Analyses of Online Monitoring Signals for a GMAW Process Before and After Improvement

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ABSTRACT

The ability to detect the onset of welding instability is a very powerful tool in welding process monitoring and control. Toward this goal, this study investigates a gas metal arc welding (GMAW) process by analyzing online monitoring signals. Two separate data sets are obtained from the process, which correspond to (a) a stable process after improvement and (b) a relatively unstable process which exhibits spatter and poor weld bead geometry. Voltage, current, wire-feeding speed and line speed signals for both data sets are analyzed and features are extracted from the raw signals using different signal processing techniques. Specifically, phase diagrams, signal distributions, and fast Fourier transform (FFT) methodologies are implemented. The process parameters differ for the data corresponding to the stable and unstable processes rendering the two data sets incomparable. As such, an overlapping region of parameters is selected and this data is used to develop a multi-layer neural network model. The model uses the features extracted to distinguish between the two datasets under the similar input conditions. The trained model is then used to classify data as being from a stable process or an unstable process.

1. INTRODUCTION

Gas Metal Arc Welding (GMAW) is a major welding process used in various engineering applications. GMAW involves the use of a high energy electrical arc shielded by a fed gas to coalesce two or more pieces of metal. Continuous GMAW welding has been widely used in automated manufacturing processes. One major problem associated with continuous GMAW, particularly when CO_2 is used as the shielding gas (MAG), is the incidence of weld spatter which results in poor finished weld quality. An ideal stable welding process will consist of no instances of spatter. Since poor quality welds may lead to defective finished products, spatter is undesirable. To this end, the continuous GMAW processes in industry are often monitored in real time.

Owing to the significant industrial benefits of the ability to determine welding process stability, there has been much effort in developing methods to accomplish this task. Online weld quality monitoring has been attempted using various sensing techniques. Infrared, ultrasound, visual, acoustic emission and arc sensor signals are a few of the tools used to monitor the welding process during production. Using any of these techniques generally involves analyses of the signals and modeling with the input parameters. Acoustic emission has been an effective tool in instability recognition due to distinct sound patterns made by spatter [1]. However, arc sensor signals, specifically current and voltage, may be of more interest as they provide a direct and reliable way of observing the behavior of the arc. Arc sensing has been used as an online monitoring technique by [2] in an effort to detect flaws in an automatic GMAW process. Major flaws in the welding process such as a sudden absence of shielding gas resulted in direct changes in arc signals. In cases where instability or flaws are not sizable enough to yield direct visible changes in the signal, feature extracting tools need to be employed. Several time and frequency domain tools make it possible to observe certain characteristics of the signal waveforms which can provide information on the stability of the process. Statistical techniques have been used with arc signals using spectral analysis, signal variance and standard deviation [3]. Energy spectrum analysis, probability distributions and cyclograms were successfully extracted from arc signals to determine stability in a short circuit GMAW process [4]. Similarly, spectral analysis was used to classify and detect major defects in the welding process in real time [5]. Signature analysis using power spectrum and other time-frequency tools has

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also yielded positive results in determining the stability of a process [6]. Once features have been extracted, they can be used to predict output conditions such as stability using modeling techniques and algorithms. Techniques such as fuzzy c-means modeling, neural networks and fuzzy Kohohen networks have been implemented to use features extracted from signals to monitor arc weld processes [7].

Artificial neural networks (ANN) have been widely used in developing models for the GMAW process. ANN models are very useful in analyzing non-linear processes. Furthermore, ANN models are very useful even in the absence of much knowledge of the behavior of the process. The neural network methodology was first applied to modeling the arc welding process by [8,9]. The artificial neural network methodology was seen to be effective in predicting the physical weld geometry modeling and was applied to welding process control. As a result, many efforts have been made to use ANN models to relate input parameters to a specific desired output. One such study was conducted in [10] in which the shielding gasses were modeled against desired outputs. Specifically, the hardness, tensile strength, elongation and impact strength were modeled. Similarly, other outputs related to quality such as bead geometry [11], tensile strength, distortion and deposition efficiency [12] as well as weld joint strength [13] have been investigated through input arc signals with neural network modeling. The specific problem of welding process instability due to spatter has been addressed through neural networks using acoustic emission [14].

