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Statistical analysis of the arc behavior in dry hyperbaric GMA welding from 1 to 250 bar

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ABSTRACT

In this paper, mathematical approaches were developed for predicting the hyperbaric GMAW process arc behavior and stability. The variation of stochastic parameters is related to the electrical stability that can be resolved into a number of varying parameters. The results show that most of the arc instability can be traced to the frequency domain of the voltage or current waveform. Uncorrelated current and voltage wave frequencies at higher pressures are found to have a great influence on process stability.

1. Introduction

Acquisition and analysis of real-time electrical signals have been reported by a number of authors including Subramaniam et al. (1998). Because these data are produced in a sequence with defined intervals, Witt (2007) provided the possibility to consider them as stochastic variables and analyze the dataset as a time-series. Diongue et al. (2008) modeled time-series by developing the theory of seasonality that resulted in visualization of recurrent components of a waveform. Such analyses may form the basis of a model for further predictions. However, Dilthey et al. (1996) found that a universal model can be too intricate with regard to monitoring and predicting the effect of the welding parameters involved.

Jones (1988) has described that welding under high pressure conditions is often required in a variety of industries. One example is subsea pipeline tie-ins and hot tapping in the oil and gas industry. Such a welding process should be performed in a sustainable and reliable way, meeting the standard metallurgical and mechanical requirements for a welded joint. Performing the welding operation under the water without protecting the weld pool from water media can suffer from low toughness and ductility as well as low process productivity. Dry hyperbaric welding was developed to ameliorate the characteristics of wet welding. Nixon (1995) has defined different types of dry hyperbaric welding which generally require a chamber to protect and seal the workspace from seawater.

Waller et al. (1990) proposed implementing high-speed charge-coupled device (CCD) cameras inside the welding chamber to study metal transfer phenomenon. However, existing chambers do not offer enough space for such a device, and a suitable instrument for very high pressures does not exist. Moreover, this kind of data recording can also be very costly at the industrial scale. Thus, alternative methods are sought. According to Mazzaferro and Machado (2009), monitoring the welding voltage and current waveforms using stochastic approaches can be a reasonable substitute to correlate the behavior of a specific parameter with the stability of the welding process. However, the sampling frequency should be sufficiently high in order to achieve statistical significance. McLarty and Bahna (2009) discussed the effects of sampling frequency on waveform approximation and showed that high sampling frequency results in a longer analysis time, while lower frequencies result in data loss. Nevertheless, Zhu (2006) described the existence of a specific frequency above which the analyses do not show any major change in any subset of the waveforms, while the minimum statistical significance is met, which is an indication of ergodic behavior.

Oliveira and Werlang (2007) defined ergodicity of a signal when the frequency of a data collection is high enough to meet the statistical significance. They assigned "ergodic" to a process in which every sequence or sizable sample is equally representative of the

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entire process. Alfaro et al. (2006) have applied the definition to the processes in which an event recurs with a dominant frequency, as in welding, where metal transfer occurs periodically.

A stable process could also show stationary behavior, which means that calculated stochastic parameters are similar to those of the "time-shifted" series. Once the welding process stabilizes after the ignition phase, such behavior can be observed. Newland (2005) argues that once a welding process shows both ergodic and stationary characteristics, it can be monitored using any subset of waveforms with a fixed number of samples. Thereafter, the statistical parameters of each subset can be compared to the adjacent set to study the instabilities during the process.

In the dry hyperbaric GMA welding case, Fostervoll et al. (2009) used the most outstanding statistical features on the entire process regardless of its variation in subset waves. Although the general trend was visualized, the optimization of the parameters and significance of the calculation could not be verified. The objective of this paper is to report on more advanced statistical analyses and signal processing techniques to ensure the trustworthiness of the trends.

2. Background

2.1. Stationary and ergodic processes

Box et al. (2008) defined a stochastic process as an infinite ensemble of random variables. Let Ω be the sample space that consists of members $\theta \in \Omega$. A continuum or discrete-time stochastic process can be denoted by $X(t,\theta)$, where there is one and only one random value for each time t.

Because θ is a random variable, it can take any real positive nonzero value from 1 to n. The number n shows how many times the process is repeated, and it is called the "realization" of the process. If these conditions are met, the group of $X(t,\theta)$ is representative of a single process.

