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INTEGRATION OF AE FEATURES USING BELIEF NETWORK FOR CLASSIFYING NDT DATA

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ABSTRACT

This paper proposes an implementation of Belief Network based on Bayes' rule to classify Nondestructive Testing (NDT) data. Two NDT application works which are micro spot welding and corrosion monitoring were chosen to exhibit the performance of the Belief Network. Acoustic emission (AE), a premature NDT method, was used to capture transient elastic waves generated by the rapid release of energy from the sources of the two applications. In micro spot welding, AE parameters correlated with the stage of nugget deformation were investigated and extracted to divide quality of the nugget into three levels according to strength and size of the nugget. In corrosion monitoring, AE parameters related to the severity of the pitting corrosion were used to grade corrosion severity into five levels depended on the pitting depth. Experimental works were set up and data were cautiously recorded .Consequence the Belief Network, named Netica operated on the principle of "Bayes rule" was utilized. The set of feature vectors of the correlated data from the two applications were divided into two sets one to train the network and the other to test it. The outcomes of prediction showed that the overall success rate of the network in detecting perfection of the nugget in micro spot welding and in monitoring of corrosion severity were high with low error rate.

1 INTRODUCTION

Acoustic emission (AE) is a nondestructive testing (NDT) technique that has been used in various applications. The advantage of AE, compare to other NDT techniques, are its real time and less intrusive. Acoustic emissions, by definition, are transient elastic waves generated by the rapid release of energy from localized sources within a material [1]. These elastic waves can be detected by transducer attached to the surface of the specimen. Then the surface waves was converted into electrical signal and AE parameter such as count, peak amplitude and AE-rms can be carried out.

AE is random signal and most of AE signal obtained from a range of applications are complex. Consequently the large amount of AE data are difficult to analyze by humans. In the last decade various artificial intelligent systems such as neural network has been implement with some success in many fields of application such as tool wear monitoring [2], spot welding[3] and corrosion monitoring[4-6]. However the performance of the neural network is depended on the quality of the input data, the training sequence, and the number of iterations, the number of hidden layers, the learning rate and the type of transfer function. The best configuration of a neural network is often achieved through trial and error.

This paper proposed the development of novel condition monitoring systems for spot welding and corrosion monitoring. An expert system called the Believe network" based on bayes rule was utilized to integrate the information of AE to predict the quality of welding nugget and the stage of corrosion.

2 THEORIES

2.1 Acoustic emission

Acoustic Emission is the class of phenomena whereby an elastic wave, in the range of ultrasound usually between 20 KHz and 1 MHz, is generated by the rapid release of energy from the source within a material. The elastic wave propagates through the solid to the surface, where it can be recorded by one or more sensors. The sensor is a transducer that converts the mechanical wave into an electrical signal. In this way information about the existence and location of possible sources is obtained. The basis for quantitative methods is a localization technique to extract the source coordinates of the AE events as accurately as possible. The typical AE parameters are shown in figure1.

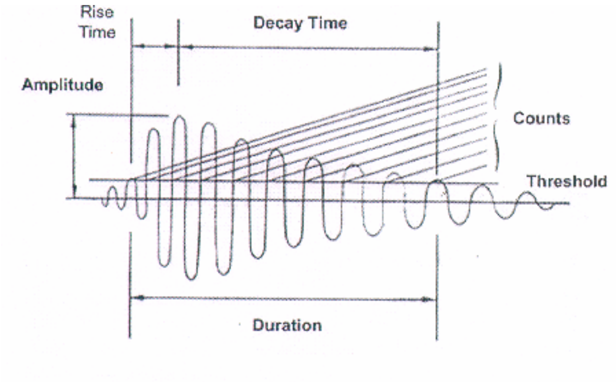

Figure 1: typical of AE parameter.

The AE parameters that extensively used are AE count, amplitude and energy.

- AE count is the number of time that the AE signal amplitude exceeds threshold any selected portion of the test.
- AE amplitude is the peak voltage of the largest excursion attained by the signal waveform from an emission event.
- AE energy is the total elastic energy release by an emission event for a short time periods.

Rise time is the time between the point at which the event first exceeds the threshold and the point at which the amplitude reaches its peak value.