In many industrial situations, it may be difficult to monitor on-line any direct output condition such as welding spatter, weld strength or weld bead geometry. However, information may be available regarding whether a process is predominantly stable or unstable. This paper proposes a methodology which uses only the arc sensor input signals and this information to classify whether a process is stable or unstable based on collected online monitoring data. The study intends to use a neural network to model extracted and selected feature data with the objective being to distinguish between stable and unstable process conditions.

2. WELDING PROCESS SIGNALS AND FEATURE EXTRACTION

The data used in this study was obtained from a continuous MAG welding process in an industrial spiral pipe manufacturing facility. The welding process is fully automated and data is collected through an online data acquisition system. The process signals obtained were the arc voltage, arc current, wire feeding speed and the welding/line speed. Arc voltage, arc current and wire feeding speed signals were each collected at 1kHz while line speed was collected at 100Hz. The arc voltage and arc current are of key interest as they contain information on both the input conditions of the welding process as well as the behavior of the arc during the process. Features were extracted from these two signals. Wire feeding speed and welding speed were treated primarily as input conditions and most features were not extracted from these signals. The ratio of the wire speed to the welding or line speed was also considered.

The process most closely represents a globular metal transfer process. This process is characterized by drops forming at the welding tip and detaching due to the force of gravity once drops grow to a certain critical size [15]. However, short-circuiting transfer behavior is also present. The metal transfer mode can depend on the droplet rate or the rate of deposition [16,17]. The rate of deposition is related to the wire speed. For greater wire speeds, the energy through the arc must also be greater to facilitate melting. As such the wire feeding speed is an important parameter to consider in such a process. The ratio of line speed to wire speed dictates the amount of deposition per unit length of weld. This ratio is kept constant within a run to maintain a linear relationship between the two parameters. However, in some cases, the ratio has been altered between runs in an effort to optimize process conditions. The wire speed plays an important role in stability [17] and must be considered in the analysis. The voltage is controlled to be constant throughout the process. The variation in the voltage signal is hence due to the behavior of the arc and not by manual changes in the process conditions. The magnitude of the current is directly related to the operating wire speed. This is due to the phenomenon that at a constant voltage, more current is required to melt more fed wire. The line speed is the main process condition which is manually varied through changing. A high line speed is desirable to maximize throughput but may result in greater chance of welding instability.

The data obtained spanned over a time frame of over a year. During this time period enhancements were made to the process which resulted in significant improvements in process operation. The process before the improvement was seen to result in abundant spatter and poor quality welds. Conversely, the process after the improvement was seen to exhibit a very stable process with very minimal spatter and defects. The raw signals for both the process before and after the improvement are shown in Figure 1. As seen in the figure, the signals for both cases are visually very similar and are difficult to classify by observing the raw signals alone.

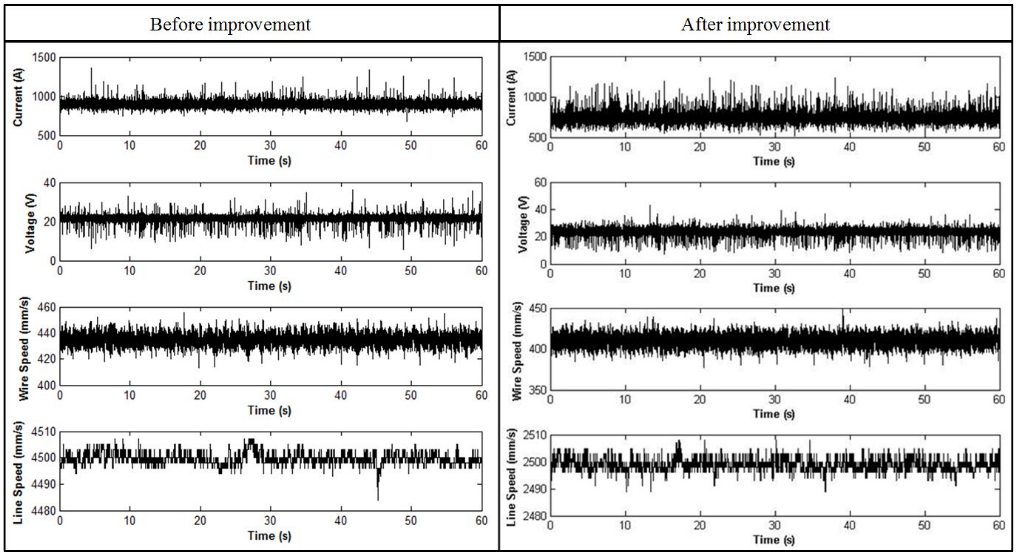

Figure 1. Process signals observed for a selected 60s window for data before and after improvement.

