DOI: https://doi.org/10.37434/tpwj2024.06.01

APPLICATION OF AI-BASED WELDING PROCESS MONITORING FOR QUALITY CONTROL IN PIPE PRODUCTION

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ABSTRACT

The paper presents the experimental results into the development of a multi-channel system for monitoring and quality assurance of the multi-wire submerged arc welding (SAW) process for the manufacture of large diameter pipes. Process signals such as welding current, arc voltage and the acoustic signal emitted from the weld zone are recorded and processed to provide information on the stability of the welding process. It was shown by the experiments that the acoustic pattern of the SAW process in a frequency range between 30 Hz and 2.5 kHz contains the most diagnostic information. The on-line quality assessment of the weld seam produced is carried out in combination with methods of artificial intelligence (AI). From the results obtained, it can be concluded that the use of the latest concepts in welding and automation technology, combined with the high potential of AI, can achieve a new level of quality assurance in pipe manufacturing.

KEYWORDS: submerged arc welding, high-strength fine-grain steels, pipe production, artificial intelligence, acoustic signals, quality control

INTRODUCTION

Submerged arc welding (SAW) makes a significant contribution to cost-effective production in industrial manufacturing. Numerous construction units and components from various sectors of industry, such as the oil and gas industry, shipbuilding, petrochemical industry, hydroelectric and offshore wind energy plants, use SAW. SAW guarantees a continuous production cycle and is characterized by high efficiency, which is primarily due to the high deposition rate of this welding process. In practice, single-wire SAW is usually used for component wall thicknesses of up to approx. 10 mm. Parts with a larger thickness, require an increased deposition rate, which can be achieved through the application of multiple wire SAW [1]. Especially, multi-wire SAW processes with up to five electrodes have been proven successfully [2]. Multi-wire SAW techniques are known where a cold wire is added to the welding zone to increase the deposition rate, adjust the welding temperature cycle, and thereby improve the properties of the welded joint [3]. Thick-walled large pipes for transporting oil and gas, foundations and towers for wind turbines are examples of structures where the advantages of multiple wire SAW can be utilized [4]. The Arctic offshore shipbuilding industry also requires a safe and efficient welding process for joining thick steel plates [5]. In these applications, welded constructions must guarantee safe operation of the systems even after years of extreme stress. The welded joints must therefore be of a correspondingly high quality.

In welding practice, it is generally known that the submerged arc welding process is characterized by a relatively high level of robustness. However, it should be noted that due to the increasing demand for welded steel structures in the energy sector and the existing competition, companies are aiming to increase the throughput in the manufacture of their products. This means that welding processes are reaching their limits, which can lead to an increased defect and scrap rate [6, 7]. This problem also applies to multi-wire SAW, in which the consumable welding wires form a common weld pool and each wire electrode is controlled individually. The quality of individual weld seams cannot always be guaranteed in multi-wire SAW. Interaction between the welding wires if the parameter settings are not optimized, for example, can lead to a disrupted welding process. The reproducibility of optimum welding process parameters and technological conditions, particularly with regard to a competitive and consistent high level of production quality, is essential [8].

In welding production, the quality of the products is ensured by the expertise of the personnel and the application of process parameters that have been determined through many years of manufacturing experience. Increased automation of welding does not exclude the possibility of welding defects. Surface defects can be easily recognized, while defects such as slag inclusions, lack of fusion or pores can only be detected by radiographic or ultrasonic testing of the weld seam.

Ensuring that the actual parameters of the ongoing welding process match the set target parameters can be guaranteed by using suitable measuring and moni-

Figure 1. Five-wire SAW test stand for welding sheets and tubes at Fraunhofer IPK in Berlin (left) and multi-wire SAW welding head (right)

toring systems [9, 10]. The most important parameters to be monitored are usually welding current, voltage, welding speed and filler wire feed speed. Such signal recordings provide the operator of the welding system with qualitative information about the stability of the welding process. The decision on the quality of the weld seam is made subjectively.

For reliable quality control with logging and traceability of data, the use of testing methods such as metallographic examinations, ultrasound and X-ray examinations is necessary. The use of the latest concepts in welding and automation technology in combination with the high potential of artificial intelligence (AI), on the other hand, enables a new level of quality assurance for welded products by combining various sensor signals [11].