AErms is the root mean square value of the AE signal. Since acoustic emission activity is attributed to the rapid release of energy in a material, the energy content of the acoustic emission signal can be related to this energy release. AErms can be defined as

$$V_{rms} = \left(\frac{1}{T}\int_0^T V^2(t)dt\right)^{\frac{1}{2}} \qquad (1)$$

where

V(t) = the voltage signal from an AE transducer, and

T = the duration of the signal.

2.2 Belief Network

In order to improve the robustness of corrosion and spot welding monitoring system, information from each AE parameter must be fully exploited. An expert system, named Netica, was used. The advantages of Netica are its ease of use, user-friendly graphical interface and low cost. Netica operates on the principle of "Bayes rule" which can be defined as

$$P(S_i \setminus A) = \frac{P(A \setminus S_i)P(S_i)}{\sum_{j=1}^{k} P(A \setminus S_j)P(S_j)} \qquad (2)$$

for i = 1,2,....k

where $P(S_i \setminus A)$ = posterior probability of *Si* given *A*.

$P(A \setminus S_i)$ = conditional probability of *A* given *Si*

$P(S_i)$ = prior probability

$S_2, S_3 \ldots S_k$ = a set of events

2.3 AE for spot welding monitoring

In spot welding, two or more metal sheet are pressured and heated together at the weld area without using any filter material. Copper alloy electrodes are used to apply pressure and convey the electrical current through the work pieces. In all spot welding, the parts are locally heated. The material between the electrodes is yield squeezed together. The material is melted and destroyed at the interface between the parts. When the current is switched off, the nugget of molten material solidified and formed the joints.

The spot welding process consists of 5 stages. First, the electrodes are brought in contact with the specimens of set-down stage. Second, the current is initiated to electrodes and the electrodes are brought in contact with specimen that needs to be welded. Next, the electrodes are forced and current flows through the sheet interface where the nugget is produced. Then, the current is turned off and the fully grown nugget is allowed to cool slowly and is solid under constant pressure. Final, electrode is raised from the weld sheet and move to the next welding location.

Accordingly, AE technique can be used for online monitoring of spot welding. By cautious analysis of signals generated during different periods of the welding cycle, it is possible to identify good and bad welds and also the shear strength of the nugget can also be estimated using AE parameters. The generated AE can be related to the weld quality parameters such as strength and size of nugget, the amount of expulsion and the cracking. The AE signals are produced during each stages of the welding process. These signals can be identified with respect to the nature of their sources. The individual signals element may be greatly different, or totally absent, in various materials, thickness and so forth.

When the material in the welding zone in heated, the pressure is applied by the top electrode will plastically deform the material and AE signals will be generated. Further heating results in melting in the welding zone and grown of the nugget. The nugget information and expansion produce AE signal that can be correlated with the strength of the weld. As soon as the welding current is start to decrease, the nugget begins to solidify and residual stress are present in around the weldment. If these residual stresses are still exists, hot cracking may occur. The ideal AE signal of the welding process is depicted in figure 2.

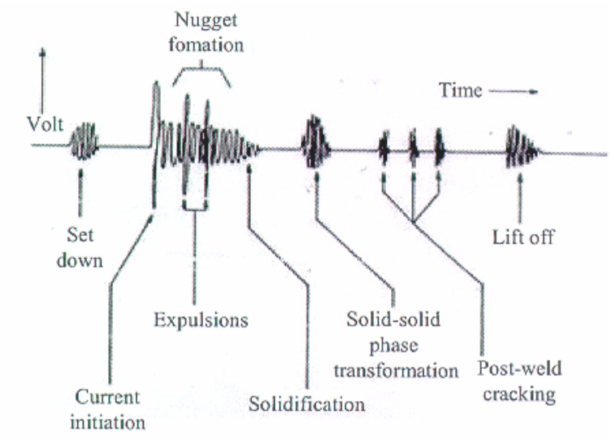

Figure 2: AE signal from spot welding process.

2.4 AE for corrosion monitoring

Corrosion, especially pitting and exfoliation are always of a great concern because they often cause significant damages to metals and structures. Although pitting corrosion takes place in a few individual locations, it can develop and becomes pits, even through holes, which are potentially the most dangerous structural faults. If we let pitting develop without proper counter-measures, the whole structure may collapse at anytime.