Moreover, each random process exhibits a single probability distribution function (PDF), and a set of these functions represents $X(t)$ in particular. The number of functions that take the value between x and $x+\mathrm{d}x$ form the first probability distribution $f_X(x,t)\mathrm{d}x$. The joint probability distribution at times t_1 and t_2 can then be defined as $f_{XX}(x_1,t_1;x_2,t_2)\mathrm{d}x_1\mathrm{d}x_2$, and the third, fourth and subsequent distributions can be defined in the same way; representing a random process. The value of each function is positive, and the joint integration of all the functions is unity. In addition, it is assumed that PDFs are dependent on time intervals. Engelberg (2007) showed that if the following condition is met, the stochastic process will be of a stationary type:

$$f_X(x,t)=f_X(x), \quad f_X(x_1,t_1;x_2,t_2)=f_{XX}(x_1,t_1+\varepsilon;x_2,t_2+\varepsilon) \qquad (1)$$

More restrictively, Porat (1994) stated that the ergodic process can be calculated as the expected values at time averages over a single instance of the stochastic process:

$$E(X(t,\theta))=\lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2}X(t,\theta=\theta_0)\mathrm{d}t \qquad (2)$$

$$E(X(t,\theta)X(t+\Delta t,\theta))=\lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2}X(t,\theta=\theta_0)X(t+1,\theta=\theta_0)\mathrm{d}t \qquad (3)$$

where the left hand sides of the equations are the expectations over all θ and the right hand sides are the expectations of a particular θ. If the time average is used in this way, the stochastic process must be stationary.

2.2. The auto-correlation function

According to Tabachnick and Fidell (2007), auto-correlation is a mathematical representation of the degree of similarity between a given time series and a lagged version of itself over successive time intervals. It gives the measure of the correlation of $X(t)$ with itself at two different times and is defined as

$$R_{XX}(t_1,t_2)\equiv E(X(t_1)X(t_2)) \qquad (4)$$

If $X(t)$ is stationary, the auto-correlation could be defined as a function of time interval variable τ:

$$R_{XX}(\tau)\equiv E(X(t)X(t+\tau))=\lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2}X(t)X(t+\tau)\mathrm{d}t \qquad (5)$$

A stochastic process where $E(X(t))=\mu$ (μ: statistical average) and $R_{XX}(t_1,t_2)=R_{XX}(\tau)$ is called *wide sense stationary*. It is assumed that the welding waveforms are of this kind. According to the definition of an ergodic process, Eq. (5) shows that the ensemble average (right hand side) can be used to represent the time average (left hand side). The following equation describes this condition:

$$R(\tau)=\iint_{-\infty}^{\infty}x_1x_2f_{XX}(x_1,x_2;\tau)\mathrm{d}x_1\mathrm{d}x_2 \qquad (6)$$

If x_1 and x_2 are not correlated, $f_{XX}(x_1,x_2;\tau)=f_X(x_1)f_X(x_2)$, which zeros Eq. (6). In other words, a perfectly random process has an auto-correlation value equal to zero. In addition, the auto-correlation of a periodic function is periodic, with the same period as events in the original signal. The auto-correlation function evaluates the time dependent behavior of a stochastic process.

2.3. Power spectral density (PSD)

Brockwell and Davis (2002) showed that the auto-correlation function does not resolve the periodicities of a waveform because it is periodic itself. Moreover, the power or energy of the waveform has not been taken into account because the auto-correlation function is only concerned with the statistical average of the waveform. As a result, the power state of the time series over a range of frequencies (ω) could be visualized by applying the Fourier transformation of the waveform:

$$\Phi(\omega)=\left(\int_{-\infty}^{\infty}f_X(t)\mathrm{e}^{-2\pi i\omega t}\mathrm{d}t\right)^2 \qquad (7)$$

Nevertheless, because the time-series has been recorded discretely, the Fourier integral does not exist. Alternatively, according to the properties of the auto-correlation function and the Wiener–Khinchin theorem defined by Strube (1985), the power spectral density (PSD) can be calculated by applying the Fourier transform on the auto-correlation function.

$$\mathrm{PSD}_{\mathrm{average}}=\lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2}E(|X(t)|^2)\mathrm{d}t=\int_{-\infty}^{\infty}\mathcal{F}(R(\tau))(\omega)\mathrm{d}\omega \qquad (8)$$

According to Eq. (8), if the waveform being analyzed is the welding current, the standard deviation of the signal ($|I(t)|^2$) will represent the average power spectral density between the time set-points $(-T,T)$. Moreover, according to Luksa (2006) and Joseph et al. (2003), the momentary arc power can be calculated by multiplying the average PSD with the momentary arc resistance. At high sampling frequencies, the average values can be calculated using