In contrast to empirical and statistical models, AI models do not require any assumptions or prior knowledge regarding the physical phenomena of a relationship to be modelled, which is why AI models are referred to as data-driven models [12]. This approach enables AI models to capture very complex, highly non-linear relationships [13]. Recent studies have investigated the applicability of various nonlinear methods with AI capabilities in the field of welding, such as the Taguchi method, response surface method (RSM), artificial neural networks (ANN), genetic algorithms (GA), fuzzy logic systems, adaptive neuro-fuzzy inference systems (ANFIS), decision tree methods and particle swarm optimization (PSO) [14–16].

The aim of this study was to investigate the feasibility of AI-based process monitoring in SAW based on process signals such as welding current and voltage, as well as acoustic signals. The results will be used to develop a knowledge-based expert system to assist the operator in determining the optimum parameters for the selected welding task, and to monitor and record these during production.

WELDING EQUIPMENT AND MATERIALS

The welding experiments were conducted on a full-scale industrial welding system (SMS group GmbH) for longitudinal five-wire SAW on large-diameter pipes. The arcs are supplied with current by five electronically controlled current sources of type PERFECTarc® 1500 AC/DC (SMS group GmbH) with a total current of up to 7500 A. The resulting advantages are not limited to high deposition rates and welding speeds. With a programmable waveform for current and voltage, the welding result can be modeled with respect to various factors (e.g. weld geometry) [17]. Both, flat specimens with a length of two meters and large pipes with a length of up to six meters can be welded on the system. The transport carriage with the component to be welded can be moved at a speed of up to 6 m/min. The five-wire SAW system is shown in Figure 1.

Welding tests were carried out on sheets of pipeline steel grade X70 according to API 5L or L485MB according to DIN EN 10208-2 (material no. 1.8977). The welding consumables used were solid wire BA

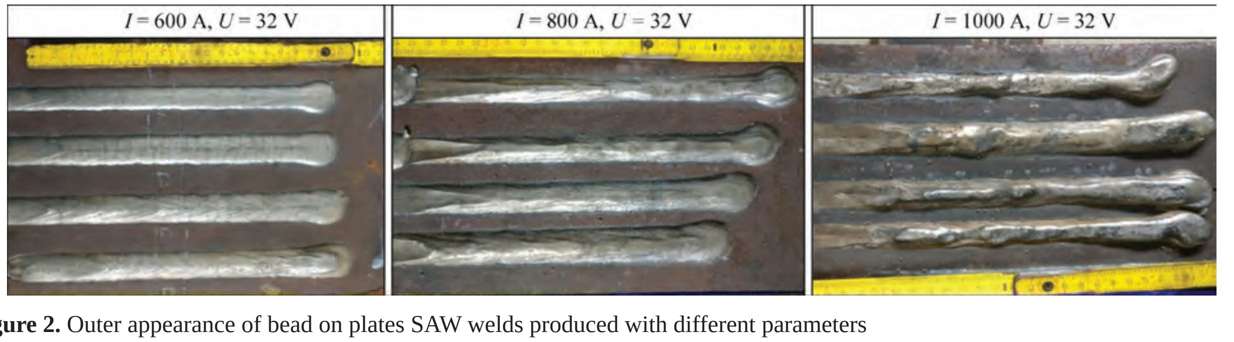

Figure 2. Outer appearance of bead on plates SAW welds produced with different parameters