The source mechanism of acoustic emission from pure corrosion activity is much debatable, but it is generally accepted that the most plausible source is the nucleation of hydrogen gas bubble from solution, or the breakage of a local passivation film. It is also generally accepted that pitting process is caused by the breakage of passivation film. In a system of metal-solution medium, there exists a specific threshold value of anode polarization potential, above which pitting corrosion will take place and below which, on the contrary, no pitting shall occur. This special potential is called the breakdown voltage of passivation film, or the critical potential of pitting nucleation. Because the breakage of passivation film is a dynamic process and will apply a pulse force onto the metal surface, it is therefore expected that acoustic emission will be produced by this process. In return, we can hence use AE to monitor corrosion. This is the theoretical basis for using AE to monitor and evaluate pitting corrosion process.

3 EXPERIMENT STEP

3.1 Spot welding monitoring

The spot welding system used is a capacitor discharged DC into spot welding model SW-1-160. Power 160 joules can be charged in the period of time between 2.5 and 7.0 ms. The adjustable pressure of the electrodes are 1-1.5 kg. In the experiment, the welding energy was adjusted for investigating by AE. There are 16, 24, 32, 40, 48, 56, 64 and 72 joules respectively. The specimen is Nickel grade 200, which is widely used in the electronic part as an electrical bride. Its composition is nickel 99%, iron 0.4%, manganese 0.35% and copper 0.25%.

The AE system, utilized to investigate, comprises of 4 main parts, an AE sensor, an electronic preamplifier with a filter built in, a data acquisition system (DAQ) and a monitoring and recording unit. The 150 kHz resonant AE sensor was mounted at the base electrode of the spot welder. The electronic pre-amplifier has selectable amplification at 40 and 60 dB which the range of filter frequency 100-1000 kHz. A 5 ms/s samples DAQ system was utilize to obtain the experimental AE signal which are monitored and recorded at a PC. The monitor system is illustrated in figure 3.

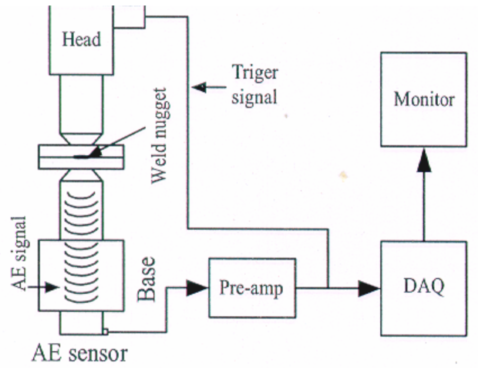

Figure 3: Diagram of AE system for spot welding monitoring

3.2 Corrosion monitoring

AE parameters related to the severity of the pitting corrosion was used to grade corrosion severity into five levels depended on the pitting depth: less than 0.1 mm is good condition, 0.1-0.2 mm and 0.2-0.3 mm is acceptable conditional , 0.3-0.4 is serious condition that needs maintenance and 0.4-0.5 mm is extremely serious condition that need immediately maintenance. Experimental works were set up and data were cautiously recorded. The experiments were conducted on the specimen which of type stainless steel 304. The size of the specimen is 4x6x0.05 cm. The electro- chemical method is used to accelerate the corrosion. This method is to supply the external constant electric current by using the voltage current converter to the electric chemical cell system to accelerate the corrosion. It makes chemical reactive between chemical solution and the specimen. The electric current used is computed by $I = V/R$ which is suitable for lowest resistance. The experiment is started by supplying the small current ,1 mA/cm^2 , to the electrical chemical cell. The chemical composition is

3%NaCL and adjust the pH=2% by using HCI acid. The time from the beginning to the end (specimen was broken through) is approximately 3 hours.

The diagram of AE system for corrosion monitoring is shown in Figure 4. The AE system, utilized to investigate, comprises of 4 main parts, an AE sensor, an electronic preamplifier with a filter built in, a data acquisition system (DAQ) and a monitoring and recording unit. The 50-150 kHz resonant AE sensor model R15 was mounted at the base of the specimen. The electronic pre-amplifier has selectable amplification at 40 and 60 dB which the range of filter frequency is 100-1,000 kHz. The 5 ms/s samples DAQ system was utilized to obtain the AE signal which are monitored and recorded at the PC. The input of AE parameters are amplitude, rise time, duration time, count and AE energy respectively. The output is corrosion stage which is divided into 5 levels based on its severity. The corrosion levels are segregated by the depth of pitting corrosion measured by a depth gage.