The features were extracted using methods observed in past research [4]. Specifically, the standard deviations, energy spectra and other time domain factors were obtained. There is no direct disadvantage to including more features at the start. Incorporating more features in the model may ensure a more comprehensive analysis. If certain features are not effective in determining stability, they will be excluded in the feature selection phase of this study. Each feature was obtained for the same 60 second windows selected. The welding was observed to be conducted in approximately 10-30 minute runs. Each run involved operating the process at a certain initial line speed and then incrementing the line speed in steps until a known maximum speed without instability was achieved. The windows were selected such that they incorporated 60 second segments of the run in which the line speed was kept constant. As much as possible, each steady condition was captured through the windows. The mean conditions for each of the windows were obtained.

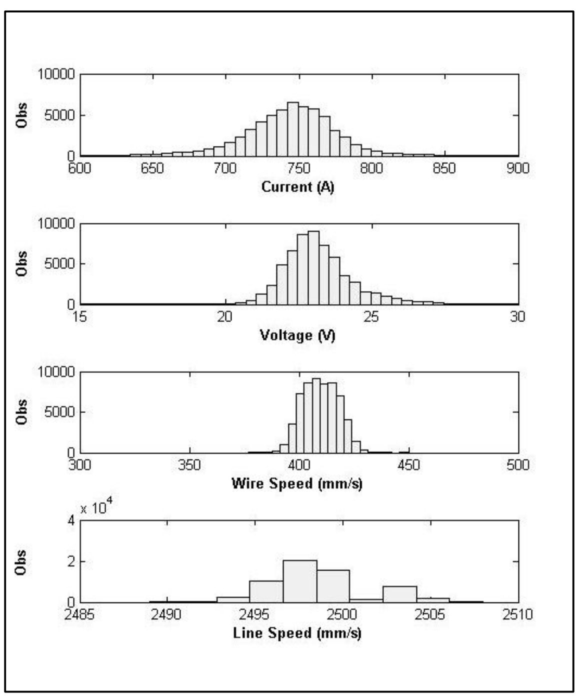

Figure 2. Probability distributions of the four signals in the 60s window.

For each window, the distributions for each signal were obtained as illustrated by Figure 2. Standard deviations of signals have been successfully used in past research as a tool in determining welding stability. As such, the standard deviations of each of the four signals were selected as features to be extracted from the windows.

The signals were also observed through the frequency domain using the Fast Fourier Transform (FFT) to obtain the energy spectrum. The FFT is essentially a sinusoidal waveform for which the frequency is varied and aligned with the signal. This enables the extraction of the dominant frequencies of the signal in the window. The FFT was applied to both the current and the voltage signals. The energy spectrum was computed from the FFT of the signal using equation (1) according to the methodology by [4].

$$S(\omega) = |F(\omega)|^2 \tag{1}$$

where S(ω) represents the energy spectrum and F(ω) is the discrete wavelet transform.

The next features extracted were the locations of the four most dominant frequencies in the spectrum. To avoid clusters of these frequencies a separation function was used to ensure a minimum spacing of 10Hz before frequencies were qualified as the dominant frequencies. The FFTs obtained for a single window for both the current signal and the voltage signal are presented in Figure 3. The 4 circles plotted on each of the spectrum indicate the peaks which were extracted from the window. A total of 8 features, namely the 4 locations of the dominant frequencies for each of the two signals, were extracted using this method.