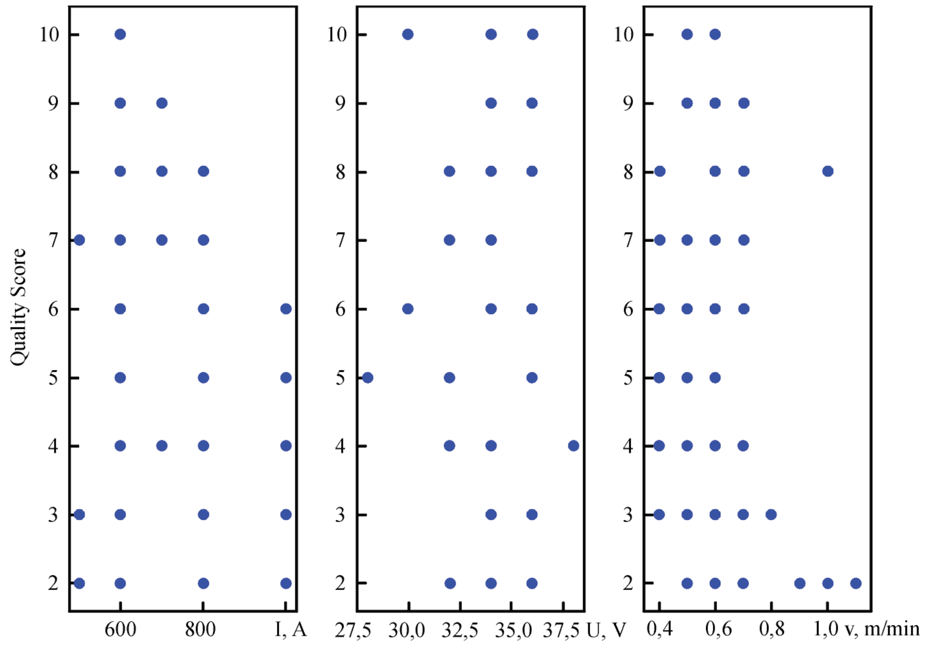

Figure 3. Subjective quality score. Scores are plotted against current (*I*), voltage (*U*) and welding speed (*v*)

S2Mo according to EN ISO 14171-A (EN 756) and an agglomerated welding powder of type BF 5.1.

RESULTS AND DISCUSSION

As a first step, a series of experiments were produced with a single-wire SAW process as bead on plate welds. Parameters such as welding current (*I*), welding voltage (*U*) and welding speed (*v*) were varied. These tests were used to teach the AI model and to analyse the correlation between the welding parameters and the welding result. Examples of bead on plate welds for different welding parameters are shown in Figure 2.

To quantify the weld quality of each specimen, a subjective quality rating was implemented. The rating was measured on a ten-point scale ranging from 1 (unacceptable) to 10 (excellent). The welds were visually inspected by eye to identify any surface discontinuities. These include surface cracking, porosity, undersized welds, undercutting and excessive and uneven reinforcement. Approximately 40 weld seams were characterised. The results of the subjective quality judgement are shown in Figure 3. It is worth noting that increasing the welding current and welding speed above a certain limit decreases the weld quality. This statement is in line with practical welding experience. A single-wire SAW process with a 4 mm thick wire is typically performed with welding currents in the range of 500 to 600 A and welding speeds of 0.4 to 0.6 m/min. As expected, higher values of these process parameters lead to process instabilities and a loss in seam quality.

To assess the internal quality of the welds, metallographic cross sections were taken. A selection of cross sections for welds made with different welding parameters is shown in Figure 4. Although no internal defects such as pores, cracks and slag inclusions were detected, external weld irregularities were confirmed for not optimal welding parameters.

A process signal recording was performed to document the welding tests. All relevant process data such as welding current, voltage, welding speed and wire feed speed (v_f) were recorded during welding and used for further analysis of the welding process. In particular, these recordings were necessary to determine the correlation between signal progression and weld quality. The recorded data of the welding process are shown as an example in Figure 5. The signal curves were ana-