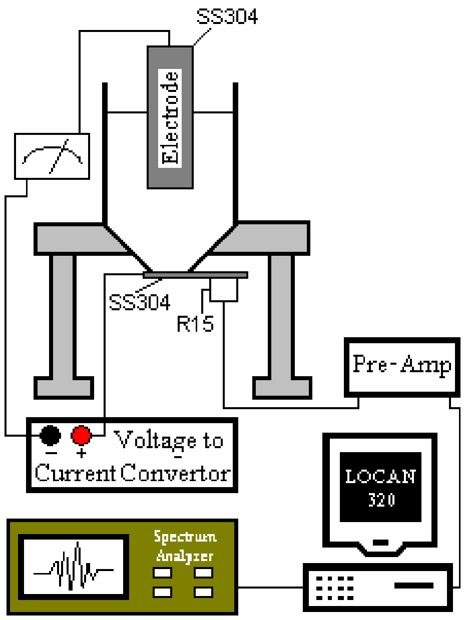

Figure 4: Diagram of AE system for corrosion monitoring

4 EXPERIMENT RESULTS

4.1 Results of Spot welding monitoring

The results from the experiment showed that AE parameters correlate with weld energy. The relation between weld energy and AE parameters, which are AE count, amplitude and energy, are shown in figure 5. It can be seen that AE parameters rapidly increase at the initial energy state (from 16-24 joule) and keep approximately constant at the energy between 24 to 48 joules, The AE parameters showed speedily increase again at the weld energy at 56 joule. As a consequence, it can be concluded that AE parameter can be used to divide the level of welding energy.

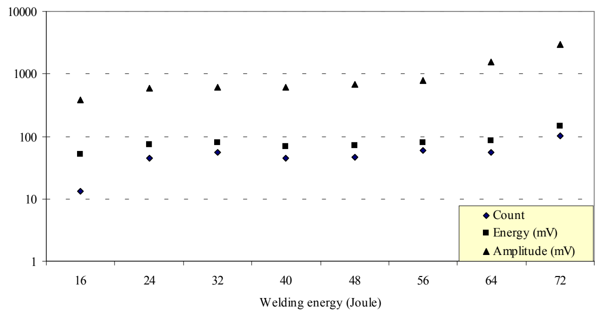

Figure 5: Relationship between AE parameters and different welding energy.

Figure 6. shows the relation between welding energy and the strength of the weld joint received by using peel test. The peel test is mainly intended for weld strength testing (shear strength) in a relatively thin plate. It is mainly used for process control, and selecting of the weld condition. The experimental results were revealed that the shear strength at 16 joules is under standard. In addition, the strength increases with welding energy. However, the expulsion or spatter occurred when using welding energy higher than 40 joules. Consequence in this paper the quality of nugget will be divided into three classes: bad weld quality (NG) due to low bonded strength, good weld quality (OK), and bad weld quality due to spatter occurring (SPT).

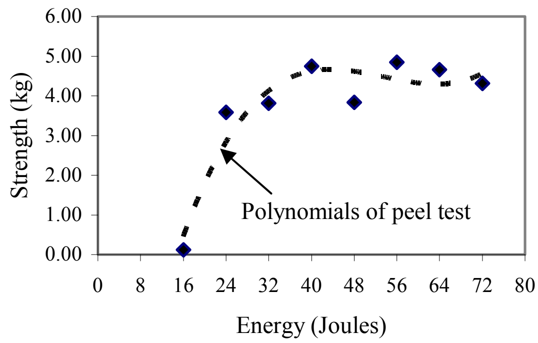

Figure 6: Relationship between weld strength and weld energy

However the results shown are the average value where the number of experiment is 12. Hence, the AE parameters computed from only individual signal may not be able to distinguish the welding quality accurately. To improve the monitoring system, the believe network was utilized to prove the accuracy of the prediction result.

Figure 7 shows diagram of belief network learn from the case file. The five node of the belief network are referred to as weld energy, AE amplitude, AE energy, count and weld nugget quality. In the weld nugget quality node, the first column shows quality of the weld nugget. The second column indicates the probability value learn from the case file.