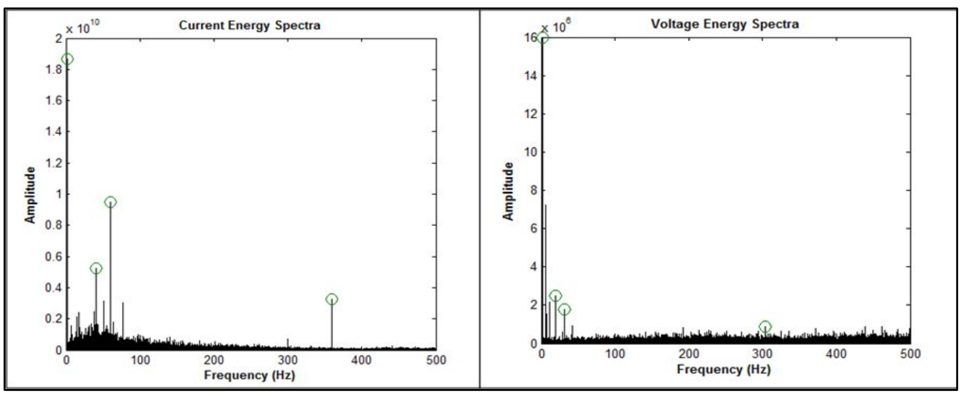

Figure 3. Energy spectra of the current and voltage signal.

Due to their successful implementation with acoustic emission signals, specific time domain techniques were applied to the arc signal data to extract features. Through the methodology used in [19], the RMS amplitude, absolute peak value, shape factor, crest factor, clearance factor, impulse factor and the fourth root of kurtosis were calculated for each of the two signals. Each of these was extracted as an independent feature and was added to the final table.

All the features along with the corresponding mean input conditions were compiled into a large data table. A small portion of the table is shown in Table 1. Each row of the table represents a single window while each column aside from the first four represents a single feature extracted from the window. Only the standard deviations are shown in the table. However, the complete table consists of 1022 rows and 30 columns. These 1022 windows were selected from both data before and data after improvement. Of these, 686 windows were selected from the data before improvement and 336 windows were selected from the data after improvement.

Table 1. Extract from the data table containing means and features extracted.

Mean LS	Mean C	Mean WS	Mean V	Stdev LS	Stdev C	Stdev WS	Stdev V
2999.59	580.12	265.47	22.05	3.40	62.94	17.28	1.99
3999.81	748.10	347.73	22.07	4.20	55.68	19.95	1.49
2198.53	461.52	191.76	22.05	3.15	65.40	9.39	1.99
4246.28	697.83	331.77	21.61	4.76	35.47	63.19	1.54
3999.82	779.43	388.48	22.10	5.12	32.41	36.07	1.44
2049.55	418.92	176.72	21.73	3.25	101.11	10.46	2.55
4498.85	728.99	352.31	22.12	3.19	38.43	64.44	1.65
4000.60	725.57	350.55	22.09	5.66	49.96	18.62	1.34
4449.56	813.96	387.56	22.10	4.98	63.43	20.97	1.53

As mentioned before, wire speed plays a very important part in the stability of the process. The values for the wire speed, line speed and the ratio were observed to be on average much different in the "after improvement" process than those in "before improvement". After the improvement, greater line speeds could be achieved without the onset of spatter and instability. To yield greater throughput, the line speeds and wire speeds were incremented to much higher values. With such data, the model would have to use extrapolation to deal with the different input parameters used in the before and after improvement processes. To avoid this and to build a more accurate model, more efforts were placed on acquiring data from an overlapping region of input parameters. As the current is directly related to the wire speed throughout the process and since the voltage is kept constant, the ratio and the wire speed were used to define this overlapping region. Figure 4 shows a scatter plot of the final data used in the model with regards to wire speed and ratio. Each point represents an extracted window. The final data after the definition of an overlapping area contained 178 windows. Of these, 97 windows are from the data after improvement while 66 windows are from the data before improvement.

In the interest of model simplicity and performance, the voltage means and the current means were not considered in the final model. The voltage is kept constant and the current-wire speed relationship is maintained throughout the process regardless of whether before or after improvement.

