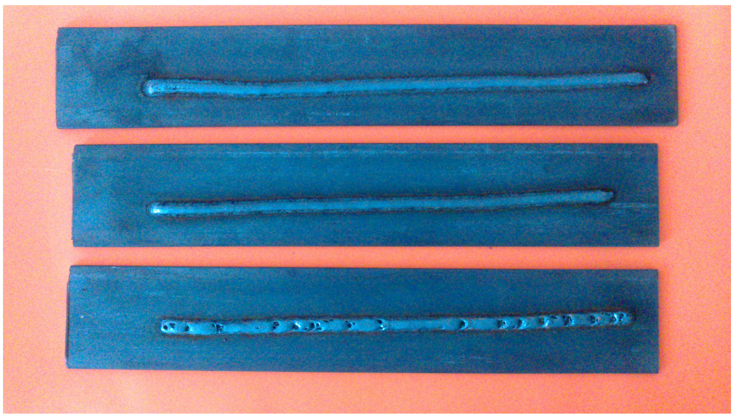

Figure 2. Weld beads for Argon gas flow rates of 16, 8 and 2 L/min (top-down)

The choice of gas flow rate was intentionally done in order to allow weld beads with defects (2 L/min) and visually no defects (16 and 8 L/min). The experiment carried out in 8 L/min is outside of the classical range but still showing no visual defects. Although carefully analysis needs to be made (such as macro and micrography), comparison between the three samples indicates that welds could be made in lower gas flow rate then what is recommended for a general case. In fact, Campbell *et al*., (2012b) conducted investigation to study the effects of reducing the shielding gas consumption in GMAW. They concluded that, according to experimental trials, the use of gas-saving devices have shown that the shielding gas flow rate can be effectively reduced, in a draft-free environment, to 6 L/min resulting in approximately 50% savings in gas cost in comparison to the 15 L/min base case, and without loss of quality.

A detailed signal comparison between the different gas flow rates shows some patterns which were crucial when devising the variables used in the MLP ANN. A typical voltage sample depicting the three gas fluxes simultaneously is shown in Fig. 3 below. Some remarks should be made, such as the evident difference in short circuit frequency, 13.4 Hz, 30.0 Hz and 66.7 Hz for 16, 8 and 2 L/min gas flow rates respectively, which is much higher for poorer flux samples. Pure argon causes high surface tension and turns the drop transfer more difficult. It could be a factor that contributes to low frequency for high flow rate of argon, since low fluxes allows another contaminant gases like oxygen.

Another aspect observed was the often occurrence of voltage drops in the middle of the open arc segment of the cycle, which motivated the inclusion of a derivative feature (explained in Subsection 2.1.2) in the MLP ANN input. Probably, it occurs because of arc instability caused by insufficient gas protection.

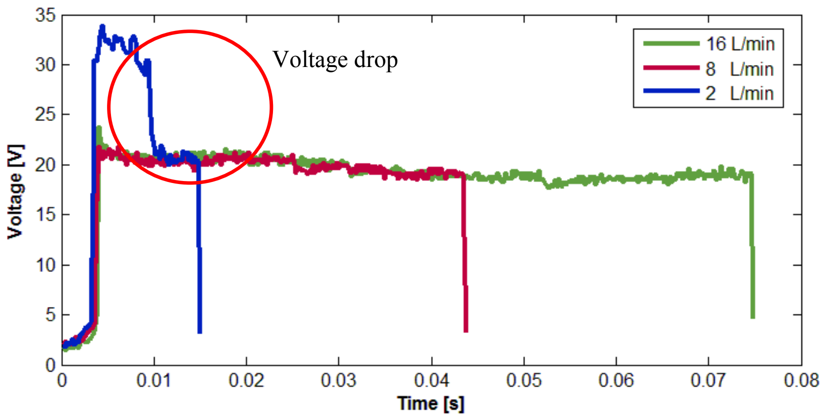


Figure 3. Comparison of typical voltage cycle for different Argon flow rates (in liters per minute)

## 4.2 Numerical results

The MLP ANN has $K_p = 8$ inputs, $N_q = 1$ hidden layer with 10 processors and one output layer with three outputs, namely 16, 8 and 2 L/min gas flow rates. Different configurations of the hidden layer were also evaluated, but the best performance was obtained with 10 processors. The experiments with the MLP ANN considered 100 epochs for training. In addition, out of the 60 units used as input for the MLP ANN, 42 (70%) were used in the training phase, 9 (15%) in the validation phase and 9 (15%) in the testing phase.