Next step is to test network using case. The objective of this command is to grade the belief network of real case to see how well prediction of diagnosis of the network to match the actual case. To test manually case ,as shown in figure 8, an interval of each node must be selected. Each combination of an interval of all 4 nodes is configuration of the parent. An example input weld energy 32-40 joule, amplitude 0.4-0.6, count 40-60, AE energy 0.05-0.07 joule respectively. So, the belief network cloud be predicted quality of weld nugget at 88.3% as good quality. The 88.3% is probability which was computed by "Bayes rule" as in equation 2, P(Weld_qua = OK| AE amplitude = 0.4 to 0.6, AE energy = 0.05 to 0.07, weld energy = 32 to 40, AE Count = 40 to 60) = 88.3%. The belief network, illustrated in table 1, was tested by the case file in order to check the error rate. The results showed that the misclassification error is zero.

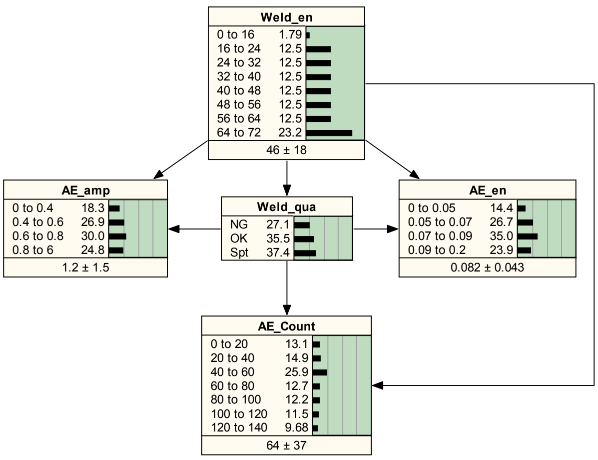

Figure 7: Belief network trained by the training case file.

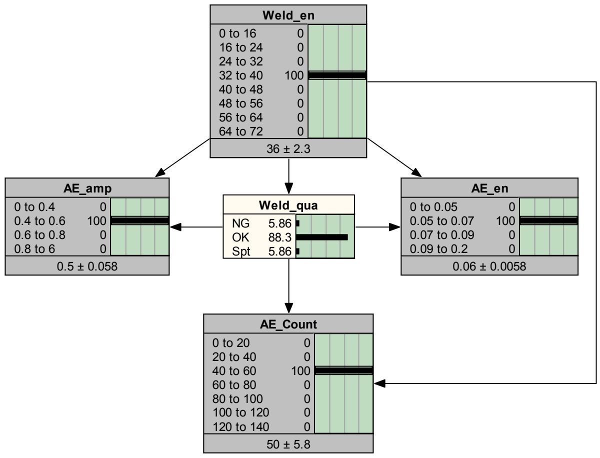

Figure 8: Belief network implemented to predict the probability of weld nugget quality.

Predicted

Weld nugget quality			Actual
NG	OK	Spt	
12	0	0	NG
0	18	0	OK
0	0	18	Spt
Error rate = 0%			

Table 1: shows the error rate by the case file.

4.2 Results of corrosion monitoring

It can be observed that the pitting corrosion emerged at the surface of the specimen at the fifth minute. AE data were captured until the pitting broke through the thickness of the specimen. It was found that the depth of pitting corrosion increase with time. In addition the AE parameter in time domain which are count , amplitude, duration and rise time were correlated with corrosion severity or the depth of pitting. AE signal were also analyzed in frequency domain. AE energy in the frequency range of 50-500 kHz was computed and used as a feature vector in the believe network. The AE energy of class 1 was higher than class 2. It was expected that the passive film was broken at class 1 and repassivation in class 2. Class 3 and 4 were corrosion diffuse stage which showed equivalent AE energy. Class five was the last stage of corrosion that the pitting broke through the thickness of the specimen.

As the above results it was confirmed that the acoustic emission technique was the effectiveness method which can be detected the corrosion of stainless steel 304. However each AE parameter exhibited complex relationship to the corrosion severity. Only one AE parameter can not be used to predict effectively. In order to establish the robustness of the monitoring system, correlated AE parameters will be fused using the believe network. The selected AE parameters are amplitude, rise time, duration time, count and AE energy respectively.