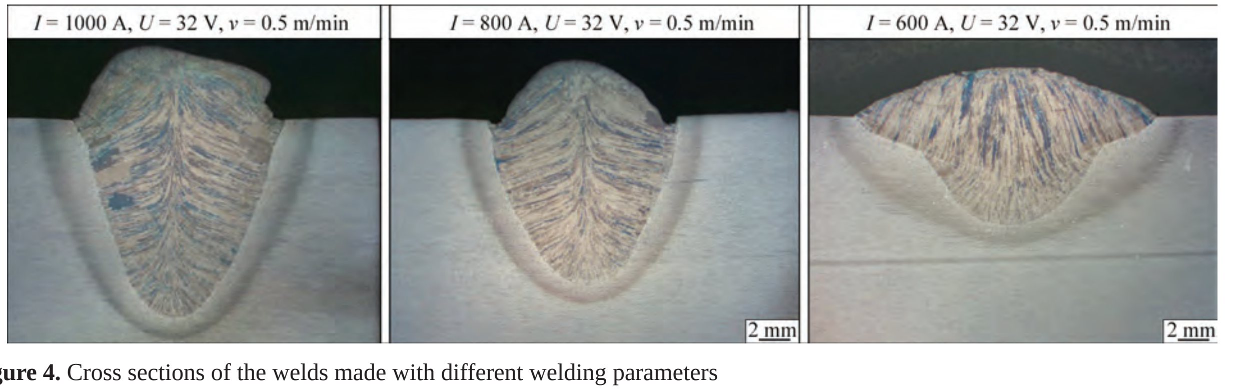

Figure 4. Cross sections of the welds made with different welding parameters

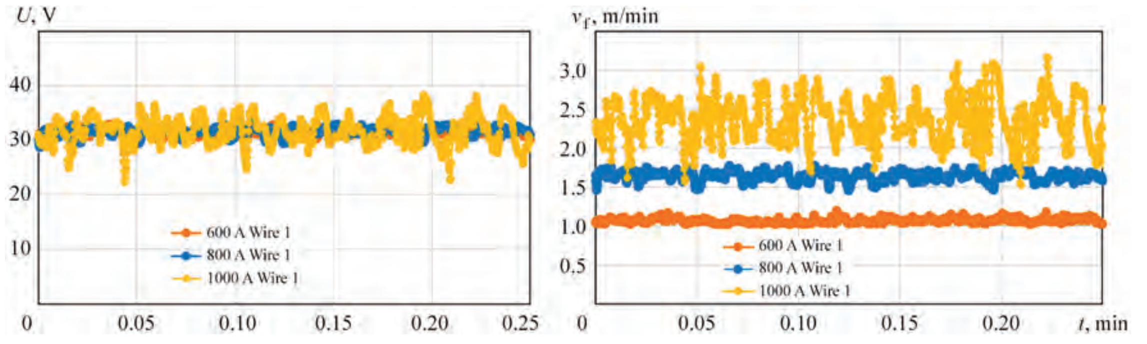

Figure 5. Progressions for the welding voltage and wire feed speed for different welding currents at constant welding speed of the single-wire SAW process

lyzed and a standard deviation was determined for the recorded values. It was found that the higher the welding current, the greater the variation in welding voltage and wire feed speed. The smooth progressions of the welding voltage and wire feeding signals for 600 and 800 A welding current indicate that the welding process is stable. The relatively high fluctuations in welding voltage (31.6±2.6 V) and wire feed speed (2.4±0.6 m/min) at a welding current of 1000 A indicate that the process is leaving the stability range.

The physical explanation for the relationship between the welding voltage and the wire feed speed lies in the control concept of submerged arc welding. The welding current is constant during the welding process. In the case of process faults, the voltage and therefore the wire feed speed is regulated in order to keep the arc length constant. For this reason, the level of voltage signal fluctuation can be used as a diagnostic feature for evaluating process stability.

The next step in signal acquisition was to record the acoustic signals of the welding process. This method is based on the assumption that each type of welding has its own noise, and this noise can indicate quality problems. For example, metal transfer during welding is a key element of weld quality, and welders use the "noise" of metal transfer to make fine adjustments to

