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ANALYSIS AND CLASSIFICATION OF WELDED JOINT DEFECTS BY ULTRASONIC TESTING AND ARTIFICIAL NEURAL NETWORKS

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Abstract: *In this work, the main objective is to evaluate the structural integrity of welded joints in steel components through the ultrasonic nondestructive test, applying computational-mathematical methods in order to reduce the time needed to evaluate the integrity of a joint and improve the production rate. Thus, artificial neural networks and mathematical concepts will combine to detect the higher variance points, such as principal component analysis. In other words, the aim is to get the best rate of accuracy compared to the computational cost needed, also other possible architectures to the neural network and the mathematical concepts to reduce inspection time.*

Keywords: Artificial Neural Networks, Ultrasonic Testing, Welding Defects, Welding Profile.

1. INTRODUCTION

In most industrial applications, nondestructive methods are applied to ensure the integrity of structures and its components in order to detect, locate, and measure the existing flaws inside the welding beads (AWS, 1994; Babkin and Gladkov, 2016), such as lack of penetration, lack of fusion, porosity and internal cracks. According to Veiga, *et al.*, (2005) and Manjula, *et al.* (2014), the benefits of ultrasonic testing are the high velocities of inspection, high probability of detection, and the low number of false results. In the other hand, it depends on operator's experience and knowledge.

Based on these counterparts of the process, and aiming to reduce the time needed to proceed with an inspection, many efforts have been made to adapt mathematical concepts to evaluate the data from the test and reduce the influence of this potential of human error (Veiga, *et al.*, 2005; Filho, *et al.*, 2013; Yi and Yun, 1998). One of these attempts comes through the application of artificial neural networks and principal component analysis to evaluate and rank the kind of defect in the welding bead (Veiga, *et al.*, 2005; Filho, *et al.* 2013; Kouche and Hassanein, 2012; Yi and Yun, 1998).

Principal component analysis is a mathematical method that evaluates variance between neighbor signals, using the eigenvalues and eigenvectors of the covariance matrix. It is a very useful tool for selection of most representative parts of a signal, such as Bae, *et al.* (1997) says that you may use it for reducing the size of a signal matrix, neglect the lesser representative part of it, and keep the most important eigenvalues.

Artificial Neural Networks are a mathematical model that mimics the human brain's neuron work, with learning ability given by relationships established between input (p_i) and output (a_i) information of a given signal. This relationship allows recognizing patterns, creating associations, identification systems, etc (Veiga, *et al.*, 2005). The training process occurs when weight functions (w_{ij}) are balanced according to which input has a major contribution to the output value and then the result of all weighted inputs added (v_i) and submitted to a certain activation function ($f(v_i=W_{ij}P_i+b)$) generates the output (Veiga, *et al.*, 2005; Filho, *et al.* 2013; Yi and Yun, 1998).

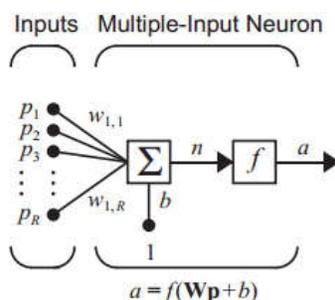


Figure 1 - Single layer neuron with R inputs.

Source: Hagan, Demuth, Beale. "Neural Network Design".

2. MATERIALS AND METHODS

Initially, 200 mm weld beads were made using automatic GMAW AR-CO₂ gas mixture (80-20) and ER 7056 1.0 mm welding wire on 9.525 mm (3/8 inches) thickness on SAE 1020 steel plates with single-V butt joints. Welding defects such as the ones seen on usual operations (porosity, lack of penetration, and internal cracks) were inserted on stable beads, made with parameters according to Babkin and Gladkov (2016), aiming to generate the desired weld beads. To do so, variables were added to these weld beads in order to generate desired defects. Porosity was inputted inside the weld bead by two different methods: adding contaminants to the weld pool, such as rust, paint, and oil, which are usually seen on production plants and by reducing the shielding gas flow. Lack of penetration and lack of fusion was inputted by reduction of the heat input in the weld bead.

Afterwards, the welding beads were tested by ultrasonic Pulse – Echo technique with its data stored for further analysis by mathematical – computational means in MATLAB. Ultrasonic waves were generated by 4 MHz 60° angular transducers and controlled by an Olympus 5058 PR pulse generator in intervals of 5 mm of the weld bead. The received ultrasonic signal was shown and saved by a Keysight DSO1072B oscilloscope. The weld beads were retested with X-Ray for later validation of the following code to be made at this work.

Resulting signals from ultrasonic inspection were treated in two different ways: the first attempt was simply a reproduction of the process made by Bae, *et al.* (1997), storing neighbor signals from inspection and taking its principal components from the covariation matrix. The second approach involves the preprocessing of signals through the removal of noises applying neural networks filters and then disregarding lesser importance principal components.

The results of the mathematical processing were used as input for a feedforward backpropagation artificial neural network created in MATLAB, with outputs taken from the x-ray test of the weld beads, as made by Veiga, *et al.* (2005) and Bae, *et al.* (1997). Signal samples were separated into three groups: training, validation, and testing. Tests were made in the neural network to achieve the best rate between computational cost and neural network precision, such as the relationship between input number and time taken to load all data, the accuracy of neural network related to the number of hidden layers, and the usage of filters in the data to improve the accuracy of the artificial neural network.

3. RESULTS AND DISCUSSION

Weld beads size given by Babkin and Gladkov (2016) showed compatibility with those made in laboratory applying values of parameters. Thus, weld beads profiles are predictable.

Artificial neural networks were trained and presented accuracy of nearly 80 % and 90 % for untreated and treated signals respectively in the identification of weld bead defects (Table 1). Those results are similar to the ones seen in previous studies made by Veiga, *et al.* (2005) and Bae, *et al.* (1997) and were achieved using 20 hidden layers as the best result.

Besides, most of the computational time has been used to load data from the signal database, and in most cases, about 90 % of the time was used to load these matrices. Increment on a number of inputs in neural network resulted directly in time increase in training time of the neural network but also resulted in accuracy increase. Such increase of time may be interpreted as a negative signal for the functionality of the system, which is to reduce the time of inspection of welds, but as it has low influence on the total amount of time, and it may be neglected. Thus, an alternative approach can be carried out: loading libraries of pre-trained weights of neural networks into the system and performing inspections based on these libraries. The libraries should be enough to redress the problem of excess training time on the neural networks and to go strictly to the scanned weld beads to be tested.

Table 1 – Confusion Matrix of data with and without pre-processing.

Defect	Non-processed Signals		Pre-processed Signals	
	Training	Test	Training	Test
Non Defect	100 %	83 %	100 %	95 %
Lack of Penetration	96.8 %	91 %	99 %	93 %
Porosity	100 %	57 %	100 %	70 %
Crack	68.9 %	50 %	85 %	62 %

4. ACKNOWLEDGEMENTS

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5. CONCLUSIONS

Results proved that it is possible to reduce the time needed to locate and estimate weld bead defects, being at least able to locate to the welding inspector the average location of the welding defects without the need of search through the entire weld bead for it. This may result in significant reduce of inspection costs.

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T. M. Barroso, J. F. S. Feiteira, R. P. de Siqueira

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