The same procedure as the spot welding monitoring, the data of AE parameters was divided into 2 sets. The first set was run by using odd number. The other set was run by even number. The odd number was used to train the belief network where as the even number was used to test the network and to express the prediction of the error rate. Figure 9 shows diagram of the belief network learn from the case file. The six nodes of the belief network are referred to as amplitude, rise time, duration time, count, AE energy and corrosion level (class). In the corrosion level node, the first column shows the level of corrosion or corrosion severity. The second column indicates the probability value learn from the case file. After that the network was tested how well the prediction of diagnosis of the network to match the actual case. To test manually case, an interval of each node must be selected. Each combination of an interval of all 5 nodes is configuration of the parent. An example input AE energy 15.8-19.9 , amplitude 55.8-56.5 , rise time 34-62 , duration time 128-220 and count 8.3-13 respectively. So, the belief network predicted the corrosion level as class 2 at 100%. This percentage is the probability which was computed by "Bayes rule" as equation 2, P(Corrosion_level= calss 2| AE amplitude = 55.8 to 56.5, raise time = 34 to 62, duration time = 128 to 220, AE Count = 8.3 to 13, AE energy 15.8 to 19.9) = 100%. The diagram of the network is shown in figure 10. The belief network was tested by the training case file in order to check the error rate. Table 2 shows the error rate at 0.34% of the result which was tested by the training case file (odd number) . In table 3, the testing case file (even number) was used to test the network. It can be seen that the misclassification error for the corrosion level is 2.95%.

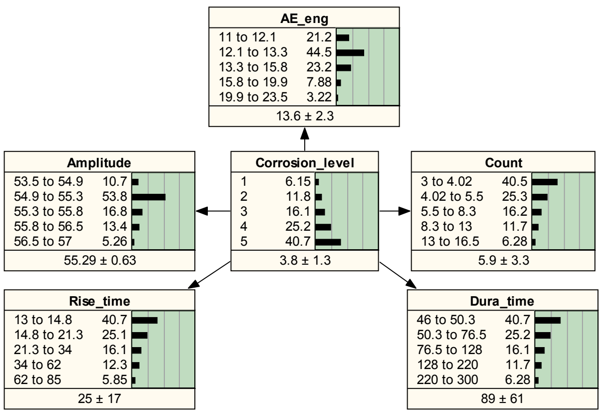

Figure 9: Belief network trained by the training case file.

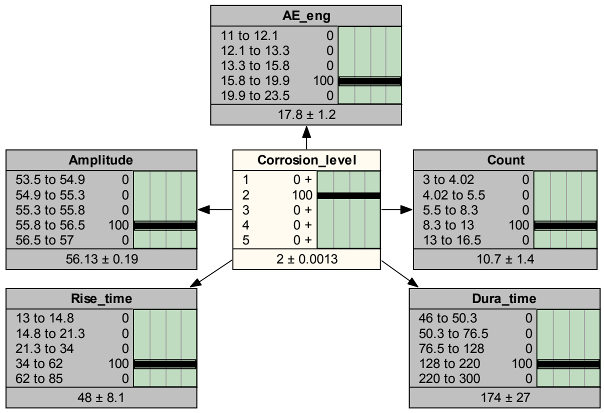

Figure 10: Belief network implemented to predict the probability of corrosion level.

Predicted

Corrosion Level					Actual
1	2	3	4	5	
52	0	0	0	0	1
1	100	0	0	0	2
0	0	138	0	0	3
0	0	1	215	0	4
0	0	0	0	78	5
Error rate = 0.3419%					

Table 2: shows the error rate tested by the training case file of odd data set

Predicted

Corrosion Level					Actual
1	2	3	4	5	
49	8	0	0	0	1
0	107	4	0	0	2
0	0	146	6	0	3
0	0	0	237	0	4
0	0	0	1	86	5
Error rate = 2.95%					

Table 3: shows the error rate tested by the case file of the even data set.

5 CONCLUSIONS

The belief network named Netica base on Baye 's rule was used to fuse AE information. The set of feature vectors of correlated data from the two applications were divided into two sets one to train the network and another one to test it. The out come of prediction showed that the overall success rate of the network in detecting perfection of nugget in micro spot welding and in monitoring of corrosion severity were high with low error rate. The percent of the error rate was 0% for prediction weld nugget quality and 2.95% for corrosion severity respectively.

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