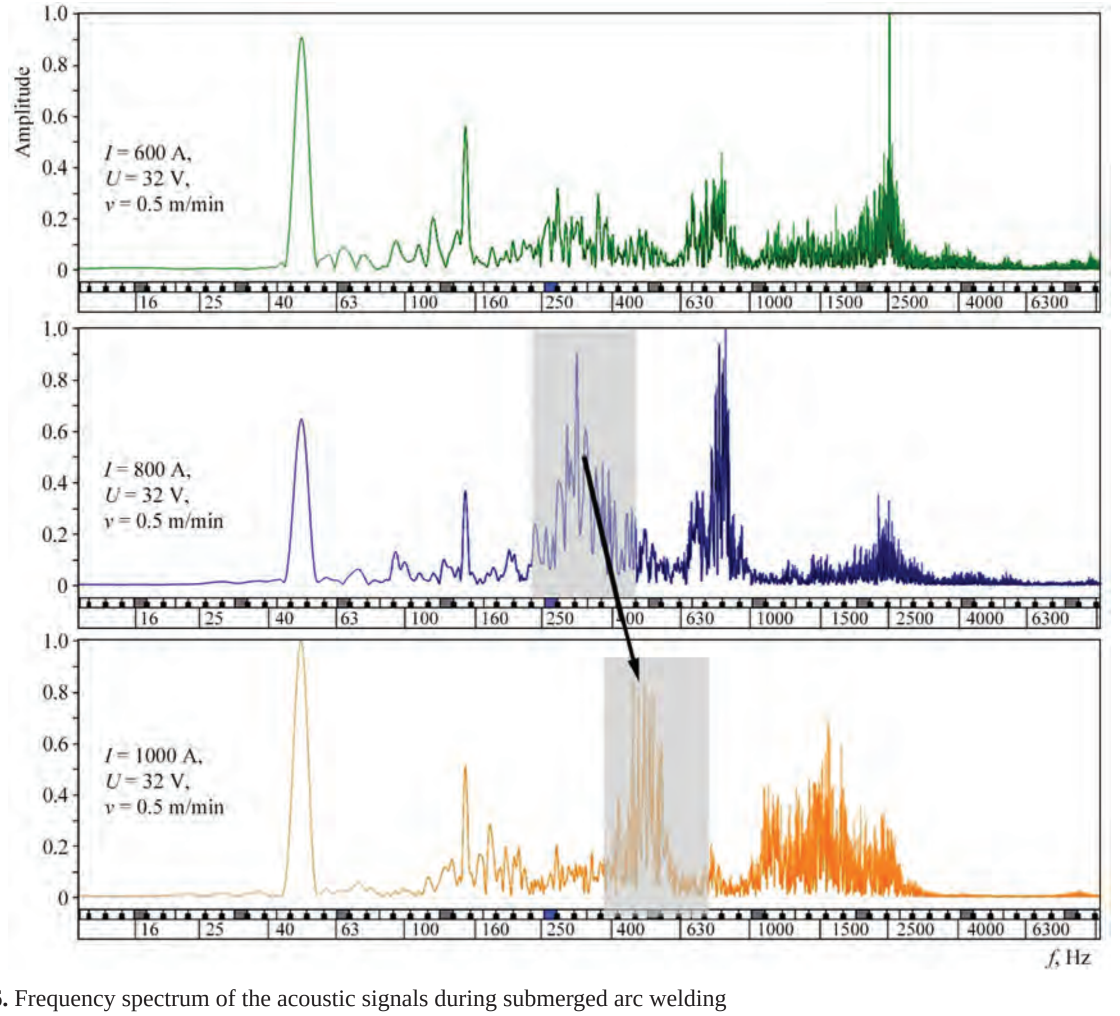

Figure 6. Frequency spectrum of the acoustic signals during submerged arc welding

Table 1. Calculated features and descriptions

Feature name	Description
Mean	Mean frequency in kHz
Standard deviation	Standard deviation of frequency
max *v*	Maximum fundamental frequency measured across acoustic signal
min *v*	Minimum fundamental frequency measured across acoustic signal
Median	Median frequency in kHz
Skew	Skewness (measure of asymmetry)
Kurt	Kurtosis (describes the availability of peaks in a distribution)
Q1	First quantile in kHz
Q3	Third quantile in kHz
IQR	Interquantile Range in kHz

welding parameters. However, in mechanized and automated systems, welding often takes place far from the operator and in noisy environments, so this process noise cannot be heard. In these situations, a welding microphone, for example, can provide operators with the sound they need to monitor and control arc stability and even predict when welding problems are occurring.

In this study, the acoustic signals were recorded with a piezoelectric vibro-acoustic sensor attached to the welding torch. The analog signal was converted into a digital form using an analog-to-digital converter. The sampling rate was selected so that the signal could be analyzed in the acoustically audible frequency range. By converting a time signal into its frequency components, it was possible to identify the dominant frequencies in a signal, detect unwanted noise and analyze harmonics. The recorded acoustic signals for various welding parameters were converted into a frequency spectrum (Figure 6).