### 4.2.1 Convergence analysis

A key element for an MLP ANN is the convergence analysis, indicating whether or not it is prone to yield consistent and numerically stable results. The number of input units for an MLP ANN is important since it will determine how well it will address further problems, and how precise the weights will be adjusted for a particular setting. Thus, it is essential to determine how a signal should be processed in order to be fed to the MLP ANN and yield decent results. Since almost all parameters here calculated involve averages by definition, for a signal section to be turned into an input unit it has to present a minimum quantity of short circuit cycles for statistical reliability. A few numbered cycles input unit will have the average and standard deviation miscalculated, while an extensive number of cycles will be computationally expensive, possibly unfeasible.

An optimization study has been performed in this sense for the present welding setting, which varied the number of short circuit cycles per input unit, and fed the latter to the same MLP ANN in order to compare the convergence and how accurate and fast each scenario would be. 100 epochs were enough to assure convergence. The number of cycles per input unit was varied, with its classification rate presented in Fig. 4 below.

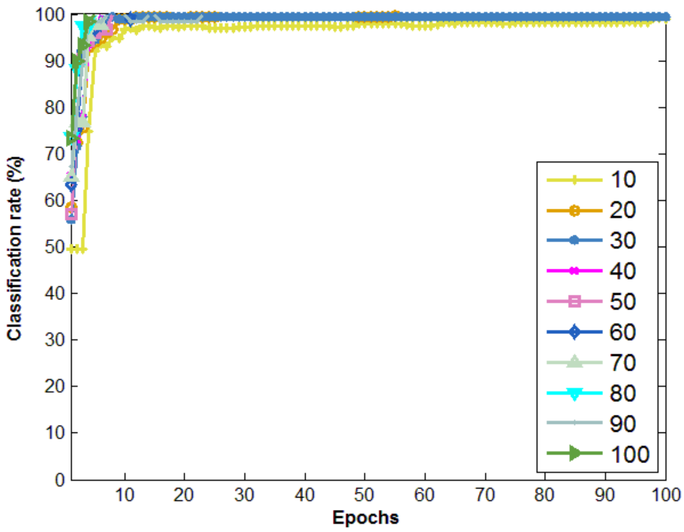


Figure 4. Classification rate varying the number of short circuit cycles per input unit

It is clear by Fig. 4 that the use of more cycles per input unit improves the statistical quality of the variables used for the MLP ANN, consequently improving the classification rate of the network. For this particular welding setting, the authors suggest that at least 30 cycles per input unit should be used, in order to preserve a trustworthy statistical metric. A higher value might accelerate the convergence, so 100 cycles per input unit was set for further simulations, in order to assure the desired classification rate without consuming much computation resources.

### 4.2.2 Performance analysis

In order to assess separately the significance of each of the features used as input for the MLP ANN, four groups of parameters were created, and the simulation was carried individually for each one. The first group comprises the Laprosolda parameters only, as described in Subsection 2.1.1; the second group makes use of the time derivative of voltage exclusively, as defined in Subsection 2.1.2; the third group takes into account voltage and current statistics, as in Subsection 2.1.3; finally, all parameters are considered together in the fourth group. The classification rate for all groups is shown in Tab. 1.

Table 1. Classification rate (%) for training, validation and testing phases for the MLP ANN.

| Features | Training | Validation | Testing |
|---|---|---|---|
| Laprosolda criterion | 97.6 | 100 | 100 |
| Minimum derivative | 88.1 | 100 | 85.6 |
| Voltage and current statistics | 97.6 | 100 | 100 |
| All parameters | 100 | 100 | 100 |

Excellent results were obtained for a relatively small number of input units. Particularly, a classification rate of 100% was achieved when including all parameters simultaneously. This result not only strengthens the effectiveness of the $IV_{cc}$ index in classifying welding quality, but also confirm that the other parameters used are also worthy predictors, and can be securely used as inputs for MLP ANN.

## 5. CONCLUSION

An application for classifying short circuit GMAW using MLP ANN was presented. It uses eight features as input for the MLP ANN obtained from the weld electrical signal (voltage and current), which are: three features from the Laprosolda criterion, time derivative of voltage parameter and finally four statistical measures from voltage and current peaks. These features lead to excellent classification rates for training and testing of up to 100% for three different gas flow rates. There is also evidence that time derivative of voltage and voltage/current peak statistics, both, could also contribute to a signature indicator for lack of shielding gas.

## 6. ACKNOWLEDGEMENTS

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