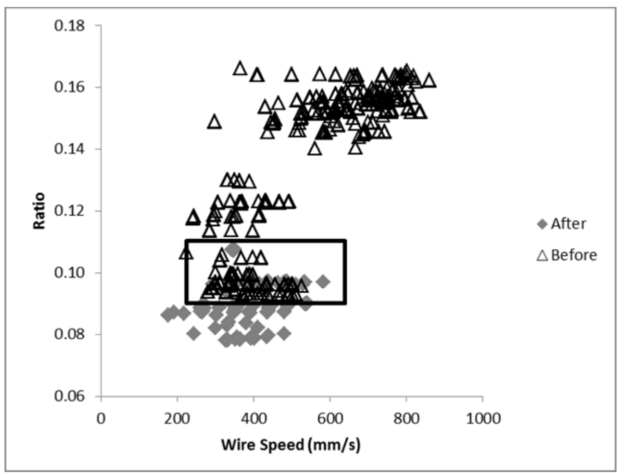

Figure 4. Plot of ratio and wire speed showing overlapping area extracted.

3. NEURAL NETWORK MODELING

The artificial neural network (ANN) methodology was used to develop a classification model to distinguish between the stable process data and unstable process data. Due to the lack of sufficient data to build one model for all features, each group of features was separately modeled and as such five models were developed in all. Specifically, models were developed corresponding to the following groups of features: the standard deviations, energy spectrum for the current signal, energy spectrum for the voltage signal, additional time domain characteristics for the current signal and additional time domain characteristics for the voltage signal.

In order to distinguish between data before and after improvement, a stability variable is assigned to each window. This variable is an indicator of whether the process in a particular window represents a stable or an unstable process. A value of 1 is defined to indicate a stable process and a value of -1 is defined to indicate an unstable process. Since the data after improvement exhibits a stable process, a value of 1 is assigned to all windows originating from this data. Conversely, all windows from the data before improvement are assigned a value of -1.

The neural network developed is a multi-layer perception (MLP) model with one input, one hidden, and one output layer as illustrated in Figure 5. In this network, four energy spectrum features are assigned as the inputs and the stability variable is assigned as the output. The hidden layer may contain any number of nodes. However, utilizing too many nodes runs the risk of over-fitting the model whereas too few nodes may lead to inefficient training of the model. This parameter in the final model will be determined using a meta-heuristic approach to obtain the best model performance for the data being analyzed. Essentially, the number of hidden nodes will be varied until best performance is obtained.

The initial results were obtained using 10 hidden nodes. The network architecture used in this study is a feed-forward back propagation network which is commonly seen in welding parameter models [14].

The input layer contains neurons each representing a particular feature extracted from a 60 second window. The output layer contains a single neuron corresponds to the stability variable assigned to the window. The goal of the network is to model the relationship between these nodes. This is accomplished through a hidden layer of nodes. Each input node and output node is connected to the neurons in this hidden layer.

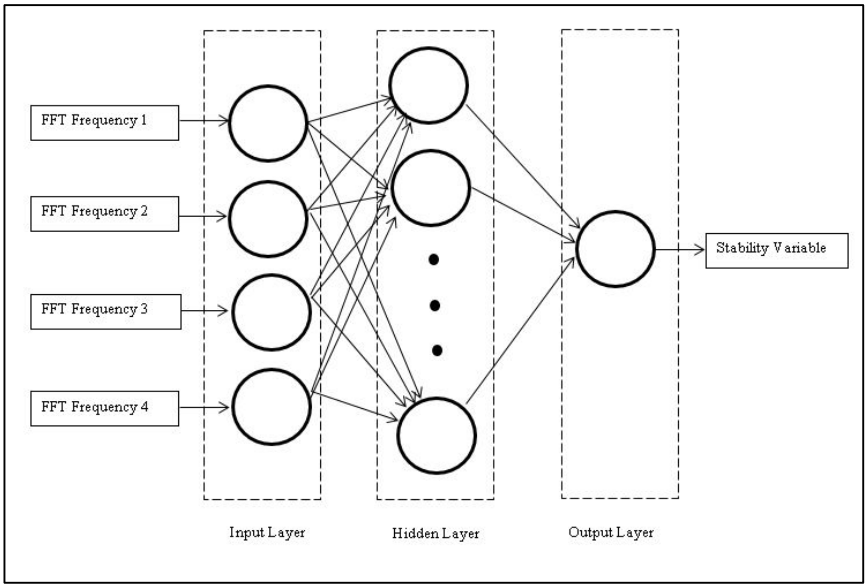

Figure 5. Multi-layer perception model structure for energy spectrum model.