The analysis of the frequency spectrum shows that the acoustic profile of the welding process tends to be in the low and medium frequency range from approx. 30 to 2.5 kHz. It is worth noting that increasing the welding current from 600 to 800 A results in a visible change in the spectrum. The frequency amplitudes in the range between 270 Hz and 430 Hz increase significantly. A further increase in the welding current up to 1000 A resulted in the amplitudes shifting to the 550–600 Hz range. Such changes in the spectrum of the acoustic signal allow the assumption that the acoustic profile of the welding process clearly depends on the welding parameters applied. In addition, it is assumed that both defect-free and defective weld seams can be identified using the acoustic weld signal.

The welding data from around 40 welds were evaluated in an attempt to classify defective and defect-free seams. The subjective quality points were considered as a reference (see Figure 2). Welds with quality points of five and less were considered defective.

The distribution of the frequency and its amplitude from the spectrum were evaluated using an approach

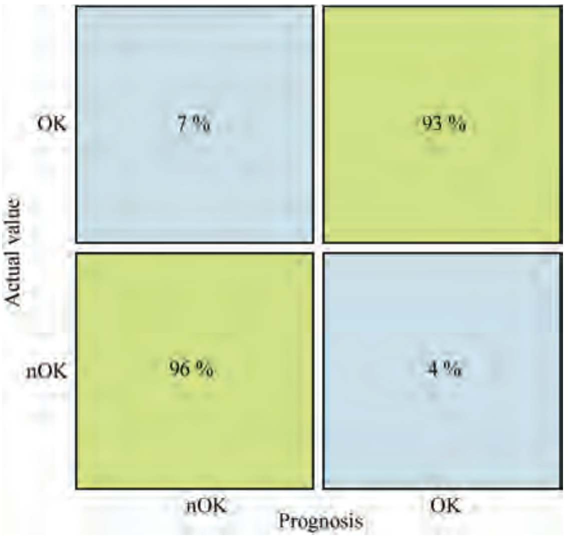

Figure 7. Confusion matrix for precision and accuracy assessment

from the field of AI based voice recognition in Python [18]. The author was able to determine the gender based on the voice with an accuracy of 99 %. The method calculates several statistical features from the frequencies of each signal. The calculated features are listed in Table 1. Preliminary tests have shown that these features are significant for the application in the present use case of this paper. Therefore, the features were extracted from the signals that served as input variables for the AI model.

The AI algorithm was designed to classify the joining quality as “OK”/“nOK” based on the features. A decision tree algorithm was implemented and its predictive capability was investigated using a confusion matrix. The algorithm was trained using 90% of the available data and validated with the rest.

It was shown that the algorithm can predict both classes “OK” and “nOK” equally well (Figure 7). If the prediction is “OK”, then the prediction is correct in 93 % of all cases and if the prediction is “nOK”, then the prediction is correct in 96 % of all cases.

The results confirm that the algorithm used can predict the joining quality with a high level of precision and accuracy.

CONCLUSIONS

Submerged arc welding (SAW) offers high deposition rates and is widely used in the production of thick-walled large pipes. Since the multi-wire SAW processes reach their limits, there is a high risk of welding defects and rejects. For this reason, it is necessary to introduce process monitoring in order to reduce reject rates and to maintain a constant high level of pipe manufacturing quality. A multi-channel system for monitoring and quality assurance of SAW process offers a solution to this task. The system keeps records of welding current, voltage and wire feed curves, which serve as the basis for process and quality control. In addition, acoustic signals generated by the SAW welding process are recorded. Through the subsequent signal processing, features can be extracted from the signals, which served as input variables for the AI model.

With the proposed AI algorithm using a decision tree, good precision and accuracy in predicting the weld quality could be achieved. The results will be used to develop a knowledge-based expert system to assist the operator in determining the optimum parameters for the selected welding task, and to monitor and record these during production.

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CONFLICT OF INTEREST

The Authors declare no conflict of interest

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SUGGESTED CITATION

S. Gook, B. El-Sari, M. Biegler, M. Rethmeier (2024) Application of AI-based welding process monitoring for quality control in pipe production. *The Paton Welding J.*, **6**, 3–8.
DOI: https://doi.org/10.37434/tpwj2024.06.01

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Received: 23.05.2024
Received in revised form: 26.06.2024
Accepted: 29.07.2024