Each link has a particular weight assigned. The weights are varied throughout the training process according to the back propagation algorithm which is being used. In this case, the Levenberg-Marquardt (LM) back propagation algorithm was employed as it is a fast algorithm and is widely used for input to output mapping. The LM algorithm has been successfully implemented in welding modeling networks and was shown to be the optimal algorithm when used to model input signals to bead width [20]. The hidden nodes and output nodes each contain transfer functions which determine the values which feed into the subsequent layers. Hidden nodes use the tangent sigmoid function shown in equation (2).

$$f(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)} \tag{2}$$

The output nodes use a purely linear transfer function shown in equation (3)

$$f(x) = x \tag{3}$$

The output values are determined through the weights and transfer functions and the final outputs are compared with the actual outputs observed in the training data. The resulting difference is the error in the model. The model was developed using functions available in the MATLAB neural network toolbox.

Of the combined dataset of 178 samples, 30 samples were allocated for independent testing following a k-fold cross validation scheme. The remaining data was used to train and validate the model. These samples were divided such that 80% were allocated for training and the remaining 20% for validation. The validation data was used to determine the number of iterations for which the model would train. The iteration which yielded the minimum validation mean squared error was considered to be the optimal model. This validation mean squared error is calculated through equation (4).

$$MSE = \frac{1}{N} \sum (T - Y)^2$$

(4)

where, T = the target value for the model and Y is the value predicted by the model at that iteration.

For the independent tests, the inputs of the 30 samples were simulated through the optimally trained network. Outputs from the network yielding values below 0 predicted an unstable process while outputs above 0 predicted a stable process. These outputs were compared with the actual stability variable values and the classification rate was obtained. This process was repeated to perform 5 tests. Each time, a different segment of the data was used for training and for testing.

Table 2. Classification performance for each feature group model.

Feature Group	**Test 1**	**Test 2**	**Test 3**	**Test 4**	**Test 5**	**Average**
Inputs	80%	70%	57%	67%	67%	68%
Standard Deviation	100%	100%	100%	100%	100%	100%
Energy Spectrum - Current	90%	97%	97%	90%	90%	93%
Energy Spectrum - Voltage	93%	83%	87%	100%	73%	87%
Time Domain Features - Current	83%	93%	80%	90%	93%	88%
Time Domain Features - Voltage	97%	77%	93%	80%	90%	87%

The classification model was run using groups of features based on the technique used to extract them. Specifically, the standard deviation, energy spectrum and the remaining time domain features were grouped. Table 2 shows the classification performance for each group of features for the 5 independent tests conducted following k-fold cross validation. From Table 2, it can be seen that the features are very effective in classifying the data. In particular, the standard deviation yields a perfect classification performance. The other features also gave promising results and may further improve after optimization of the model and its parameters. The values of the inputs do have an effect on classification and the corresponding test yielded an average classification rate of 68%. This is due to presence of small differences in the input conditions between the two datasets even after obtaining an overlapping area. However, it is evident that the extracted features outperform this rate and can independently be used to distinguish between the two datasets.

The next intended step of this study is to effectively select the most important features to use in the subsequent classification phase. Some features will have greater power in distinguishing between the two processes. Furthermore, certain features may not independently be good indicators but when combined with other features may prove to be important. The current model, in which features are grouped by method, may not be using an optimal combination of features. As such all features and combinations should be explored. To do this a meta-heuristic approach is employed to select the most optimal combination of features which may best differentiate between stable and unstable. Only these features will be used in the final model and the other features will be discarded for the sake of model simplicity and efficiency. Finally, the neural network structure, particularly the number of hidden nodes, should be optimized to yield the best classification results.

4. Summary

This paper has presented a new methodology to analyze welding process signals collected under different operating conditions in an effort to determine the stability of a GMAW welding process. Signal data before and after process improvement was analyzed and various features were extracted from both data sets. A multi-layer neural network modeling approach is implemented to build a relationship between features extracted and a binary stability variable. The classification model successfully distinguishes between the process before and after improvement for an independent test. A possible future work is to further explore features which can be used to better detect changes in process stability. Certain intrinsic differences between the signals from the process before and after may not be detected by the current features used but may be detected by other techniques. Implementing a wider array of features, which analyze different aspects of the signals, may yield better performance by the classification model.

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